Confidence Indicator for Fire Event Alerts Based on Geostationary Remote Sensing in Brazil and ACTO Countries

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Abstract

This work presents a methodology for anticipating the emergence of fire events using hot spot products. It is based on the high temporal resolution and ultra-real-time availability of data from the ABI sensor of the geostationary satellites GOES-16 and GOES-19. The scope involves predicting the formation of events in Brazil and in the Amazon biome of the Amazon Cooperation Treaty Organization (ACTO) countries. It uses the K-Means algorithm for classifying clusters of recurrent alerts, formed by the spatio-temporal grouping of hot spot detections and considering the averages of: a) brightness temperature; b) estimated area; and c) radiative power. The data were processed through min-max normalization and the Euclidean distance from alerts to clusters was calculated. The differential of the approach lies in assigning a confidence estimate to each alert, indicating the probability that it anticipates the emergence of a fire event within up to 12 hours. The results obtained suggest that the methodology can contribute significantly to optimizing monitoring and directing actions, especially in remote regions, where early detection is crucial.

1. Introduction

Forest fires have become an increasingly alarming threat to global ecosystems, with particularly devastating effects on the Amazonian biome. This region, which extends across Brazil and several countries of the Amazon Cooperation Treaty Organization (ACTO), is not only the world's greatest biodiversity hotspot in the world but also plays a determining role in climate regulation, as pointed out by Jézéquel et al. (2020) and Lovejoy and Nobre (2018). The occurrence of these fires – often linked to deforestation and agricultural practices, as well as extreme weather events – results in substantial vegetation losses, greenhouse gas emissions, public health impacts, and socioeconomic damage to local and traditional populations. Recent data are alarming: in 2024, there was a 79% jump in the burned area in Brazil compared to 2023, according to the MapBiomas Monitor do Fogo system, while the Management and Operational Center of the Amazon Protection System (Censipam) Painel do Fogo also recorded a 66.2% increase in the area under the influence of fires.

In this context, the early detection and continuous monitoring of hot spots are essential to support effective prevention and combat strategies. Historically, this monitoring has relied on polar-orbiting satellites, such as those equipped with MODIS (Moderate Resolution Imaging Spectroradiometer) and VIIRS (Visible Infrared Imaging Radiometer Suite) sensors. Although they offer satisfactory spatial resolution, their revisit frequency over the same point is limited, which can lead to considerable delays in identifying new ignitions. Furthermore, simple detections of thermal anomalies tend to provide superficial analyses regarding the severity of the fire and its propagation history. To mitigate these limitations, Censipam developed the Painel do Fogo platform (Bernini et al., 2023), which introduced the concept of a "fire event," grouping hot spots close in space and time. However, the effectiveness of this system for anticipation purposes is still restricted by the low temporal frequency of the reference sensors.

A valuable opportunity to overcome this gap lies in the use of geostationary satellites, such as those in the GOES (Geostationary Operational Environmental Satellite) series. Equipped with the ABI (Advanced Baseline Imager) sensor, satellites like GOES-16 and the recently launched GOES-19 can image South America every 10-15 minutes, offering nearly continuous monitoring (Vandal et al., 2023). This very high temporal frequency allows capturing the initial stages of hot spots and identifying recurrence patterns that may signal the development of a significant fire even before its detection by polar-orbiting sensors.

Given this scenario, the justification for this work lies in the need for a methodology that explores the high cadence of geostationary data to create a predictive alert system. The proposed approach aims to fill a critical operational gap, transitioning from a reactive monitoring model to a proactive one, enabling resource optimization and anticipatory decision-making. The main objective is, therefore, to develop and validate a confidence indicator for fire alerts generated from ABI sensor data, which indicates the probability of a grouping of detections converting into a real fire event. To this end, the specific objectives are: 1) to classify recurrent alerts into distinct typologies, using the K-Means algorithm based on their physical characteristics (temperature, area, and radiative power); 2) to statistically calibrate the confidence of each typology, correlating them with fire events validated by reference sensors (MODIS and VIIRS); and 3) to provide a tool that allows decision-makers to prioritize responses to alerts with a higher probability of evolving into fires within a 12-hour window.

