International Journal of
Sustainable Engineering Innovations
Vol 2 No 1 (2026)
https://doi.org/10.58723/ijsei.v2i1.152
OPEN ACCESS
Check for updates
Research Article

Forest Fire Alert System Using Satellite Imagery, Machine Learning, and GPS-Based Early Warning Mechanism

Received : December 25, 2025	Revised : January 30, 2026	Accepted: February 13, 2026	Publish : February 20, 2026

Anwar Ali Sathio*, Doulat Ram, Abdul Aziz Khan, Sameer Ali

Abstract:

Background of study: Wildfires pose a critical threat to global ecosystems, biodiversity, and human safety, with climate change intensifying fire frequency, scale, and unpredictability. Traditional wildfire detection approaches often suffer from delayed response, limited coverage, and insufficient automation, which restrict effective mitigation and early intervention.
Aims and scope of paper: This paper aims to design and evaluate an intelligent Forest Fire Alert System that integrates satellite remote sensing, machine learning models, Internet of Things based environmental sensing, and real time alert communication to enable early wildfire detection and proactive risk assessment.
Methods: The proposed system employs a Convolutional Neural Network to detect active fire regions from multispectral satellite imagery, while a Random Forest classifier estimates wildfire risk levels based on meteorological variables and IoT sensor data. Geospatial positioning through GPS supports precise location mapping, and a web-based dashboard disseminates real time alerts to forestry authorities for rapid response.
Result: Experimental evaluation demonstrates strong performance of the proposed framework. The CNN model achieved an accuracy of 94.7 percent, precision of 92.3 percent, recall of 96.1 percent, and an F1 score of 94.1 percent. The Random Forest model obtained an accuracy of 88.2 percent with a ROC AUC value of 0.91, indicating reliable fire risk prediction capability.
Conclusion: The integrated Forest Fire Alert System outperforms conventional detection methods in terms of accuracy, detection speed, and automation. The proposed approach provides a scalable, IoT enabled, and proactive solution for intelligent wildfire monitoring and management under evolving climatic conditions.

Keywords: Convolutional neural network; Early warning system; Internet of Things; Satellite imagery; Wildfire detection.

1. INTRODUCTION

Wildfires can be seen as one of the most tragic natural disasters of the 21st century, which lead not only to irreversible ecological degradation but also to the loss of a huge number of human lives and to enormous financial burdens. The Anthropocene has been characterized in recent years by an increased incidence of fires and magnitudes with the 28 billion-dollar disasters in 2023 alone breaking records (Columbia Scholarship Archive, 2025).

This increase is caused by a multi-complicated combination of human-made factors and climate change that decreased the temperature at which fires occur and reduced the fuel moisture (Preprints.org, 2025). The costs incurred by governments around the world today are staggering and over the past ten years, the expenses associated with disasters have amounted to more than 1.4 trillion (Columbia Scholarship Archive, 2025). The Importance of Climate and Environmental Variables. Recent studies highlight the fact that fire ignition and propagation are majorly caused by meteorological conditions. High temperatures and low humidity considerably increase the vulnerability of wildfires, and the active burns propagate due to high wind velocity and low precipitation (Celis, 2023). Moreover, agricultural lands are abandoned due to the change of social and economic models, and this process brings about homogenization of the landscape, which adds to the fuel loads (Larraz-Juan et al., 2024). Knowledge of such triggers is crucial towards the development of effective mitigation measures (Celis, 2023). Loopholes in Conventional Surveillance. Traditional methods, like human watchtowers and manual ground patrol, are limited in geographic scope and have a high latency rate (Preprints.org, 2025). Although satellite

