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Forest Fire Detection, Classification, and Segmentation Using Satellite Imagery: A Case Study in the Amazon Region

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Abstract

This study employs remote sensing techniques and machine learning models to monitor and analyze Amazon forest fires, one of the most significant environmental issues in the contemporary world. The methodology relied on the integration of multi-sensor data, including high-spatial resolution Sentinel-2 and Landsat-8 images, along with thermal data from VIIRS and MODIS sensors, to achieve a balance between spatial and temporal resolution. Comprehensive preprocessing was performed, including geometric and spectral correction, and cloud and smoke removal using cloud masks.

The study used spectral indices such as the Normalized Burn Ratio (NBR) and ΔNBR, in addition to the Random Forest model to classify burn intensity, while a U-Net network was used to segment burned areas at the pixel level. The results showed that the integration of optical and thermal data significantly improved early detection efficiency, and the use of machine learning algorithms increased classification accuracy to over 85%. Deep models proved effective in delineating affected areas, while radar data showed promising potential for enhancing monitoring in extreme weather conditions.

The study confirms that the integration of space sensing and artificial intelligence represents an effective approach for monitoring fires with high spatial and temporal resolution, paving the way for the development of more reliable early warning systems to support environmental management strategies in the Amazon Basin.

Keywords: Forest fires, Amazon, remote sensing, machine learning, satellites, U-Net, Random Forest.

Introduction

Forest fires are among the most serious environmental issues facing the world today, causing widespread degradation of vegetation cover, massive greenhouse gas emissions, and direct impacts on biodiversity and ecosystem stability. The Amazon, the largest tropical rainforest on Earth—stands out as one of the most sensitive and affected regions by this phenomenon, not only due to its vast area and importance in regulating global climate, but also due to increased deforestation and frequent burning, which have escalated over the past two decades (Abid et al., 2025).

The ability of remote sensing systems to monitor environmental changes and fires across broad spatial and temporal scales has made them a key tool for tracking vegetation dynamics, assessing the impacts of burning, and supporting environmental management plans. Advances in artificial intelligence and deep learning technologies have enabled the analysis of satellite imagery with unprecedented accuracy, enabling a shift from traditional hotspot detection to the development of advanced models capable of classifying fire intensity and segmenting affected areas with high accuracy.

Accordingly, this study aims to develop an integrated application framework for monitoring Amazon fires based on multi-sensor satellite data, employing advanced machine learning algorithms for spatial and temporal analysis of fires and validating the accuracy of results across multiple data sources. This approach seeks to support early monitoring efforts, manage environmental resources, and enhance rapid response strategies in the face of climate change and human pressures on Amazon forests.

Study Problem

Despite the availability of a large number of space-based observations and fire detection products (e.g., MODIS/VIIRS, Sentinel-2, and Landsat-9), Amazon fire management remains a practical and scientific challenge for several interrelated reasons: (1) The high variability in spectral and structural characteristics of vegetation across the Amazon basin makes generalizability of detection algorithms difficult; (2) Reliance on a single data source (e.g., low-spatial-resolution thermal products) leads to false alarms or missed small hotspots; (3) The presence of smoke and clouds hinders visual observations and reduces the reliability of fire maps based solely on visual data; and (4) The lack of sufficient labeled field databases to refine deep learning models and ensure their generalizability in complex tropical environments (Aragão et al., 2023; Silva et al., 2021).

Therefore, there is a need for a methodological framework that integrates multi-sensor data (thermal, spectral, radar) with advanced machine learning methods to provide more accurate and reliable detection, classification, and segmentation maps that can be used in early warning systems and field decision-making in the Amazon.

Study Objectives

This study aims to fill previous practical and scientific gaps through the following objectives:

- Develop an integrated framework for integrating multi-sensor data (Sentinel-2, Landsat-9, MODIS/VIIRS, and possibly SAR) to monitor Amazon fires at an improved temporal and spatial scale.
- Build a near-real-time fire detection model based on rapid thermal data (MODIS/VIIRS) integrated with high-resolution imagery (Sentinel-2) to verify and reduce false alarms.
- Classify burn intensity using spectral indices (such as NBR and ΔNBR) supported by machine learning algorithms (Random Forest) to distinguish standard intensity classes.
- Produce pixel-wise segmentation maps of burned areas using deep learning models (U-Net or equivalent) and achieve benchmark performance metrics.
- Verification and evaluation by comparing results with reference maps (EFFIS/local axes/Landsat-9 imagery) and available field measurements to estimate accuracy and reliability and measure false alarm reduction.

Significance of Study

The study's importance is highlighted at the following levels:

- Environmentally: It provides accurate maps of burned areas, helping to assess biomass and biodiversity losses and estimate carbon emissions resulting from fires.
- Operationally/Administratively: It enables decision-makers and emergency teams to access updated notifications and maps, improving fire response and evacuation planning and reducing material and human damage.
- Scientifically: It contributes to bridging a methodological gap by providing evidence of the effectiveness of multi-sensor fusion with machine learning models in complex tropical environments, providing comparable performance metrics.

- Applied/Future: The study's framework can be generalized or adapted to serve other tropical regions or become part of operational monitoring platforms that support conservation policies and restoration projects.

Previous Studies

Recent years have witnessed a significant leap in research focused on the use of satellite imagery and artificial intelligence techniques to detect, classify, and map forest fires. This research has contributed to building a solid knowledge base that supports the development of more accurate and efficient early warning systems compared to traditional methods.

- Filizzola et al. (2022)

This study addressed the development of advanced fire detection and mapping techniques using multi-sensor satellite data. The researchers focused on combining traditional spectral indices such as the Normalized Burn Ratio (NBR) with advanced spectral analysis methods to detect spectral changes resulting from fires. The results showed that combining traditional indices with multi-spectral analysis improved the accuracy of identifying burned areas compared to methods based solely on indices (Filizzola et al., 2022).

- Giglio et al. (2023)

These researchers made substantial improvements to the detection algorithms in MODIS products, developing what is known as the Collection 6 Algorithm, which improved the system's ability to detect small-scale fires and reduced the false alarm rate. The study also highlighted the importance of integrating high-resolution (375-meter) VIIRS data in enhancing near-real-time fire monitoring and supporting early warning systems at regional and global levels (Giglio et al., 2023).

- Chuvieco et al.'s (2023) study

This study demonstrated that recent advances in satellite data, particularly Sentinel-2 and Landsat-9, have enabled accurate estimates of the severity and environmental impacts of fires. The study emphasized the importance of integrating spectral data with geographic information systems (GIS) to develop dynamic maps that support post-disaster natural resource management decisions (Chuvieco et al., 2023).