This methodology differs from previous works, which focused

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on tracking already detected fire events (Bernini et al., 2023) or assessing the severity of already identified fires (Faria et al., 2022). The focus here is anticipation. By associating a quantitative measure of confidence with each alert, the approach complements and expands the capability of the Painel do Fogo system. The low spatial resolution of GOES data does not represent an impediment, as the objective is to delimit an approximate area with a high probability of a fire event occurring, allowing the very high update rate of these data to be effectively utilized. This work represents an evolution in fire monitoring in Brazil and ACTO countries, strengthening the fire response system, especially in remote and hard-to-access areas.

2. Methodology

2.1. Data Collection and Preprocessing

The primary data used in this study comes from the ABI Level 2+ FHS product, generated by the GOES-16 and GOES-19 satellites. These sensors provide thermal anomaly detections with high temporal frequency (10-15 minutes), which represents a substantial advantage over polar-orbiting satellites for continuous monitoring.

The raw data were acquired directly from the AWS S3 Bucket repository maintained by NOAA-NASA. Preprocessing begins with a careful filtering of detections, selecting only those classified with high confidence fire characterization masks (codes 10, 11, 30, and 31), as established in the official FHS product documentation. Each valid detection provides three essential parameters: pixel brightness temperature (in Kelvin), estimated fire area (in m²), and fire radiative power (FRP, in Megawatts). Detections with invalid or missing values ('NaN') in any of these fields are discarded to preserve the integrity of subsequent calculations – a procedure that, although slightly reducing the data volume, significantly increases the reliability of analyses.

The spatial scope of the analysis encompasses not only Brazilian territory but also the regions of ACTO member countries where the Amazon biome is present. This transboundary approach is essential, considering that the impacts of forest fires in the Amazon region rarely respect political borders, affecting the ecosystem as a whole.

2.2. Formation of Recurrent Fire Alerts

The methodology focuses on identifying recurrence patterns, grouping detections that are close both spatially and temporally. The ST_ClusterDBSCAN function of PostGIS, a density-based clustering algorithm, is employed to identify clusters of detections that potentially represent the same evolving fire event. This approach resembles that used by Singh et al. (2025) regarding active fire detection via satellite images, but was specifically adapted for high temporal frequency geostationary data.

In spatial analysis, a square buffer with a 2200 m edge is applied from the centroid of each detection. This value represents a slight extrapolation of the nominal dimension of the ABI sensor pixel (2 km), aiming to compensate for perspective distortions and ensure connectivity between adjacent pixels, especially in regions further east and south of the area of interest. Distortions or shape alterations occur due to the reprojection of GOES data to an ellipsoidal geocentric reference system. Factors such as perspective, capture angle, and terrestrial curvature are some causes of such anomalies. This adjustment significantly improved the ability to group detections related to the same physical event, mainly in the Amazon region.

An 'alert' is formally defined as a grouping resulting from ST_ClusterDBSCAN that contains at least two GOES detections whose buffers intersect or overlap. For each formed alert, the following aggregated characteristics are calculated:

- **Average Temperature ($\bar{T}$):** Arithmetic mean of temp_kelvin values of all detections in the alert
- **Average Area ($\bar{A}$):** Arithmetic mean of area_m2 values of all detections in the alert
- **Average Radiative Power ($\bar{P}$):** Arithmetic mean of power_mw values of all detections in the alert
- **Number of Recurrences (n):** Total count of the number of individual detections that compose the alert

2.3. Data Normalization

The aggregated characteristics of alerts ($\bar{T}$, $\bar{A}$, $\bar{P}$) have very distinct scales and units of measurement among themselves. Temperature is measured in Kelvin (in the order of hundreds), area in square meters (varying from thousands to millions), and power in Megawatts (from tens to thousands). If used directly in distance-based algorithms, such as K-Means, variables with larger numerical magnitudes would inevitably dominate the calculation, distorting the analysis.