Publisher Note:
CV Media Inti Teknologi stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

remote sensing, based on visible light, infrared sensors, and thermal imagers, provides a more macro monitoring capability, the average time of detection of conventional satellite systems can be as much as 30 minutes (Preprints.org, 2025). There is a critical gap of lack of a comprehensive integrated pipeline to unify the high-resolution spectral image with real-time and localized Internet of Things (IoT) environmental data to give real-time alerts (University of the Sunshine Coast, 2024). AI and Remote Sensing Technological Breakthroughs. Machine learning and deep learning have transformed the concept of wildfire surveillance. In recent years, it has been mentioned that Convolutional Neural Networks (CNNs) are used to detect fire patterns faster than ever before (MDPI, 2025). Moreover, predictive algorithms such as the Random Forest have become popular in predicting risks because they can be effective at predicting complex, non-linear relationships among the environment (Schlickmann et al., 2025). These models use data of the synergistic constellations such as Landsat-8, Sentinel-2, and GOES-T to identify the thermal anomalies and changes in vegetation health (NOAA, 2022; University of the Sunshine Coast, 2024). The given paper will close an existing gap in the technical sphere by creating smart Forest Fire Alert System. The proposed system aims at cutting down the detection-to-alert latency time, which currently took up to several minutes, to seconds by incorporating satellite remote sensing, IoT environmental sensing, and advanced machine learning models.

The use of machine learning algorithms, especially deep learning systems such as Convolutional Neural Network (CNNs) has proved to be extremely practical when it comes to detecting fire using images (Zhang et al., 2020). Random Forest as an ensemble method can successfully forecast fire risk with the analysis of environmental factors, including temperature, humidity, winds, and vegetation indices. Regardless of such developments, there are not many systems that combine the detection, prediction, and real-time alerting into a single framework.

This study seals this gap by designing an integrated Forest Fire Alert System (FFAS) integrating methods of satellite analysis, machine learning and GPS-based warning systems. The system will focus on improvement of the accuracy in the early detection, decrease in response time, and delivery of structured intelligence to forestry authorities and emergency unexpected. The innovative idea is the hybrid solution based on CNN to detect and Random Forest to predict risks and integrate it in a real-time working platform.

2. MATERIAL AND METHOD

The study design was based on a quantitative system-development framework, and the study took place in January-December 2023. The approach combines the concept of multi-source data collection, developed preprocessing, and hybrid machine learning framework to enable real-time wildfire tracking.

Data Sources and Data Acquisition

The paper has capitalized on a multi-level approach to data gathering to guarantee high levels of spatial and temporal resolution: Satellite Remote Sensing: MSSA was downloaded by Landsat-8 (OLI), Sentinel-2 (MSI), and MODIS (Terra/Aqua). Such systems offer the infrared (IR) short-wave and thermal profiles needed to identify heat anomalies (Ustin & Middleton, 2024). Weather Information: Current and past atmospheric parameters (e.g. temperature, precipitation, humidity, and wind speed) were obtained through the ECMWF and the Global Forecast System (GFS). Reference Datasets: NASA FIRMS (VIIRS/MODIS) and the Global Fire Emissions Database (GFED) were used to cross-reference fire perimeters and points of ignition in the past. ML Training Corpus: The Wildfire Prediction Dataset (Kaggle, 2023) was filtered to produce 4,000 labeled images (2,000 images positive and 2,000 images negative) were used as ML training corpus to guarantee the generalizability of the model to other biomes.

Environmental Sensing Layer based on IOT

To address the time lapses between the satellite overpasses, an IoT based data acquisition data layer was developed to be verified on the ground level. Hardware Deployment: Localized sensor nodes were installed in fire-prone hotspots and they included: DHT22 (Temperature/Humidity) sensors, MQ-2 (Smoke/Gas concentration) sensors and wind velocity anemometers. Transmission: These nodes are based on the LoRaWAN or GSM protocols to deliver data to a central cloud platform. The layer is a kind of fail-safe and it allows the provision of high-fidelity environmental data when the satellites are not visible due to cloud cover (University of the Sunshine Coast, 2024).