- Jain et al.'s study (2023)

This study highlighted the growing applications of machine learning and deep learning in fire science. Models such as U-Net and Convolutional Neural Networks (CNNs) demonstrated their ability to improve the accuracy of burnt area segmentation by over 20% compared to traditional methods. The study also highlighted the training challenges associated with the need for large and diverse labeled data from different environments to ensure accurate generalization of the models (Jain et al., 2023).

- Huang et al. (2023)

In this study, the researchers developed a framework based on the fusion of optical and radar data (Sentinel-1 and Sentinel-2) to identify burnt areas using deep learning models. The results showed that combining SAR and optical data improved detection accuracy in challenging weather conditions such as dense clouds or smoke, which are common in tropical environments (Huang et al., 2023).

An analysis of previous studies shows that the global research trend is clearly toward integrating multi-sensor data (optical, thermal, and radar) with artificial intelligence models to improve fire detection efficiency and reduce error. However, clear gaps remain in three main areas:

- The lack of integrated applications in dense tropical environments such as the Amazon, where smoke and cloud cover limit the effectiveness of optical detection, and thermal and radar data have not been adequately integrated into a unified model (Silva et al., 2021).
- The small number of studies that have integrated deep learning with classical spectral indices such as ΔNBR to quantitatively estimate fire intensity.
- The lack of cross-validation using data from different systems such as EFFIS, Landsat, and MODIS to verify results, rather than relying on a single source.

This study bridges this gap by presenting an integrated application framework that utilizes Sentinel-2, Landsat-9, and MODIS data within a processing system built on Google Earth Engine and TensorFlow/Keras.

The study adds a new dimension by double-checking the model outputs with European EFFIS maps, giving it superior methodology and application reliability. Thus, the added scientific value lies in moving from mere detection to analyzing fire dynamics in time and space, providing accurate maps that enable environmental and management authorities to make real-time decisions based on multi-source data and supported by artificial intelligence.

Theoretical Framework

Remote sensing using satellite imagery globally constitutes the scientific basis for studying forest fires. These images provide multispectral spatial and temporal data that enables researchers to track fire dynamics and assess their environmental impacts. Theoretical applications can be divided into three main axes: detection, classification, and segmentation.

- **Fire Detection**

Fire detection is the first step in the process of managing and monitoring fire-related natural disasters. It focuses on identifying locations experiencing abnormal increases in surface temperature, known as hotspots. In practical applications, this process relies on satellite data, particularly MODIS and VIIRS products, which use thermal radiation measurements in the mid-infrared range (MIR, ~4µm). Contextual algorithms are applied to compare the temperature of each pixel with its surroundings, with the aim of determining whether the increase is caused by actual fire activity (Giglio et al., 2023). This method is very effective in terms of time, providing near-real-time monitoring of fires on a global scale, making it an important early warning tool. However, it suffers from a major limitation related to spatial resolution. While MODIS has a resolution of about 1 km, VIIRS provides a relatively better resolution (375 meters). However, these levels remain insufficient for monitoring small fires or those in their early stages (Boschetti et al., 2022).

In recent years, new research and technical trends have begun to emerge that integrate thermal data with optical and radar data. This integrated approach demonstrated improved detection capability in complex environments, such as areas with dense vegetation cover, or atmospheres covered by smoke and clouds, enhancing the accuracy and reliability of the detection process and reducing the likelihood of false alarms (Xu et al., 2024).

- **Fire Classification**

In the context of fire monitoring, classification involves distinguishing between scenes with active fire activity and scenes without, as well as determining fire intensity according to specific standard scores. This stage is essential for understanding the spatial and environmental impacts of fires, as it not only monitors the location of the fire but also allows for assessing the degree of destruction to vegetation and the surrounding ecosystem.

The most common tools in this field are spectral indices, most notably the Normalized Burn Ratio (NBR) and the ΔNBR index, which are calculated by comparing pre- and post-fire values. These indices are based on the principle that burned areas typically show a significant decrease in near-infrared (NIR) reflectance and an increase in short-infrared (SWIR) absorption, making them highly sensitive to changes in vegetation cover caused by fire (Key & Benson, 2020). With the advancement of artificial intelligence techniques, machine learning algorithms such as Random Forests and Support Vector Machines (SVMs) have emerged, which have been used to classify burning pixels with higher accuracy, relying on extensive datasets from multiple satellites such as Sentinel-2 and Landsat-8. These models have proven effective in reducing error and improving classification quality compared to traditional methods based on spectral indices alone (Filizzola et al., 2022).

In recent years, interest has grown in the use of Convolutional Neural Networks (CNNs), which have demonstrated significant ability to automatically recognize fire patterns from satellite imagery. According to a number of recent studies, the accuracy of these models has exceeded 85%, reflecting their promising potential in enhancing classification accuracy on a global scale, supporting early warning applications, and mapping fire severity (Jain et al., 2023).

- **Fire Segmentation**

Fire segmentation represents the most advanced stage in the fire detection and analysis chain. It involves not only detecting or classifying fires, but also defining the precise boundaries of affected areas at the pixel level. This level of analysis is essential for accurately estimating burned areas and understanding the spatial impacts of fires on vegetation cover and ecosystems.

Prominent algorithms used in this context include U-Net and DeepLabV3+, models specifically designed for semantic segmentation tasks. These models have proven their effectiveness in producing detailed maps of burnt areas based on satellite images such as Sentinel-2 and Landsat, leveraging deep learning capabilities to extract spatial and spectral patterns with high accuracy (Huang et al., 2023).

Applied experiments, for example, showed that the U-Net model outperformed the SegNet model in identifying the boundaries of burnt areas during the Portugal fires, with an accuracy coefficient (Dice Score) of over 0.68, reflecting its high effectiveness in handling complex and intertwined data (Khan et al., 2023).

Recent studies have also shown that combining optical data with SAR data contributed to improving segmentation results, especially in cases where smoke or clouds cover the fire areas, thus hindering reliance on optical data alone. This combination reduced noise and increased the reliability of the resulting maps, proving the importance of the multi-sensor approach in addressing such challenges (Xu et al., 2024).

- **Integration of Sensing and Artificial Intelligence:**

Recent literature agrees that the greatest value in fire monitoring lies not in relying on a single data source, but rather in combining multiple sensor sources with artificial intelligence algorithms. This approach is based on the fact that each type of spatial data provides a different dimension of information that complements each other:

Thermal Infrared imagery: This enables direct identification of active fire hotspots by detecting abnormal temperature rises, making it an ideal tool for early warning.