To mitigate this effect and ensure that all characteristics contribute equitably to cluster formation, min-max normalization is applied. For each characteristic X (whether temperature, area, or power) and for each specific value of n (number of recurrences), normalization is calculated as:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Where X = value of the characteristic

X_{min} = minimum value observed

X_{max} = maximum value observed

For a given characteristic, let X_{min} represent the minimum observed value and X_{max} represent the maximum observed value within the clusters of alerts with exactly n recurrences. This normalization maps each characteristic to the interval [0,1], preserving the relative distribution of original values. Normalization is performed separately for each value of n, recognizing that the distribution of characteristics can vary significantly as the number of recurrences increases – an aspect that was verified during the development phase.

This step is fundamental to ensure that the K-Means algorithm, which uses Euclidean distance as a similarity measure, is not biased by scale differences between variables, as highlighted by Jain et al. (2020) in their review on machine learning applications in forest fire monitoring.

2.4. K-Means Algorithm and Cluster Formation

The normalized data are classified through the K-Means algorithm, which groups alerts into clusters of similar characteristics. Initial definition: 10 clusters were created for each value of the number of recurrences of the spatio-temporal grouping of hot spots (*n*).

The algorithm follows a two-step grouping process:

Assignment Step: Each alert is placed in the cluster closest to it. Proximity is measured by Euclidean distance, which is the straight-line distance between two points, in the three-dimensional space formed by the normalized characteristics (temperature, area, and power).

Update Step: After distributing all alerts, the central point (centroid) of each cluster is recalculated, which then represents the average profile of alerts in that group.

Repetition: These two steps are repeated several times, until alerts stop changing clusters or until a maximum number of attempts is reached. In this implementation, iterations were not limited.

In mathematical terms, the algorithm minimizes the sum of quadratic distances between each point and the centroid of its cluster:

$$\min \sum_{i=1}^{k} \sum_{x \in C_i} ||x - \mu_i||^2 \quad (2)$$

Where k = number of clusters (10 in this case)

C_i = set of points in cluster i

μ_i = centroid of cluster i

This approach allows identifying natural patterns in the data, grouping alerts with similar characteristics and differentiating those with distinct characteristics, without the need to manually define classification criteria.

2.5. Alert Validation and Confidence Definition

Validation is the process that determines how reliable each type of alert is for predicting valid fire events. This step is crucial as it transforms mathematical groupings into practical information for decision-making.

The process works as follows: confirmation of real alerts uses data from already confirmed fire events, from Painel do Fogo platform data from satellites with higher spatial resolution (VIIRS and MODIS). These data serve as field validation, representing fires whose existence was verified by higher spatial resolution sensors.

Validation criteria: A GOES alert is considered validated when its location coincides with a subsequently confirmed fire event and the confirmed event occurs within 12 hours after the first record of the GOES alert.

The 12 hour temporal window was defined after preliminary analyses that indicated this to be the most relevant period for preventive and initial combat actions. Shorter windows (6h) proved too restrictive, while longer periods (24h) diluted the predictive capacity of the system. Such window also represents the revisit time of polar satellites that are capable of making detections that initiate new fire events.

Confidence calculation: For each group (cluster) of alerts, a percentage is calculated:

$$\text{Confidence} = \frac{\text{Number of validated alerts in the cluster}}{\text{Total number of alerts on the cluster}} \times 100\% \quad (3)$$

The confidence value allows prioritizing response to alerts with higher probability of representing the imminence of fire event emergence, optimizing monitoring and combat resources.

