Classification of Fire Risk Scenarios in the State of Pará Using Multicriteria Analysis

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Abstract. *Wildfires in the Brazilian Amazon are shaped by climatic and anthropogenic factors and require decision-support methods. This study proposes a multicriteria model to classify wildfire risk scenarios across municipalities in Pará. Environmental indicators from remote sensing and public databases are integrated with weights derived from the Analytic Hierarchy Process (AHP) and ELECTRE Tri-B classification. Municipalities are assigned to low, moderate, high, and critical risk categories. The results support the identification of priority areas for environmental monitoring and territorial management.*

1. Introduction

The Amazon rainforest plays strategic environmental functions on a global scale, influencing climate regulation, carbon storage, and regional hydrological processes [Fearnside 2005]. In 2025, Brazil registered over 134 thousand fire hotspots, of which about 18 thousand occurred in the state of Pará, representing approximately 13.4% of the national records, according to the Brazilian National Institute for Space Research (INPE) [INPE 2025].

Wildfire occurrence results from the interaction between environmental and anthropogenic factors, including deforestation, landscape fragmentation, land-use change, and climatic variability [Aragão et al. 2018, Libonati 2022]. Therefore, its analysis requires approaches capable of integrating multiple environmental indicators derived from geospatial data.

Traditional approaches often result in continuous representations or aggregated risk indices, which may limit their direct use in operational decision-making [Silva et al. 2025]. In this context, multicriteria methods allow municipalities to be classified into ordered risk levels, transforming heterogeneous environmental data into interpretable categories for territorial management [Bozca and Akıncı 2025, Roy 1996].

This study proposes a multicriteria model for classifying wildfire risk scenarios in the municipalities of Pará, Brazil. The approach integrates remote sensing indicators and public databases, using the Analytic Hierarchy Process (AHP) to define criteria weights and the ELECTRE Tri-B method to assign municipalities to ordered risk categories. The objective is to validate the multicriteria structure of the model, including criteria definition, data sources, normalization procedures, and classification results.

2. Environmental Context and Wildfire Dynamics in the Amazon

The Amazon region is a complex socio-environmental system in which climatic, ecological, and land occupation factors interact dynamically. Forest cover influences precipitation, evapotranspiration, and atmospheric circulation, while anthropogenic pressures such as agricultural expansion, mining, and infrastructure projects modify land cover and hydrological regimes [Fearnside 2005, Winemiller 2016].

In recent decades, productive expansion has intensified landscape transformation, often involving forest removal and the use of fire as a land management practice [Nepstad 2014]. In Pará, INPE records indicate a significant concentration of fire hotspots, reinforcing the relevance of the state for wildfire risk analysis [INPE 2025]. MapBiomas data also indicate that a substantial portion of burned areas affects native vegetation, increasing risks to biodiversity and ecosystem stability.

Climatic conditions such as drought, precipitation reduction, soil moisture deficit, and increased land surface temperature influence wildfire susceptibility [Aragão et al. 2018]. Remote sensing technologies have expanded the capacity to monitor these processes by mapping fire hotspots, land-cover changes, and spatial patterns associated with wildfire occurrence.

3. Related Work

Recent studies explore the use of multicriteria methods in environmental and agricultural contexts. For instance, [Colares 2023] proposed a multicriteria system to support decision-making in smart farming environments, demonstrating the applicability of these approaches in complex scenarios.

In the context of alert systems, [Bozca and Akıncı 2025] proposed the *Forest Fire Danger Assessment System* (FoFiDAS), which integrates AHP and Geographic Information Systems to map fire danger. The model considers environmental and anthropogenic parameters, allowing for more precise identification of risk zones and supporting preventive planning.

Focusing on the Amazon biome, [Libonati 2022] developed a multicriteria severity indicator based on remote sensing data, such as NOAA-20 and Suomi NPP. The model uses variables like intensity and duration of active fire foci, showing that real-time analysis can reduce response time and prioritize critical areas.