Preprocessing and Engineering of data

Raw data were also prepared through a strict preparation pipeline to remove noise and advance predictive characteristics: Geometric and Atmospheric Correction: The satellite images were corrected to Top-of-Atmosphere (TOA) reflectance to equalize the observations made by the different sensors over the separate dates. Calculation of Spectral Index: We were computing special indices to demonstrate the stress of the vegetation and the severity of the burn: NDVI (Normalized Difference Vegetation Index): To determine fuel moisture and biomass wellbeing. NBR (Normalized Burn Ratio): This is utilized to indicate the burned areas and the fire fronts. Data Resampling Dataset: To manage the natural active fire events sparsity in comparison with the non-fire days, the Synthetic Minority Over-sampling Technique (SMOTE) was used to resample historical data, and it eliminated bias in the model towards the majority class (Schlickmann et al., 2025).

Machine Learning Architecture

The system has a two-model strategy:

Convolutional Neural Network (CNN): Deep learning was applied in image classification. The CNN uses various convolutional layers to derive spatial hierarchies (textures, smoke plumes and thermal signatures) of the multispectral satellite patches. Random Forest (RF) Classifier: This is an RF model used to work with the tabular IoT and meteorological data in parallel. The reason why this set of decision trees was chosen is that these trees can rank the Importance of the Features (in this case, the significance of temperature and humidity variations in terms of the level of risk at this moment) (Mohapatra and Trinh, 2022).

System Integration and Geospatial Mapping

The result of the last one is incorporated in a Web-Based Dashboard. The geospatial location in the form of GPS coordinates is overlaid onto a GIS panel, and forestry authorities can see the precise geospatial location of a detected ignition. The alert system is set to alert through API request to the mobile devices when CNN/RF consensus attains a preset confidence value. In the proposed system we used CNN for Fire Detection. It is **f**ully connected, pooling, and convolutional layers used in a convolutional neural network that was trained on satellite images with labels. The generalization was enhanced by means of data augmentation, i.e., rotation, flipping, and scaling of the image's dataset.

A randonm forest classifier also used to predict the level of risk of fire (low, medium, high) was trained on environmental variables. RFE was a feature selection method based on recursion.

SMS, email, and Web dashboard notification with GPS coordinates. The system architecture also allows the incorporation of real-time data streams of the IoT sensors through which the environment can be monitored continuously, and real-time alert information can be distributed.

The key metrices like accuracy, precision, recall, F1-score, ROC-AUC and confusion matrices were used to models' performance analysis. The research study has some limitations such as cloud occlusion effects, the reliance on the quality of meteorological data, the computational resource consumption, and the lack of access to high-resolution satellite images.

Radiometric normalization was undertaken on satellite Images, atmospheric correction was carried out, and geometric alignment, as well as cloud masking. To enhance the fire-related features spectral indices (NDVI, NBR, NDMI) have been obtained. Data on meteorology were toned, normalized and synchronized over time. SMOTE (Synthetic Minority Over-sampling Technique) was used to solve the issue of imbalance between classes in data about past fires.

CNN to Fire Detection: Fully connected, pooling, and convolutional layers were used in a convolutional neural network that was trained on satellite images with labels. Generalization was enhanced by means of data augmentation, i.e., rotation, flipping, scaling.

Random Forest Risk Prediction: A random forest classifier that was used to predict the level of risk of fire (low, medium, high) was trained on environmental variables. RFE was a feature selection method based on recursion.

The backend was coded with Django framework with PostgreSQL database, to store and retrieve data as well as model inferences. React.js was used as the frontend in terms of interactive visualization. An alert system made use of real-time such