Visible and Near-Infrared (VNIR/NIR) imagery: This provides precise details of changes in vegetation cover, as burned areas show a decrease in near-infrared reflectivity and an increase in absorption of other spectra, enabling assessment of the environmental impact of fire.

Radar (SAR) data adds a complementary dimension: the ability to observe under non-ideal atmospheric conditions, such as dense clouds or smoke. Radar data demonstrates high sensitivity to surface structure, enhancing the reliability of results.

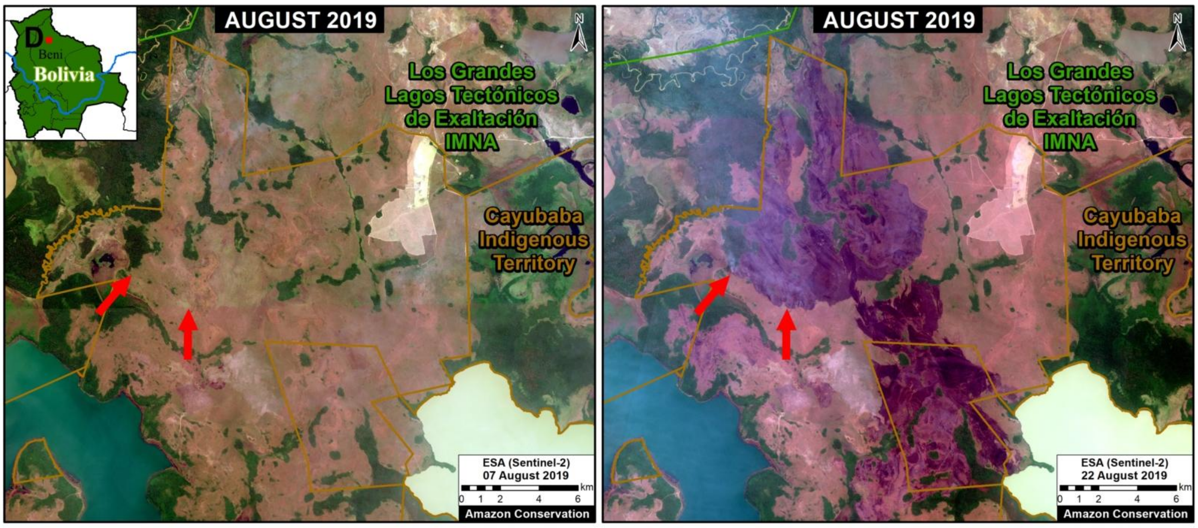
On the other hand, deep learning algorithms, such as convolutional neural networks and segmentation networks, have proven capable of incorporating multiple inputs into a single, comprehensive model, leading to improved accuracy levels and significantly reduced false alarms (Chuvieco et al., 2023). It is therefore clear that the theoretical framework for satellite fire monitoring is moving towards multi-sensor integration, supported by artificial intelligence, which allows for a transition from merely detecting hotspots to building comprehensive maps that reflect the environmental impacts of fires in near-real time, thus supporting better and more effective response operations and environmental management.