In a comparative approach, [Das et al. 2023] evaluated the performance of AHP and Fuzzy-AHP in mapping risk zones under different climatic conditions. The results indicate that fuzzy logic increases the sensitivity of classification in transition areas, highlighting the need to adapt weights to the environmental context.

Multicriteria methods are widely used to integrate variables and support decision-making in complex scenarios [Malczewski 2006]. In the Amazonian context, factors such as land use, forest dynamics, and climatic conditions directly influence the occurrence of wildfires [Nepstad 2014].

Other approaches, such as the Fire Weather Index (FWI) and machine learning models, have also been widely used for wildfire risk assessment [Van Wagner 1987, Xu et al. 2024]. While these methods are effective for meteorological fire danger estimation or predictive modeling, the proposed approach differs by emphasizing interpretability and decision support through explicit criteria weights and ordered risk categories generated by AHP and ELECTRE Tri-B.

In general, these studies demonstrate the potential of multicriteria approaches in analyzing wildfire risk, both in alert systems and in environmental and territorial management applications.

4. Methodology

The methodology analyzes wildfire susceptibility in the municipalities of Pará by integrating environmental indicators derived from remote sensing and public databases. The model combines the Analytic Hierarchy Process (AHP) for criteria weighting and ELECTRE Tri-B for assigning municipalities to ordered risk categories [Saaty 1980, Roy 1996, Figueira et al. 2005].

The process includes data acquisition, preprocessing, criteria definition, indicator normalization, AHP weight determination, and ELECTRE Tri-B classification. The 144 municipalities of Pará were considered as alternatives in the multicriteria model.

4.1. Data Source Acquisition

The data were obtained from official sources widely used in the literature. The integration of heterogeneous geospatial datasets was supported by spatial data infrastructure principles [Davis Jr. 2009]. Fire hotspots were obtained from NASA FIRMS [NASA 2024]. Climatic variables, such as land surface temperature (LST), precipitation anomaly, and soil moisture, were extracted from the Copernicus Climate Data Store (ERA5-Land) [Copernicus CDS 2024]. Territorial limits and municipal data were obtained from the Brazilian Institute of Geography and Statistics (IBGE) [IBGE 2023].

After summarization and spatial aggregation, the indicators were calculated at the municipal scale, considering the 144 municipalities of the state of Pará as alternatives in the multicriteria model.

4.2. Data Ingestion and Processing

After acquisition, data were collected through APIs, structured files (CSV and JSON), and geospatial services. Treatment procedures included removing inconsistent records, handling missing values, controlling extreme values, and harmonizing databases.

The cleanup involved validating spatial information and excluding invalid records. IBGE records without municipality identification (`NM_MUN`) and NASA FIRMS hotspots outside Pará were discarded through spatial filtering.

Extreme values (*outliers*) were truncated by critical thresholds to avoid distortions in the indicators. Identifiers were standardized to the official 7-digit IBGE municipality code, and temporal variables were converted to *datetime* format.

The data were aggregated at the municipal scale, generating comparable indicators, with scale inversion for variables inversely proportional to risk, such as rainforest cover and soil moisture.

The indicators were calculated as averages for the period 2019–2025, reducing interannual variation. These indicators formed the basis for AHP weighting and ELECTRE Tri-B classification.

Table 1 summarizes the data sources used to build the environmental indicators.

Table 1. Data sources used for building the environmental indicators

Source	Data type	Format	Access method
MapBiomas	Forest Cover	Raster / GeoTIFF	Download
NASA FIRMS	Fire hotspots	JSON	API
Copernicus ERA5	Climatic variables	JSON	API
IBGE	Territorial limits	GeoJSON	Download

4.3. Wildfire Risk Criteria

The model considers six criteria associated with the susceptibility to wildfire occurrence, defined based on the scientific literature on fire regimes in tropical regions [Nepstad et al. 2008, Aragão et al. 2018, Bowman et al. 2009, Archibald et al. 2013].