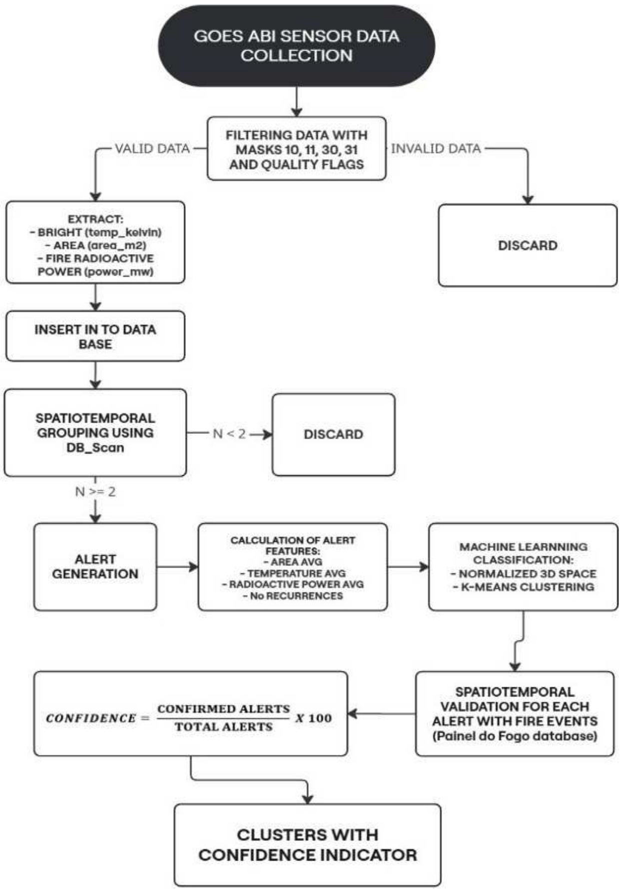

Figure 1. Flowchart of the Confidence Indicator Methodology for Fire Event Prediction.

Figure 1 illustrates the complete workflow of the proposed methodology, encapsulating the sequential steps from initial data acquisition to final confidence assignment.

2.6. Euclidean Distance Calculation in Classification

When a new alert is detected, it is necessary to determine which group it belongs to and, consequently, what its confidence is. For this, the concept of Euclidean distance is used, which is a way to measure how close the new alert is to each of the already known groups.

The classification process follows these steps:

2.6.1 Preparation of the new alert: The average characteristics of the alert (temperature, area and power) are calculated and normalized using the same scale parameters used in training. This step ensure comparability with existing clusters.

2.6.2. Similarity measurement: The distance between the new alert and the center (centroid) of each of the 10 available groups for that number of recurrences is calculated. The Euclidean distance is calculated as:

$$\text{Distance} = \sqrt{(\text{temp}_{\text{alert}} - \text{temp}_{\text{group}})^2 + (\text{area}_{\text{alert}} - \text{area}_{\text{group}})^2 + (\text{power}_{\text{alert}} - \text{power}_{\text{group}})^2} \quad (4)$$

This formula represents the straight-line distance between points in three-dimensional space.

2.6.3. Assignment to the most similar group: The alert is classified as belonging to the group whose calculated distance is the smallest.

2.6.4. Confidence definition: Once the alert's group is determined, the pre-calculated confidence of that group is assigned to it.

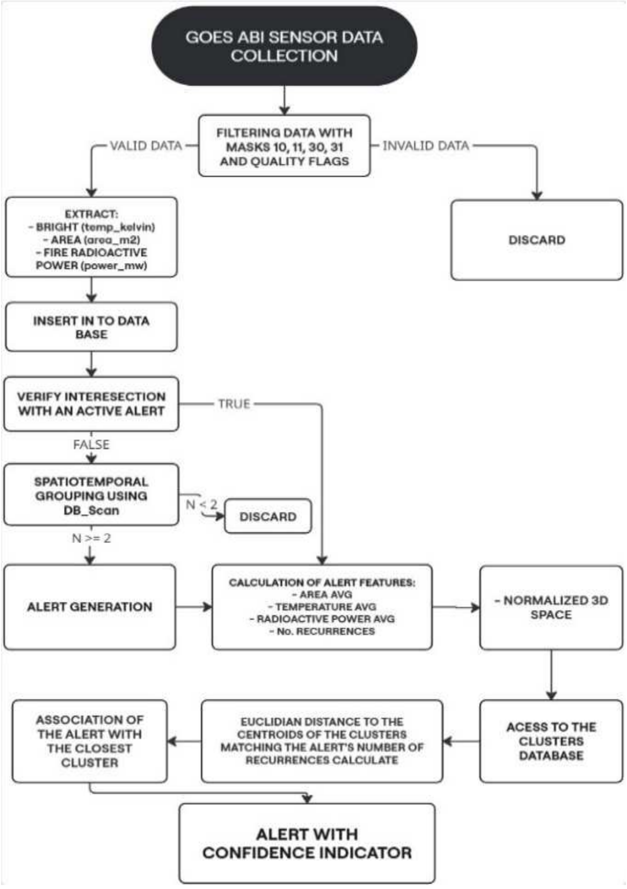

Figure 2. Flowchart of the workflow of the alert system.