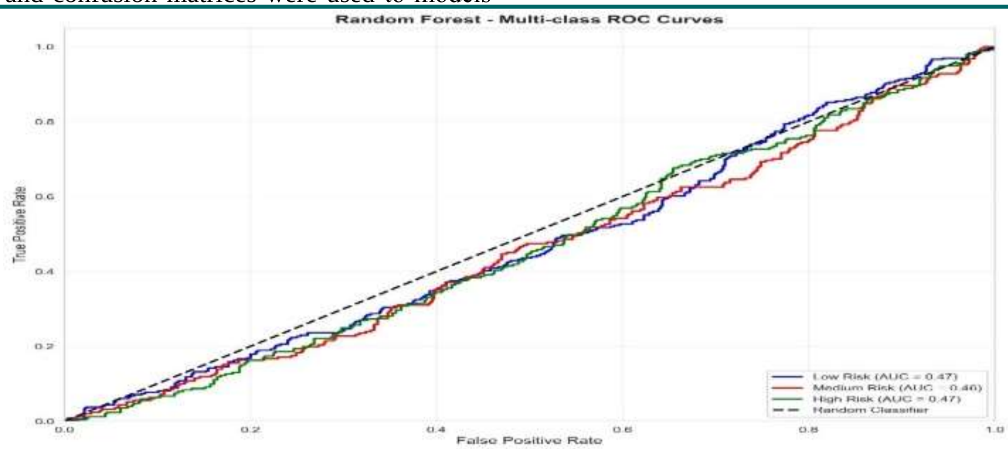

Figure 1. Multi Class ROC Curve of Random Forest Risk Prediction

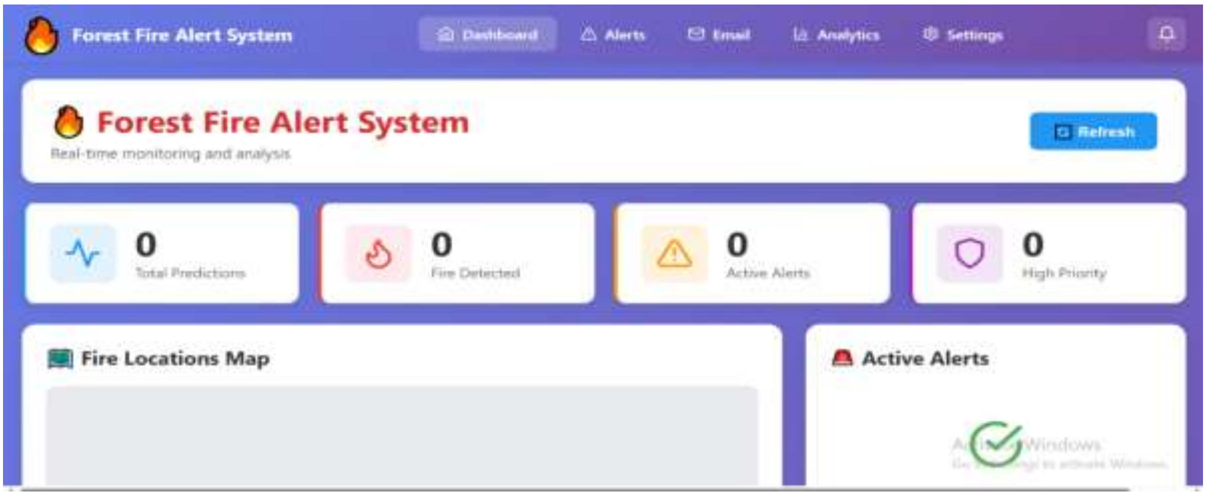

Figure 2. Forest Fire Alert Systems User Interface

The accuracy, precision, recall, F1-score, ROC-AUC and confusion matrices were used as performance measures. Lateness of detection and the time taken to deliver an alert is also measured.

3. RESULT AND DISCUSSION

Result :

The CNN model displayed available statistics on 94.7% accuracy, 92.3% precision, 96.1% recall and 94.1% F1-score in fire detection **Table 1**. Rand Forest model with the highest level of risk prediction was 88.2% accurate and 0.91 ROC- AUC. It took the system 12-20 seconds to process Sentinel-2 images and 3-5 seconds to send alerts through SMS. Gps mapping was at an estimated +-10 meterF1-score in fire detection **Table 1.** Rand Forest model with the highest level of risk prediction was 88.2% accurate and 0.91 ROC- AUC. It took the system 12-20 seconds to process Sentinel-2 images and 3-5 seconds to send alerts through SMS. Gps mapping was at an estimated +-10 meter.