Table 2 presents the criteria considered in the model and their respective AHP weights.

Table 2. Criteria considered in the model

Criterion	Weight (AHP)
Forest Cover (inverse)	0.25
Historical Fire Hotspots	0.20
Bare Soil	0.20
Precipitation Anomaly	0.15
Soil Moisture	0.10
Land Surface Temperature (LST)	0.10
Total	1.00

The forest cover indicator was derived from MapBiomas land use and land cover data [MapBiomas 2023], which has been used in environmental classification studies [Paiva 2020]. Forest formation areas (code 3) were considered as forest cover, while the remaining classes were grouped as non-forest areas. The municipal forest cover proportion was then transformed into an inverse indicator, so that lower forest cover represents higher wildfire susceptibility.

Historical fire hotspots represent the recurrence of fire events detected by orbital sensors, while bare soil indicates land-use conversion and agricultural expansion. The climatic criteria include precipitation anomaly, soil moisture, and Land Surface Temperature (LST), representing rainfall deviations, water availability, and thermal surface conditions related to ignition and fire spread.

4.4. Normalization of Indicators

The considered indicators have different measurement scales, making normalization necessary to allow comparison between criteria. The values were normalized to the range $[0, 1]$, where higher values indicate a greater contribution to wildfire risk.

In the equations, CF, F, SE, ΔP, US, and T denote forest cover, fire hotspots, bare soil, precipitation anomaly, soil moisture, and land surface temperature, respectively; $F_{\max}$, $SE_{\max}$, $P_{\max}$, and $T_{\max}$ represent the maximum reference values used for normalization.

$$\begin{aligned} r_1(a_i) &= 1 - \frac{CF(a_i)}{100} & r_4(a_i) &= \min\left(\frac{\max(0, -\Delta P(a_i))}{P_{\max}}, 1\right) \\ r_2(a_i) &= \min\left(\frac{F(a_i)}{F_{\max}}, 1\right) & r_5(a_i) &= 1 - \frac{US(a_i)}{100} \\ r_3(a_i) &= \min\left(\frac{SE(a_i)}{SE_{\max}}, 1\right) & r_6(a_i) &= \min\left(\frac{T(a_i)}{T_{\max}}, 1\right) \end{aligned} \tag{1}$$

where a_i represents the analyzed municipality and $r_j(a_i)$ corresponds to the normalized value of criterion j.

4.5. AHP Weight Determination and ELECTRE Tri-B Classification

The criteria weights were defined using the AHP method, proposed by Saaty [Saaty 1980]. The method is based on pairwise comparisons between criteria, allowing their relative importance in the decision process to be determined.

The pairwise comparison matrix was defined from the final weight vector $w = (0.25, 0.20, 0.20, 0.15, 0.10, 0.10)$, using $a_{ij} = w_i/w_j$.

Table 3 presents the resulting reciprocal matrix.

Table 3. AHP pairwise comparison matrix

Criterion	FC	HFH	BS	PA	SM	LST
FC	1.00	1.25	1.25	1.67	2.50	2.50
HFH	0.80	1.00	1.00	1.33	2.00	2.00
BS	0.80	1.00	1.00	1.33	2.00	2.00
PA	0.60	0.75	0.75	1.00	1.50	1.50
SM	0.40	0.50	0.50	0.67	1.00	1.00
LST	0.40	0.50	0.50	0.67	1.00	1.00

The normalized criteria weights obtained from this matrix correspond to the values presented in Table 2. These weights were used to compute the aggregated AHP score and the ELECTRE Tri-B concordance.

For the classification stage, the ELECTRE Tri-B method was used, proposed by Roy [Roy 1996], and widely employed in multicriteria classification problems. This method allows allocating alternatives into ordered categories based on comparison with reference profiles.

Four ordered categories of wildfire risk were defined: low, moderate, high, and critical. For the application of the ELECTRE Tri-B method, three reference profiles (b_1, b_2, b_3) were established, delimiting the boundaries between these categories.