Figure 2 depicts the complete workflow of the alert system, operational after the clusters with confidence indicators are calculated and stored in the database.

This approach allows rapidly classifying new alerts as they are detected, associating them with a confidence value that represents their probability of preceding a real fire event. The smaller the distance to the center of a group, the greater the similarity of the alert with the characteristic pattern of that group.

In practice, this process was implemented in a system that operates in near real-time, processing new GOES detections in ultra real-time as they become available (approximately every 15 minutes). The average processing time for classifying a new alert and reclassifying existing alerts (when their characteristics change due to addition of new detections in their areas) is less than 10 seconds, which allows immediate operational response.

3. Results and Discussion

The application of the proposed methodology resulted in the creation of a predictive alert system with different confidence levels, allowing prioritization of areas for intensive monitoring and early intervention. Figure 3 presents the relationship between the number of recurrences of GOES detections (counter) and the average confidence of corresponding alerts.

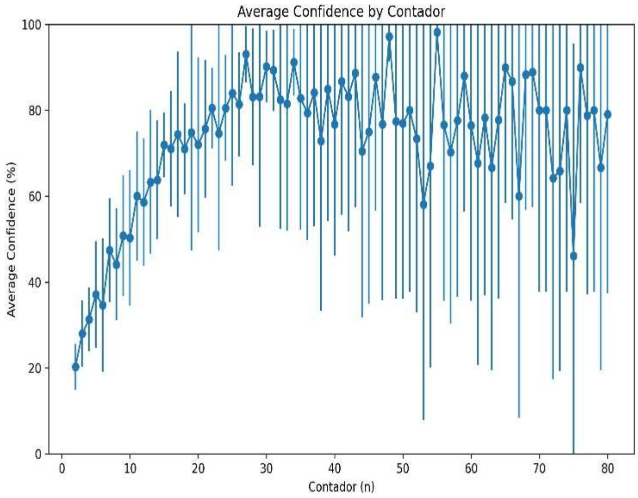

Figure 3. Relationship between the number of recurrences of GOES detections and the average confidence of alerts.

A general trend of increasing confidence with the number of recurrences is observed, which is intuitively expected: the more persistent a thermal anomaly is, the greater the probability that it represents a real fire in development. However, it is important to note that this relationship is not perfectly linear, and there is significant variability within each recurrence category. This justifies the clustering approach adopted, which allows capturing nuances beyond recurrence counting.

Figure 4 illustrates the distribution of cluster centroids for alerts with two recurrences (n=2). Each point represents the center of a cluster in the normalized three-dimensional space of temperature, area, and radiative power. The color scale represents the confidence level associated with each cluster.

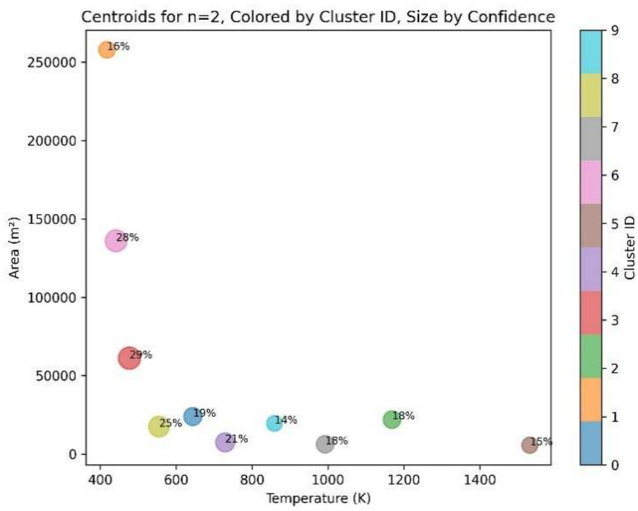

Figure 4. Distribution of cluster centroids for alerts with two recurrences (n=2). The color scale represents the confidence level associated with each cluster.