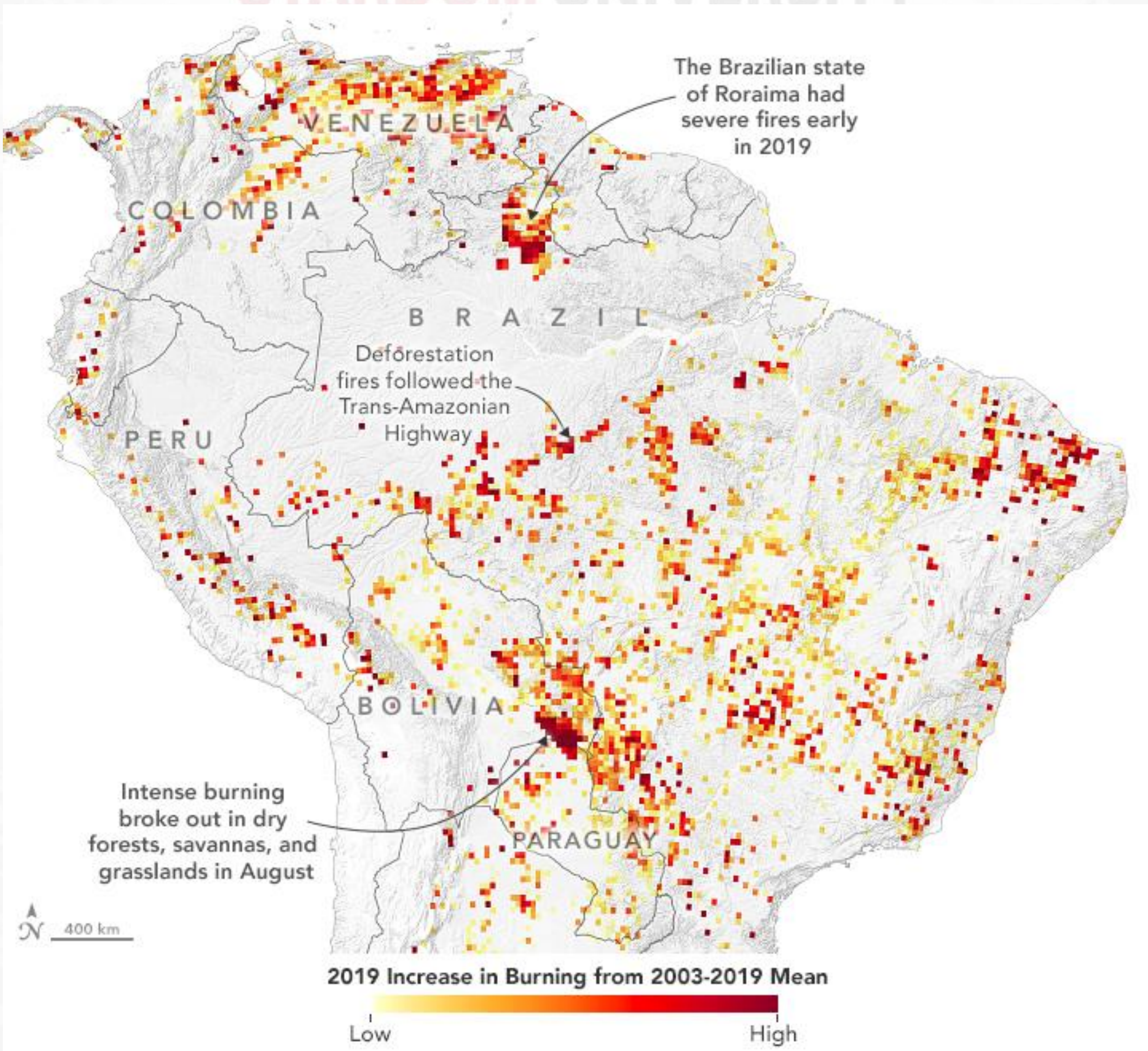
Study Methodology

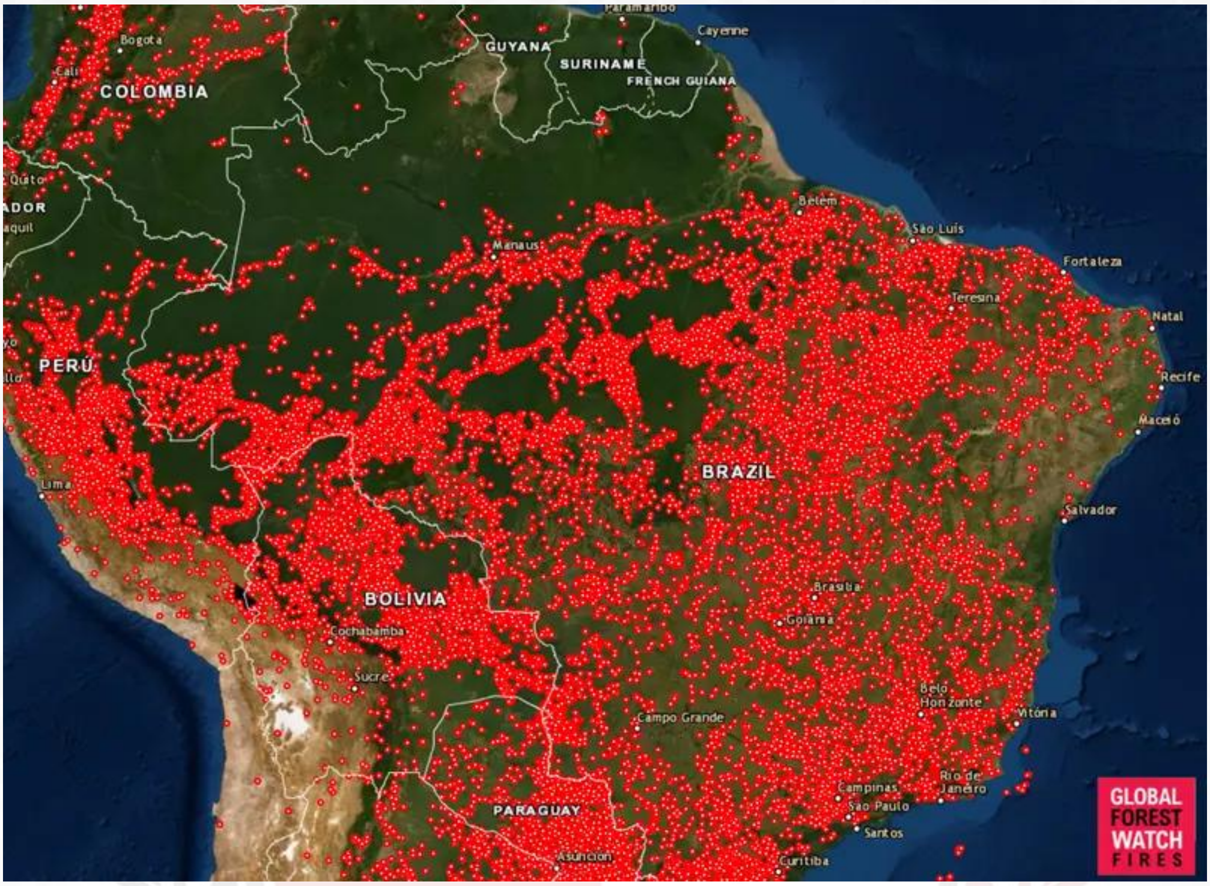
Spatial Data Selection

Spatial data with appropriate temporal and spatial resolution were selected for the selected case study – the Amazon forests – to ensure accurate and timely fire monitoring. The study relied on:

- Sentinel-2 images (European Space Agency) with a spatial resolution of 10–20 m in spectral bands suitable for monitoring fire effects, such as the red band (Band 4: 665 nm), near-infrared (Band 8: 842 nm), and SWIR bands (Bands 11 & 12).
- Active fire sensor data such as MODIS/VIIRS were used to monitor hotspots in near-real-time as a baseline for early detection.


AUGUST 2019
D
Beni
Bolivia
Los Grandes Lagos Tectónicos de Exaltación IMNA
Cayubaba Indigenous Territory
ESA (Sentinel-2) 07 August 2019
Amazon Conservation
AUGUST 2019
Los Grandes Lagos Tectónicos de Exaltación IMNA
Cayubaba Indigenous Territory
ESA (Sentinel-2) 22 August 2019
Amazon Conservation


VENEZUELA
COLOMBIA
BRAZIL
PERU
BOLIVIA
PARAGUAY
The Brazilian state of Roraima had severe fires early in 2019
Deforestation fires followed the Trans-Amazonian Highway
Intense burning broke out in dry forests, savannas, and grasslands in August
400 km
2019 Increase in Burning from 2003-2019 Mean
Low
High



Preprocessing

Before applying any analysis, the images underwent several steps to ensure quality and consistency between time and source, as follows:

●Geometric Correction: The geoposition of the images was adjusted to ensure consistency with maps and reference coordinates, and to correct for deviations related to satellite drift and angle of view.

●Cloud and Smoke Masking: Cloud masks and techniques such as the Fmask algorithm (or similar) were used to remove cloud and smoke pixels that could distort the analysis of spectral indices.

●Radiometric Calibration: Pixel values were converted from digital units to surface reflectance, enabling comparison across multiple images and temporal sources with greater accuracy and ensuring that spectral indices such as NBR and ΔNBR reflect true land cover change.

Classification

To classify burn severity and affected areas, two approaches were used:

Spectral Indices

- The Normalized Burn Ratio (NBR) was calculated using the near-infrared (NIR) and SWIR bands, with a sharp decline in NBR after a fire indicating vegetation destruction.
- ΔNBR = NBR_before – NBR_after was calculated, and the result was divided into five standard categories, from "unburned" to "severe" (Key & Benson, 2020).