Table 4 presents the reference profiles and thresholds used in the ELECTRE Tri-B classification.

Table 4. ELECTRE Tri-B reference profiles and thresholds

Boundary	Profile	q	p	v	λ
Low/Moderate	$b_1 = (0.20, 0.20, 0.20, 0.20, 0.20, 0.20)$	0.05	0.10	0.80	0.75
Moderate/High	$b_2 = (0.50, 0.50, 0.50, 0.50, 0.50, 0.50)$	0.05	0.10	0.80	0.75
High/Critical	$b_3 = (0.80, 0.80, 0.80, 0.80, 0.80, 0.80)$	0.05	0.10	0.80	0.75

The thresholds q, p, and v represent indifference, preference, and veto limits, respectively, while λ denotes the cutting level used in the assignment procedure. This classification allows identifying different levels of susceptibility to wildfire occurrence and supports territorial analyses aimed at environmental monitoring and risk management.

5. Results and Discussion

The application of the multicriteria model allowed classifying the municipalities of the state of Pará into different levels of wildfire risk. The classification was obtained from the integration of the environmental indicators considered in the model, weighted through the AHP method and subsequently evaluated by the ELECTRE Tri-B method. This approach allowed identifying territorial patterns associated with the susceptibility to wildfire occurrence at a regional scale.

5.1. Spatial Distribution of Risk

Figure 1 presents the spatial distribution of wildfire risk classes for the municipalities. The classification from the multicriteria model considers four risk categories: low, moderate, high, and critical.

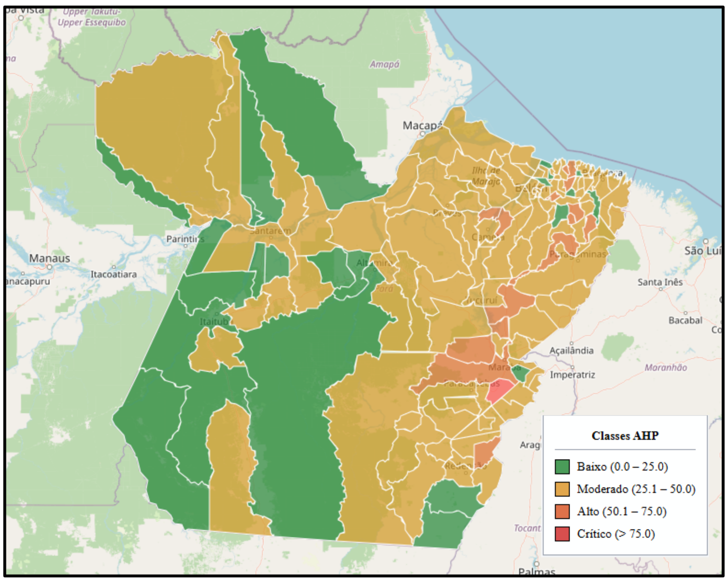

Figure 1. Spatial classification of wildfire risk.

It is observed that the municipalities classified in the higher risk categories are predominantly concentrated in regions characterized by intense landscape transformation and greater anthropogenic pressure on forest cover. This spatial pattern coincides with areas associated with the advance of the agricultural areas and productive expansion. FAPESPA data indicate greater economic dynamism in these regions, reinforcing the relationship between land use and the increase in wildfires in the Amazon region [FAPESPA 2024].

In contrast, municipalities located in regions with greater continuity of forest cover tend to present lower risk levels. In these areas, the greater availability of moisture in the vegetation and the lower fragmentation of the landscape contribute to reduce the fire spread susceptibility.

5.2. Municipalities with the Highest Risk

The territorial analysis indicates that the highest risk municipalities are concentrated in the southeast of Pará, a region located in the arc of deforestation, historically associated with the conversion of forest cover and agricultural expansion.

Studies point out that areas with high anthropogenic pressure and greater vegetation fragmentation have a higher probability of fires, especially under unfavorable climatic conditions, landscape degradation, and reduced moisture, which facilitate ignition and fire spread [Fearnside 2005].