The analysis of centroids reveals interesting patterns. Clusters with higher confidence tend to present specific combinations of temperature, area, and radiative power. Notably, some clusters with intermediate temperature values, but high radiative power, present superior confidence to clusters with higher temperature, but lower power. This corroborates the observation by Thangavel et al. (2023) about the importance of considering multiple characteristics in evaluating thermal anomalies, instead of focusing only on temperature.

To demonstrate the practical application of the methodology, Figure 5 presents a real example of a fire alert generated by the system, illustrating the complete cycle from initial detection to the formation of a fire event. This example, recorded on June 5, 2025, in the state of Mato Grosso, shows an alert with 88% confidence, indicating a high probability of evolution to a significant fire.

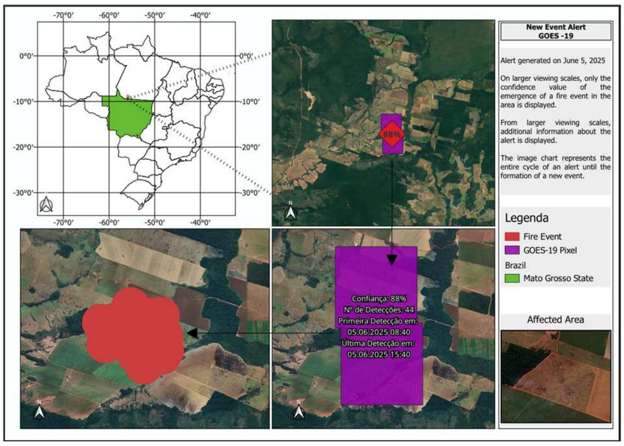

Figure 5. Visualization of a GOES fire alert and its evolution to a fire event.

Figure 5 visually demonstrates how alerts are presented to end users of the system. The confidence value (88% in this case) is displayed prominently within the purple polygon that represents the GOES pixel. At smaller visualization scales, only the confidence value is shown, allowing rapid assessment of the probability of fire event emergence in the area. On higher scales, additional alert information is made available, such as: number of detections and date and time of the fist and last detections. The lower left panel shows the confirmed fire event (in red) that developed in the alert area, validating the prediction made by the system.

The main contribution of this methodology lies in its anticipation capacity, generating predictive alerts based exclusively on the high cadence of GOES data. This differentiates from approaches focused on assessing the severity of already detected fires, such as multicriteria indices that use polar satellite data. The current methodology acts at an earlier stage, seeking to predict event consolidation, aligning with recent trends in using artificial intelligence for fire behavior prediction highlighted by Jain et al. (2020).

The integration of this methodology with existing fire events systems represents a significant advance in forest fire monitoring in Brazil and the Amazon region. While comprehensive platforms provide a view of already detected fire events and their evolution, the current approach complements the system with predictive capacity, allowing anticipation of new event emergence. This synergy between the two systems enhances the effectiveness of prevention and combat actions, especially in remote areas where response time is critical.

The proposed methodology also aligns with international forest fire monitoring initiatives, such as NASA's Fire Information for Resource Management System (FIRMS) and the European Union's Copernicus Emergency Management Service. However, it differentiates itself by emphasizing fire event prediction, by Amazon region specific adaptation to South American territory characteristics and to the operational needs of ACTO countries. The transboundary approach adapted is particularly relevant considering the shared nature of Amazon ecosystems and the regional impacts of forest fires.

Between May 22, 2025, at 9:00 AM, when the alert tool became operational, and June 13, 2025, a total of 3.387 new fire events were recorded. Of these, 1.477 (43.6%) were predicted by the tool, with alerts issued for the monitored areas. In total, 3.396 alerts were generated, of which 2.014 (59.3%) were confirmed by fire events. Notably, alerts with a confidence level above 75% resulted in confirmed fire events in 87.8% of cases within a 12-hour window from the alert issuance to the event occurrence. These results demonstrate the effectiveness of the methodology and highlight its potential for application in operational monitoring and early warning systems.