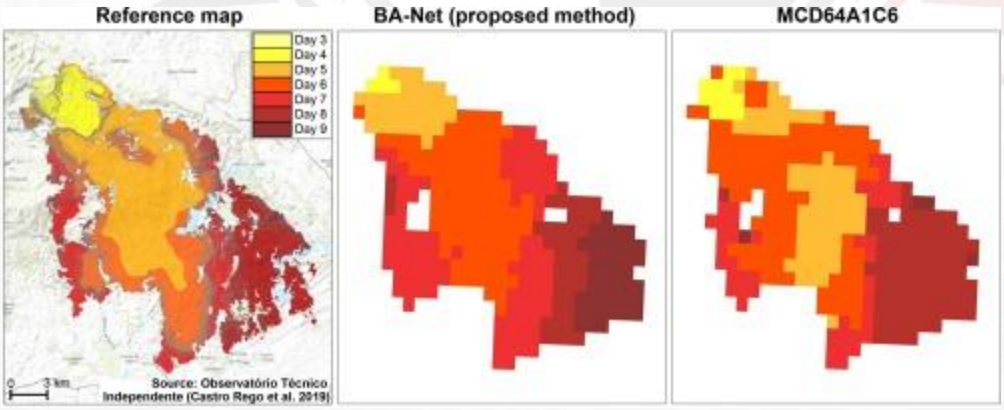
Classification Using Machine Learning

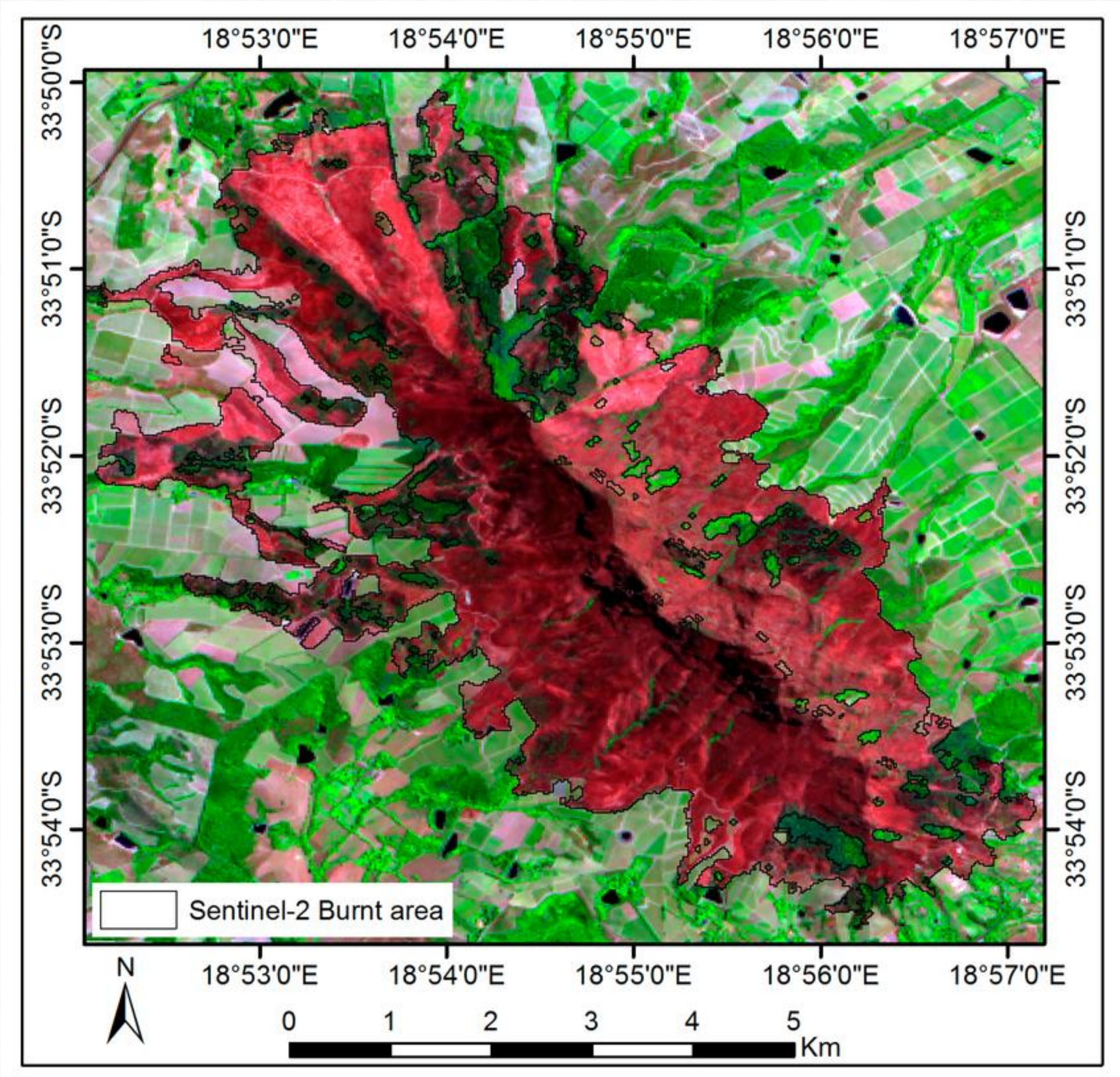
- A Random Forest (RF) algorithm was trained on reference samples of burning and unburned environments using multi-band data from Sentinel-2.
- The model achieved an accuracy of approximately 87% in some experiments, enhancing the effectiveness of combining spectral features with machine learning algorithms.