Changes in landscape structure also influence fire behavior, increasing its occurrence in ecosystems with low adaptation to recurrent fires [Bowman et al. 2009]. These results reinforce the importance of integrating environmental and territorial factors in the analysis of wildfire risk.

5.3. Classification Results of Municipalities

The application of the multicriteria model allowed the classification of the 144 municipalities of the state of Pará into four wildfire risk categories. The results show a strong predominance of the moderate risk class, with 106 municipalities (73.6%), followed by 22 municipalities classified as low risk (15.3%), 15 as high risk (10.4%), and only 1 municipality classified as critical risk (0.7%).

Table 5. Distribution of municipalities by wildfire risk class

Risk Class	Number of Municipalities	Percentage (%)
Low	22	15.3
Moderate	106	73.6
High	15	10.4
Critical	1	0.7
Total	144	100.0

This distribution indicates that most of the territory is in an intermediate risk condition, reflecting the coexistence of preserved areas and regions under anthropogenic pressure. The low number of municipalities classified as critical suggests that extreme risk conditions are spatially concentrated.

The analysis of the highest scores allowed the identification of municipalities with greater susceptibility to wildfire occurrence. Eldorado do Carajás presented the highest score (0.843), being the only municipality classified as critical.

Table 6 presents the municipalities with the highest wildfire risk scores.

Table 6. Municipalities with the highest wildfire risk scores

Municipality	AHP score	Risk class
Eldorado do Carajás	0.843	Critical
Mãe do Rio	0.608	High
Limoeiro do Ajuru	0.602	High
Jacundá	0.597	High
Itupiranga	0.591	High
Maracanã	0.591	High
Marabá	0.585	High

These municipalities present, in general, a combination of lower forest cover, higher presence of exposed soil, and greater recurrence of fire hotspots, associated with climatic conditions that favor fire ignition and propagation.

5.4. Interpretation of Results

The predominance of the moderate risk class suggests that most municipalities are in transitional conditions, where environmental preservation and anthropogenic pressure coexist. This pattern is consistent with regions undergoing gradual land-use change, particularly due to agricultural expansion and deforestation processes.

Municipalities classified as high and critical risk, representing approximately 11.1% of the total, are associated with more intense landscape transformation. These areas tend to present higher levels of environmental degradation, reduced vegetation cover, and climatic conditions that increase fire susceptibility.

In contrast, municipalities classified as low risk tend to maintain more stable environmental conditions, including higher forest continuity and greater moisture availability, which reduce fire propagation potential.

These findings reinforce the importance of integrating multiple environmental indicators, as the wildfire risk cannot be explained by a single factor but rather by the interaction between land use, vegetation conditions, and climate variables.

However, municipal-scale aggregation may smooth local extremes, especially in large municipalities of Pará where preserved areas and zones of intense land-use change coexist.

6. Conclusions

This study presented a multicriteria model for classifying wildfire risk scenarios in the municipalities of the state of Pará, integrating environmental indicators derived from remote sensing and public databases.

The results revealed a predominance of moderate risk conditions across the state, with a smaller proportion of municipalities classified as high and critical risk. These higher-risk areas are spatially concentrated and associated with regions under greater anthropogenic pressure and landscape transformation.

The methodology, combining AHP and ELECTRE Tri-B, proved effective in integrating multiple environmental factors and identifying priority areas for monitoring and wildfire prevention.

The results highlight the importance of using multicriteria approaches to capture the complexity of environmental risk, supporting territorial analysis and decision-making processes.

Limitations include the dependence on secondary data, the spatial resolution of the indicators, and the use of municipal averages, which may mask intra-municipal extreme-risk areas. Future studies may incorporate finer spatial units, seasonal analyses, air humidity, and drought indices.

Overall, the proposed model contributes to environmental monitoring and supports the development of public policies for wildfire prevention and management in the Amazon region.

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