To further assess the robustness of the clustering approach, a sensitivity analysis was conducted by evaluating the impact of individual features on cluster formation.

Ablation Metrics Across Recurrence Levels	Values
Normalized Inertia Avg. Without Area	0.51
Normalized Inertia Avg. Without Temperature	0.48
Normalized Inertia Avg. Without Power	0.38
Max. Inertia Without Area	0.59
Min. Inertia Without Area	0.40
Max. Inertia Without Temperature	0.56
Min. Inertia Without Temperature	0.40
Max. Inertia Without Power	0.48
Min. Inertia Without Power	0.26
Std. Dev. of Normalized Inertia without Area	0.04
Std. Dev. of Normalized Inertia Without Temp.	0.02
Std. Dev. of Normalized Inertia Without Power	0.04

Table 1. Sensitivity Analysis of Input Variables via Ablation Study. Summary statistics of normalized inertia scales from K-Means clustering across recurrence levels (n=2 to 80), where each feature (brightness temperature, estimated area, and radiative power) was individually removed. Lower average scales (e.g., 0.38 for radiative power) indicate greater importance, with low standard deviation (0.02–0.04) reflecting consistent impacts.

To evaluate the influence of aggregated features (brightness temperature, estimated area, and radiative power) on cluster formation, an ablation study was conducted across recurrence levels (n=2 to 80). K-Means models were retrained after removing one feature at a time, with inertia normalized against the baseline (all features) to yield scales from 0 to 1, where lower values indicate greater degradation and thus higher feature importance. Results (Table 1) reveal radiative power as the most influential (average normalized inertia: 0.38), followed by temperature (0.48) and area (0.51), with low variances (0.02–0.04) suggesting consistent impacts across recurrence levels.

This analysis emphasizes radiative power's central role in cluster separation, strengthening the approach's effectiveness for anticipating fire events. While these findings align with observed centroid patterns (Figure 4), they also highlight opportunities for refinement by incorporating additional variables to enhance alert accuracy.

It is important to recognize some limitations of the current approach. The exclusive dependence on GOES data, although advantageous for high temporal frequency, implies spatial resolution limitations (2 km) that may hinder the detection of small fires or in initial stages. Furthermore, the current methodology does not incorporate meteorological or land cover variables, which could enrich the analysis and potentially increase alert precision. These limitations point to directions for future work, including the integration of multi-sensor data and the incorporation of additional environmental variables.

Another future evolution of the methodology involves creating clusters segmented by temporal windows throughout the day, aiming to capture with greater precision the variability in alert confidence. This approach considers the start time of each alert and the passage times of satellites equipped with VIIRS sensors, the only ones capable of initiating new fire events due to their previously mentioned characteristics. Alert confidence varies according to their emission time: those generated close to VIIRS satellite passage times present higher probability of being followed by confirmed fire events, compared to alerts issued in long intervals between these passages, when detection is less immediate.

4. Conclusions

This work presented a methodology for generating predictive fire alerts based on high temporal frequency data from GOES-16 and GOES-19 satellites. The proposed approach uses the K-Means algorithm to classify alerts formed by spatio-temporal grouping of recurrent thermal anomaly detections, associating with each type of alert a confidence estimate that represents the probability that it precedes a fire event.

The results obtained demonstrate the methodology's potential to optimize monitoring and direct combat and prevention actions, allowing faster and more effective responses in scenarios that demand early detection and risk assessment. The integration of this approach with existing fire events systems represents a significant advance in forest fire monitoring in Brazil and the Amazon region.

The developed methodology contributes to strengthening forest fire monitoring and response capabilities in ACTO countries, promoting a transboundary approach to a shared environmental challenge. Its operational application can result in tangible benefits for Amazon biome preservation and for protecting communities that depend on this vital ecosystem.

Future work includes the integration of meteorological and land cover variables, and the exploration of deep learning techniques to improve alert precision. Furthermore, investigation of the possibility of further reducing alert anticipation time is planned, exploring more subtle patterns in initial detections that may indicate the imminent development of significant fires and the formation of clusters for alerts that begin in time windows during the day, to capture variations in confidence caused by the cadence of polar satellite passages that form new fire events.

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