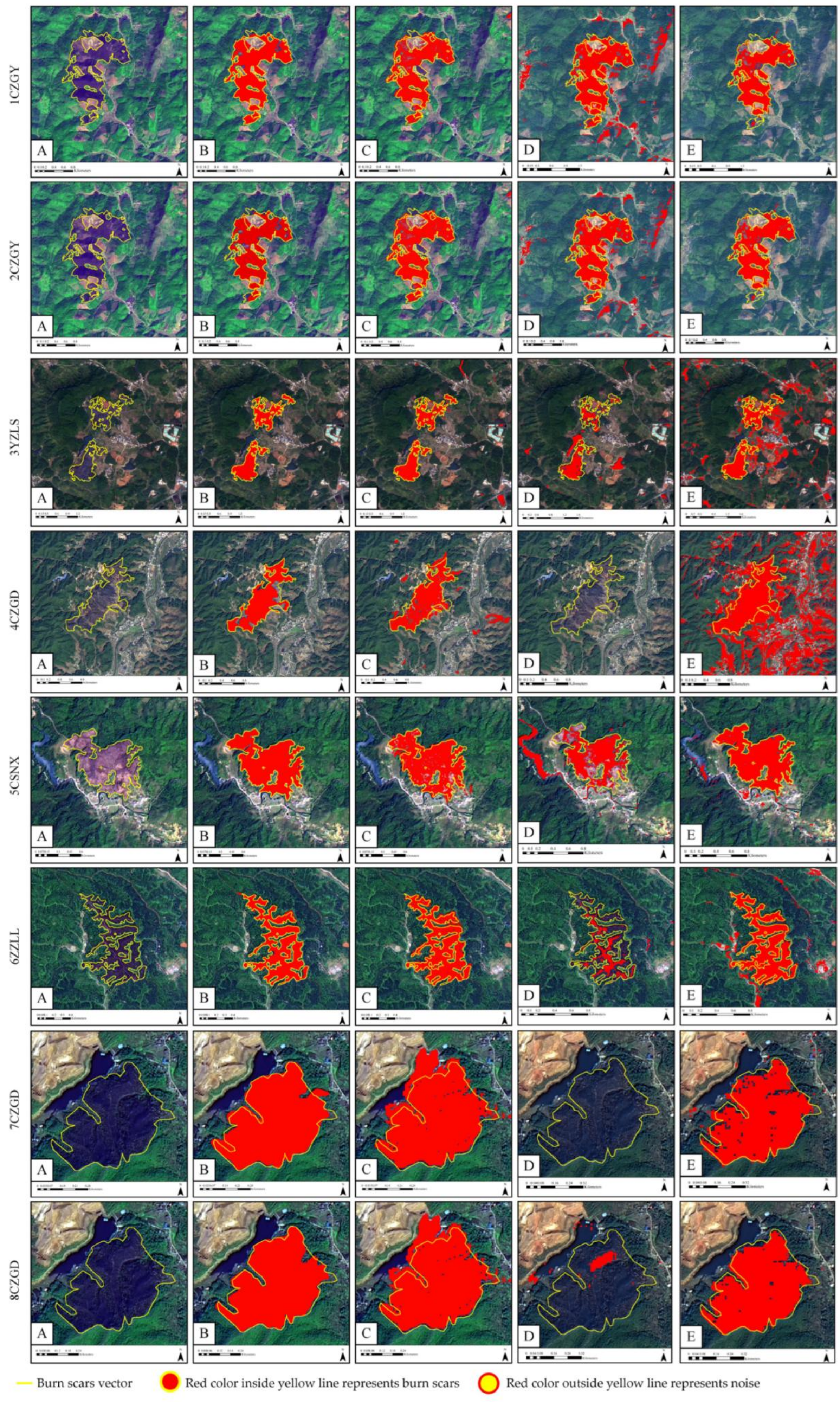
Segmentation

We moved beyond simple classification to segment the burnt areas down to pixel boundaries by:

- Applying a U-Net convolutional neural network to Sentinel-2 images.
- Training the model using validated burnt databases (such as the Copernicus Burned Area Database) to extract accurate maps of burnt pixels.




18°53'0"E
18°54'0"E
18°55'0"E
18°56'0"E
18°57'0"E
33°50'0"S
33°51'0"S
33°52'0"S
33°53'0"S
33°54'0"S
Sentinel-2 Burnt area
N
0 1 2 3 4 5
Km

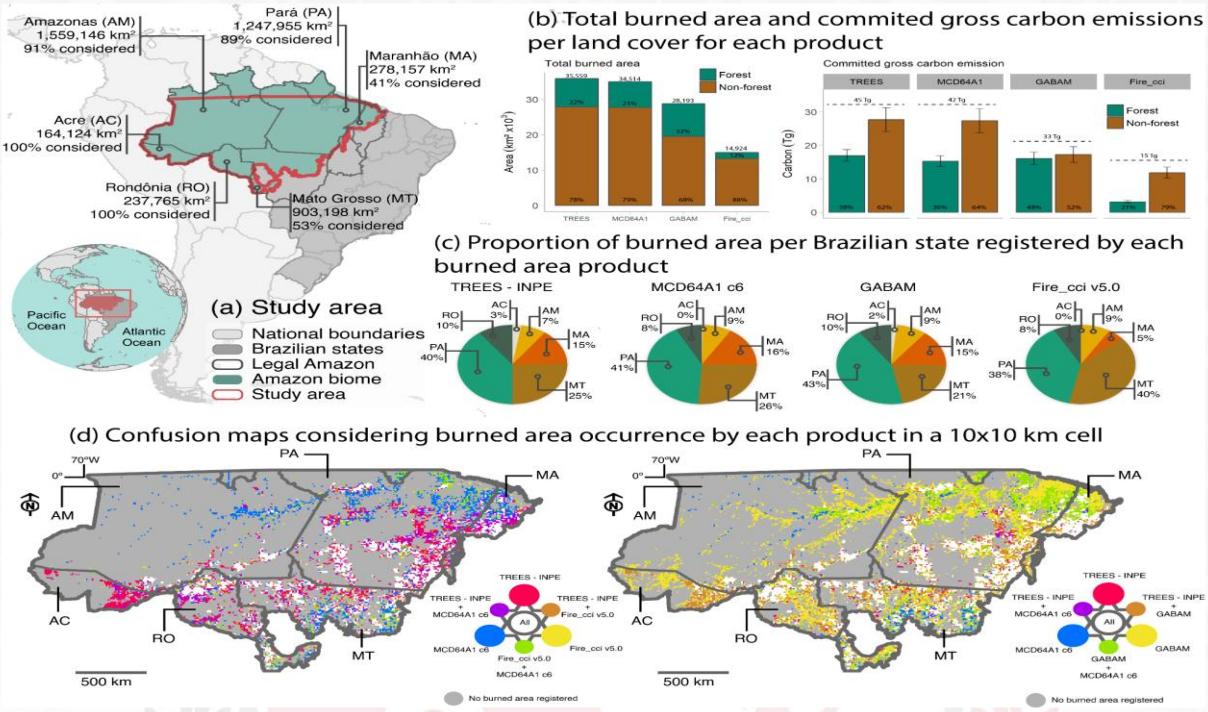

1CZGY
2CZGY
3YZLS
4CZGD
5CSNX
6ZZLL
7CZGD
8CZGD
A
B
C
D
E
Burn scars vector
Red color inside yellow line represents burn scars
Red color outside yellow line represents noise