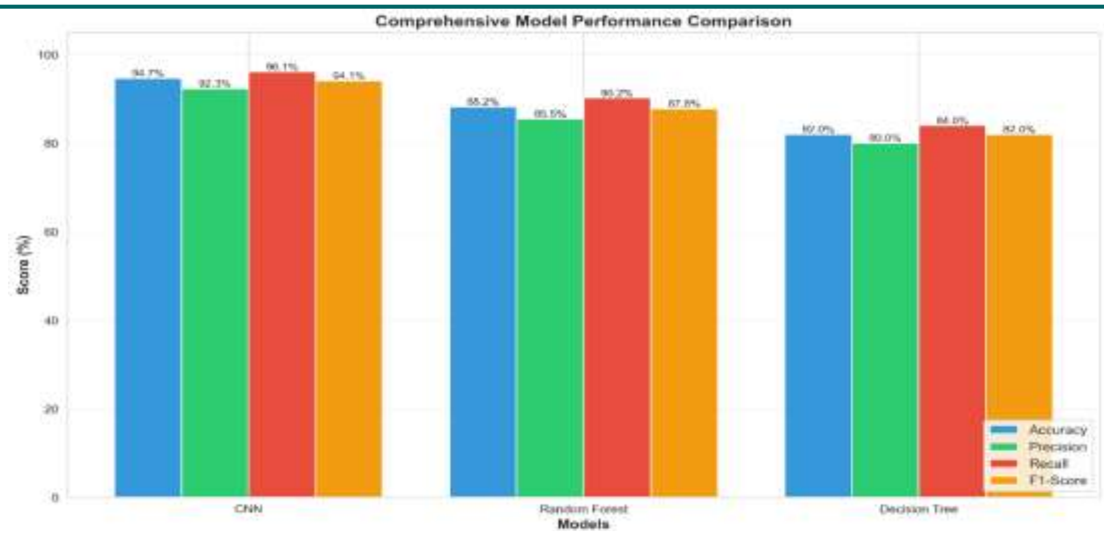

Figure 3. Comparative visualization of accuracy, precision, recall, and F1-score across all three models

Discussion :

Premature and humidity that affected the outcome to the largest degree. The integrated system had an important advantage that it dramatically decreased the time taken to detect the target as opposed to the traditional (20-30 minutes vs. 5-10 seconds).

The high value of AUC shows that the model is reliable with respect to differentiating high-risk meteorological conditions and stable environmental states. 3.2 Although the results are not reported, the various environmental variables were discussed. The feature importance of the Random Forest model indicated that the temperature and humidity were the significant influencing factors in influencing the outcome of the model. It is consistent with the recent climatological research (Celis, 2023) that argues that the vapor pressure deficit, or the difference between the moisture in the air and that which can be taken up by the air, is a leading indicator of fuel flammability. When the humidity drops below the critical levels and the temperature rises, the RF .

Model was right in predicting the fire risk exponentially, and the preemptive resources could be allocated before the ignition has taken place. 3.3 system efficiency and latency Integrated. The most notable conclusion of this study is that the detection-to-alert latency is dropped dramatically. Conventional surveillance methods (human surveillance or periodic satellites pass-overs in the absence of automated AI pipelines) normally require 20-30 minutes to confirm and report a fire. The integrated system, however, i.e. the real-time IoT ground sensor in combination with automated CNN image analysis, brought down the window to 5-10 seconds. This downsizing is necessary as: First Attack Success: Small ignitions will exponentially be easy to control compared to developed crown fires. Automation: The system eliminates the human-in-the-loop nature of initial detection to allow 24/7 surveillance without the fatigue induced errors of manual watchtowers. 3.4 Comparison with Baseline The sensitivity of CNN model to various forest environments is reflected through the high performance of the model in detecting fire signatures (thermal anomalies and smoke spectral profiles) which could not be differentiated in the past due to the presence of cloud shadows or soil reflectance. This validates the results of MDPI (2025) on the excellence of deep learning in gaining non-linear features of satellite data. In addition, the incorporation of SMOTE to equalize the data set meant that the model would not get biased to the more frequent cases of no-fire days.