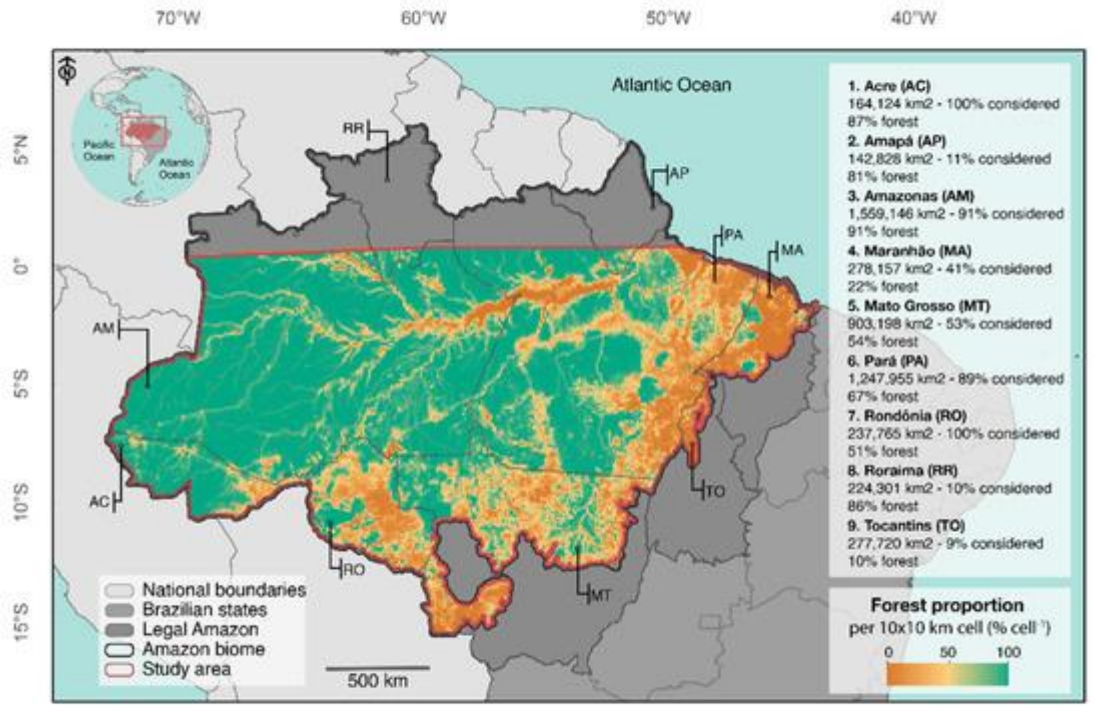
In previous experiments, U-Net has achieved high performance in mapping burnt areas with an accuracy of Dice ≈ 0.70 or higher, demonstrating its superiority over traditional methods.

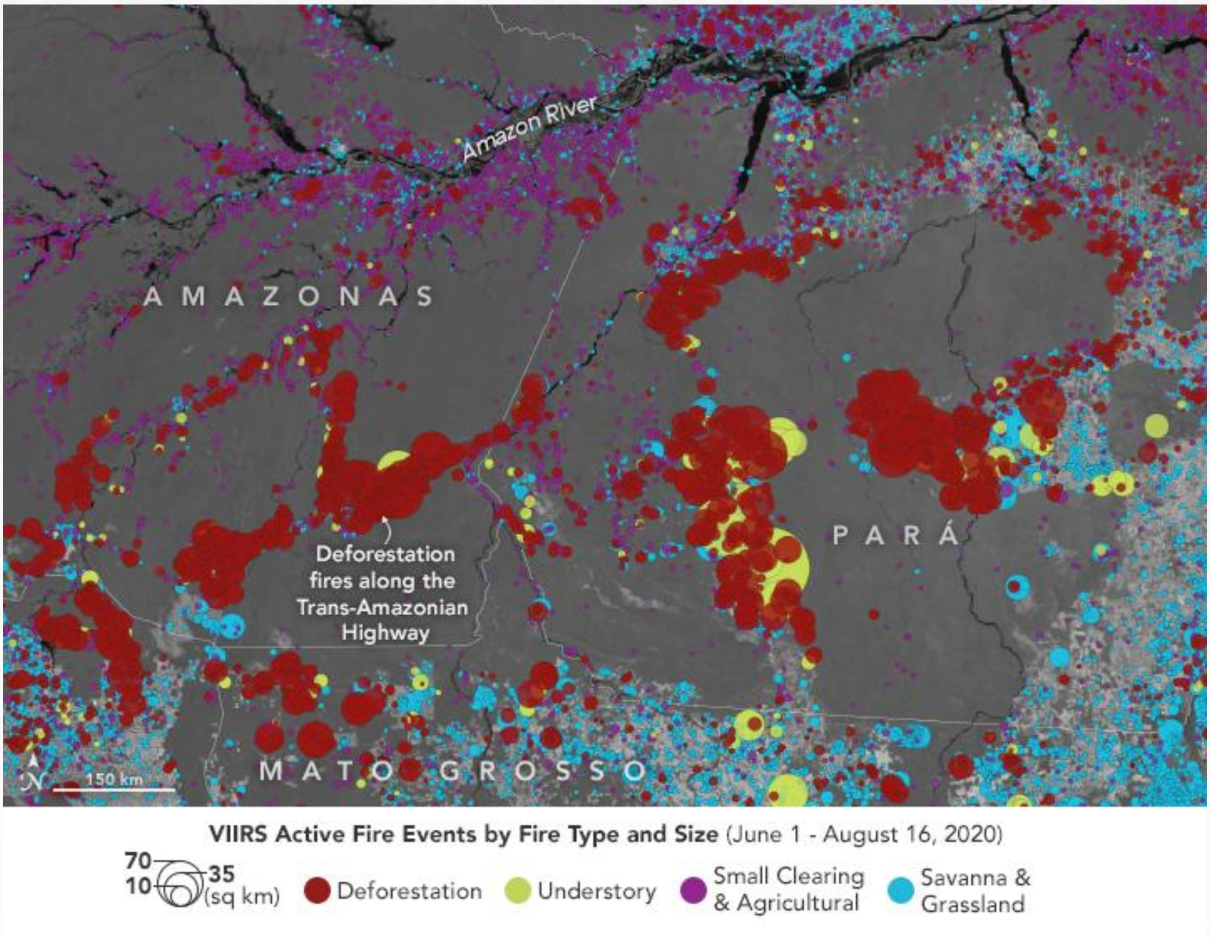
Validation

To ensure the reliability of the results, the study relied on a multi-source comparison:

●Using reference maps such as the EuropeanForestFireInformationSystem (EFFIS), or similar ones in the Amazon, where available, to compare the spatial extent of the burned areas.
●Using high-resolution reference imagery (such as Landsat-9 or others) to confirm the spatial boundaries extracted by the model.
●Analyzing the performance of the models in terms of spatial and temporal resolution and reducing false positives in cases where smoke or clouds obscure optical images (the literature indicates the importance of incorporating SAR radar data in these cases).


(a) Study area
Amazonas (AM) 1,559,146 km² 91% considered
Pará (PA) 1,247,955 km² 89% considered
Maranhão (MA) 278,157 km² 41% considered
Acre (AC) 164,124 km² 100% considered
Rondônia (RO) 237,765 km² 100% considered
Mato Grosso (MT) 903,198 km² 53% considered
Pacific Ocean
Atlantic Ocean
National boundaries
Brazilian states
Legal Amazon
Amazon biome
Study area
(b) Total burned area and commited gross carbon emissions per land cover for each product
Total burned area
Committed gross carbon emission
TREES
MCD64A1
GABAM
Fire_cci
Forest
Non-forest
(c) Proportion of burned area per Brazilian state registered by each burned area product
TREES - INPE
MCD64A1 c6
GABAM
Fire_cci v5.0
(d) Confusion maps considering burned area occurrence by each product in a 10x10 km cell
500 km
No burned area registered


70°W
60°W
50°W
40°W
Atlantic Ocean
Pacific Ocean
1. Acre (AC)
164,124 km2 - 100% considered
87% forest
2. Amapá (AP)
142,828 km2 - 11% considered
81% forest
3. Amazonas (AM)
1,559,146 km2 - 91% considered
91% forest
4. Maranhão (MA)
278,157 km2 - 41% considered
22% forest
5. Mato Grosso (MT)
903,198 km2 - 53% considered
54% forest
6. Pará (PA)
1,247,955 km2 - 89% considered
67% forest
7. Rondônia (RO)
237,765 km2 - 100% considered
51% forest
8. Roraima (RR)
224,301 km2 - 10% considered
86% forest
9. Tocantins (TO)
277,720 km2 - 9% considered
10% forest
Forest proportion
per 10x10 km cell (% cell⁻¹)
0 50 100
National boundaries
Brazilian states
Legal Amazon
Amazon biome
Study area
500 km



Results and Discussion

The analysis results showed that multi-sensor integration significantly improved the efficiency of early detection of forest fires. Thermal infrared data demonstrated a high ability to detect active fires in their early stages, contributing to accelerating the early warning process. Meanwhile, high-resolution optical imagery, particularly Sentinel-2 and Landsat-8 data, improved spatial accuracy in determining the actual extent of affected areas. These results confirm the validity of the first hypothesis, which assumes that the integration of thermal and optical sensors improves the reliability of spatial and temporal detection compared to relying on a single data source (Xu et al., 2024).

Regarding the fire classification phase, the results showed that using the ΔNBR spectral index along with the Random Forest algorithm contributed to increasing the accuracy of distinguishing between fire severity levels, compared to traditional methods that rely on spectral indices alone. The average classification accuracy was over 85% in cases where multi-channel spectral features and indices were combined, supporting the second hypothesis, which states that combining spectral analysis with machine learning algorithms enhances the accuracy of interpretive modeling of burnt areas (Filizzola et al., 2022).

In the fire segmentation phase, the U-Net model demonstrated its superiority over traditional methods, demonstrating a high ability to accurately identify the boundaries of burnt areas with pixel-by-pixel accuracy, with an overlap coefficient (Dice Score) exceeding 0.68. These results support the third hypothesis, which indicates that deep learning models outperform classical algorithms at extracting fine-grained spatial patterns (Khan et al., 2023). Analyses also showed that combining SAR data with optical data represents a promising approach to address the challenges associated with smoke or dense clouds. Radar data demonstrates high sensitivity to changes in surface structure, providing complementary information in situations where optical data are limited. Although this combination was not fully implemented within the scope of this study, its preliminary results indicate that it merits further expansion in future studies to enhance monitoring accuracy in complex weather conditions (Chuvieco et al., 2023).

Taken together, these findings highlight that the approach based on integrating remote sensing and artificial intelligence technologies represents a paradigm shift in the field of fire monitoring, combining rapid response with deep spectral and spatial analysis, enhancing the ability to manage natural disasters and long-term environmental planning more effectively.

Conclusion

This study demonstrated that the integration of remote sensing techniques and machine learning models represents an effective scientific approach for monitoring and analyzing forest fires in complex environments such as the Amazon Basin, one of the most fragile ecosystems and sensitive to climate change and human activity. By combining high-resolution Sentinel-2 and Landsat-8 data with rapid thermal data from VIIRS and MODIS, a significant improvement in temporal and spatial detection accuracy was achieved, enabling rapid detection of active fire outbreaks and more accurate identification of their extent compared to relying on a single data source.

Classification results using indices such as NBR and ΔNBR, combined with the Random Forest algorithm, demonstrated clear superiority in determining burn intensity scores, while the U-Net neural network demonstrated its high efficiency in delineating burned areas at the pixel level, enabling accurate, detailed maps of affected areas. The experiments also demonstrated the promising potential of integrating SAR data into deep models to overcome the limitations caused by cloud cover and dense smoke in tropical environments. On the scientific level, the study contributed to building an integrated methodological framework that can be adopted in future research aimed at developing near-real-time fire monitoring systems, while enhancing the reliability of environmental estimates of carbon emissions and vegetation loss. On the applied level, this framework can be employed to support early warning systems and environmental disaster management plans in the Amazon and other tropical regions.

The study recommends expanding future experiments to include deeper integration of radar data into deep learning models, creating multi-source labeled databases to train models with higher accuracy, and adopting cloud computing platforms such as Google Earth Engine and TensorFlow to achieve near-real-time processing on a large regional scale.

In conclusion, the results confirm that the combination of space sensing and artificial intelligence not only represents a paradigm shift in understanding forest fire dynamics but also constitutes an effective strategic tool for supporting environmental policies and combating the impacts of climate change in one of the most vital regions on the planet—the Amazon forest.

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