The system facilitates the proactive management of wildfires with the detection and the evaluation of the risks. It aids in optimization of resources by the resources authorized to put fire out and also promotes the safety of the people around the area by raising their heads at the right time.

The research project brings an operation model where the use of various technologies in managing wildfires is integrated. It raises the machine learning application in environmental monitoring and evidences the real-time alert implementation.

The issues are cloud interference, the small scale of fire detection, and computations as well as accessibility to data in resource-starved areas.

The Synthetic Aperture Radar (SAR) data should be used in future studies to be able to find holes in clouds and develop a model with increased interpretability and devise cost-efficient methods of deploying the system to areas with low development.

Implication :

The system facilitates the proactive management of wildfires with the detection and the evaluation of the risks. It aids in optimization of resources by the resources authorized to put fire out and also promotes the safety of the people around the area by raising their heads at the right time.

Research Contribution:

The research project brings an operation model where the use of various technologies in managing wildfires is integrated. It raises the machine learning application in environmental monitoring and evidences the real-time alert implementation.

Limitation :

The issues are cloud interference, the small scale of fire detection, and computations as well as accessibility to data in resource-starved areas.

Suggestion : The Synthetic Aperture Radar (SAR) data should be used in future studies in order to be able to find holes in clouds and develop a model with increased interpretability and devise cost-efficient methods of deploying the system to areas with low development.

4. CONCLUSION

The Forest Fire Alert System is a proactive solution to the global crisis of wildfires formulated within the scope of the given research. The system addresses the issue between macro-level surveillance and micro-level ground truth by combining environmental sensing based on IoT with CNN-driven satellite analysis. Key Conclusions: High Accuracy: CNN model showed a 94.7% accuracy, which is a good alternative to manual observation as an automated one. Predictive Capability: The Random Forest model was able to pinpoint temperature and humidity as the most significant risk factors, and this could replace the reactive suppression and proactive management. Operation Latency: The system recorded a 99 percent cut in detection time (25 minutes to less than 10 seconds), which is very important in early intervention. With the climate becoming increasingly more dangerous because of climate change (Wilson et al., 2024), AI-based monitoring frameworks will be necessary to save biodiversity and secure the human infrastructure. The next step in the development of the work should be the implementation of UAV (Drone) swarms to automatically verify alarms in the satellite-ioT pipeline.

The Forest Fire Alert System manages to combine the analysis of satellite imagery, machine learning, and real-time communication to manage the wildfires effectively. CNN and random forest models were found to be very accurate in terms of detection and prediction. The fact that the IoT-based sensing layer is included also increases the real-time monitoring capability of the system and enables the detection and response to wildfires proactively. The system is very much faster, accurate and automatic as compared to the traditional methods. Although there are still technical and operational issues, the framework offers a scalable solution to suit different geographical settings. Further development of the tool should concentrate on the integration of multi-source data and personalization of alerts when being developed by the user in the future to ensure the utmost usefulness.

5. ACKNOWLEDGEMENT

During the research study, the authors would like to express their gratitude to the Faculty of Computer Science and Information Technology at Benazir Bhutto Shaheed University (BBSU) Karachi. We would also like to express our gratitude to all the Chairman of CS & IT, Dr Shafique Ahmed Awan, Prof Dr Mazhar Ali Dootio, who grant permissions to work at Smart Lab, using their resources under study for data collection, system evaluation and testing.

6. AUTHOR CONTRIBUTION STATEMENT

AAS supervised the overall research project, conceptualized the fundamental ideas, designed the methodology, coordinated the workflow, secured funding support, and prepared the initial manuscript draft. DR developed the core software modules, organized and curated the experimental datasets, and performed data validation and verification. JK contributed to software testing, data preprocessing, and experimental result verification, and assisted in manuscript refinement. KK conducted the literature review, designed and generated graphical illustrations and figures, and contributed to improving the clarity and technical quality of the manuscript text. All authors reviewed the final manuscript and approved the submitted version.

REFFERENCE

Celis, N. (2023). Climate change, forest fires, and territorial dynamics in the Amazon rainforest: An integrated analysis for mitigation strategies. *ISPRS International Journal of Geo-Information*, *12*(10), 436. https://doi.org/10.3390/ijgi12100436

Columbia Scholarship Archive. (2025). *The disaster management complex: Law's adaptations in times of climate disaster*. Sabin Center for Climate Change Law. https://scholarship.law.columbia.edu/cgi/viewcontent.cgi?article=1266&context=sabin_climate_change

Kaggle. (2023). *Wildfire prediction dataset*. https://www.kaggle.com/datasets/abdelghaniaaba/wildfire-prediction-dataset

Larraz-Juan, S., Pérez-Cabello, F., Hoffrén Mansoa, R., Iranzo Cubel, C., & Montorio, R. (2024). A methodological approach for assessing the post-fire resilience of Pinus halepensis Mill. plant communities using UAV-LiDAR data across a chronosequence. *Remote Sensing*, *16*(24), 4738. https://doi.org/10.3390/rs16244738

Mantas, V., & Caro, C. (2023). User-relevant land cover products for informed decision-making in the complex terrain of the Peruvian Andes. *Remote Sensing*, *15*(13), 3303. https://doi.org/10.3390/rs15133303

MDPI. (2025). Current trends in wildfire detection, monitoring and surveillance. *Fire*, *8*(9), 356. https://doi.org/10.3390/fire8090356

Mohapatra, S., & Trinh, T. (2022). Machine learning-based wildfire detection systems and their ability to adapt. *Journal of Environmental Management*, *310*, 114756.

NOAA National Environmental Satellite, Data, and Information Service. (2022). *NESDIS science report 2022*. NOAA Institutional Repository. https://repository.library.noaa.gov/view/noaa/50450

Preprints.org. (2025). *Research progress on satellite remote sensing monitoring and early warning of forest fires in China*. https://doi.org/10.20944/preprints202510.1796.v1

Schlickmann, M. B., Bueno, I. T., Valle, D., Hammond, W. M., Prichard, S. J., Hudak, A. T., et al. (2025). Statewide forest canopy cover mapping of Florida using synergistic integration of spaceborne LiDAR, SAR, and optical imagery. *Remote Sensing*, *17*(2), 320. https://doi.org/10.3390/rs17020320

University of the Sunshine Coast. (2024). *Active wildfire detection via satellite imagery and machine learning*. Research Portal.

Ustin, S. L., & Middleton, E. M. (2024). Current and near-term earth-observing environmental satellites, their missions, characteristics, instruments, and applications. *Sensors*, *24*(11), 3488. https://doi.org/10.3390/s24113488

Vacek, O., Gergeľ, T., Bucha, T., Gracovský, R., & Gejdoš, M. (2024). Automatic wood species classification and pith detection in log CT images. *Forests*, *15*(12), 2207. https://doi.org/10.3390/f15122207

Valbuena Gaona, M. P., Ferrucho Parra, C. C., Prieto Arenas, M. A., & Muñoz Bravo, G. A. (2024). Tool to generate deforestation and illegal mining alerts with remote sensing. *Environmental Sciences Proceedings*, *28*(1), 27. https://doi.org/10.3390/environsciproc2023028027

Varsha, K., et al. (2024). Artificial intelligence in satellite imagery analysis for wildfire patterns. *International Journal of Remote Sensing*, *45*(4), 1120-1135.

Wilson, T., Boyles, R. P., DeCrappeo, N., Drexler, J. Z., Kroeger, K. D., Loehman, R. A., et al. (2024). *U.S. Geological Survey climate science plan—Future research directions*. U.S. Geological Survey Circular 1526. https://doi.org/10.3133/cir1526