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FOREST FIRE RISK ZONING IN AN ADMINISTRATIVE DIVISION OF CACHOEIRO DE ITAPEMIRIM (BRAZIL/ES)

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ABSTRACT. Forest fires are becoming increasingly frequent, leading to the loss of human lives, ecosystem fragmentation, and higher greenhouse gas (GHG) emissions. This study aims to identify, quantify and classify forest fire risk levels in the Headquarters District of the municipality of Cachoeiro de Itapemirim (Brazil/ES). To this end, the Analytic Hierarchy Process (AHP) was used to prioritise the factors contributing to fire risk. Three models were created: R1 included natural factors, R2 biological and socioeconomic factors and R3 the months without rain. By summing the areas classified as having moderate, high, and very high fire risk levels, we were able to identify (through zoning) those at greater risk of fire for each model, being 18.97% of the total area for R1, 59.81% for R2, and 71.41% for R3. These results highlight the significant influence of human intervention and climatic conditions on forest fire risk.

Zonificación del riesgo de incendio forestal en una división administrativa de Cachoeiro de Itapemirim (Brasil/ES)

RESUMEN. Los incendios forestales son cada vez más frecuentes, lo que provoca la pérdida de vidas humanas, la fragmentación de los ecosistemas y un aumento de las emisiones de gases de efecto invernadero (GEI). Por lo tanto, el objetivo de este estudio es identificar, cuantificar y clasificar los niveles de riesgo de incendios forestales en la sede del distrito del municipio de Cachoeiro de Itapemirim (Brasil/ES). Para ello, se utilizó el método del proceso jerárquico analítico (PJA) para priorizar los factores que contribuyen al riesgo de incendios. Se identificaron tres modelos: R1 incluía factores naturales, R2 factores biológicos y socioeconómicos y R3 los meses sin lluvia. La suma de superficie ocupada por los niveles de riesgo de incendio moderado, alto y muy alto permitió identificar una mayor zonificación del riesgo de incendio en cada modelo, siendo 18,97 % de la superficie total para R1, el 59,81 % para R2 y el 71,41 % para R3. Estos resultados ponen de relieve la importante influencia de la intervención humana y las condiciones climáticas en el riesgo de incendios forestales.

Keywords: forest fire, ecosystems, greenhouse effect, mapping, modelling.

Palabras clave: incendios forestales, ecosistemas, efecto invernadero, cartografía, modelización.

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1. Introduction

Forest fires are environmental phenomena that have received significant attention from the scientific community due to their negative environmental and socioeconomic impacts. According to the Food and Agriculture Organization (FAO, 2023), forest fires caused by human activity consume approximately 400 million/ha/year worldwide. In Latin America, the average burn area is 60 million/ha/year, with an area of 80 million/ha being recorded in 2020.

Fire (chemical pyrolysis) is an agent with considerable capacity to alter various natural and anthropogenic landscapes, but it can also be employed for other purposes (agriculture and species control) using specific management techniques (Juvanhol *et al*., 2015; Setzer *et al*., 2019). According to Schumacher and Dick (2018), a forest fire is an out-of-control fire that spreads and consumes combustible products from areas covered by vegetation.

According to Custódio (2006), the practice of burning in Brazil originated with the country's Indigenous peoples and became more widespread with the cultivation of sugarcane and the extraction of brazilwood. Due to the ongoing use of this practice, Brazilian legislation has defined "burning" as the controlled use of fire, while the term "fire" is used to refer to uncontrolled fires, which are classified as an environmental crime (Law Nº. 4.771, of 15/09/1965 and Decree No. 2.661, of 08/07/1998).

Forest fires can have both local and regional impacts, with irreversible effects, such as loss of life and extinction of endemic species, as well as reversible effects, such as vegetation recovery. When a fire occurs in the natural environment, it can impact ecosystems and disrupt the natural balance of exchanges of matter and energy, such as the emission of pollutants and silting up of water resources (Murta Júnior and Oliveira, 2024; Ramalho *et al*., 2024).

In areas predominated by agriculture and livestock farming, vegetation fires can have significant economic impacts, including crop losses, land degradation and rural exodus (Brazil, 2020; Menezes *et al*., 2021). Near urban areas, it poses a risk to human life due to higher population densities and can lead to the destruction of buildings and urban infrastructure. These incidents can trigger further consequences, such as the disruption of transportation, the impairment of various services and the interruption of essential supplies (Custódio, 2006; Luber, 2018; Brazil, 2020; FAO, 2023).

According to the FAO (2023), climate change is increasing the global incidence of vegetation fires, with more cases being reported, larger areas affected, and more intense and longer-lasting fires. As a result, fire figures are expected to increase by 14% by 2030, 30% by 2050 and 50% by the end of the 21st century (Mambile *et al*., 2025; Zhao *et al*., 2024; Jones *et al*., 2025).

In the state of Espírito Santo, several forest fires have been linked to human activity. Luber (2018) identified 112 fire incidents in conservation units in Espírito Santo between 2014 and 2017, resulting in 4,255.01 ha of burnt vegetation. Moro and Oliveira (2023) recorded 1,260 fire incidents in the southern region of Espírito Santo between 2017 and 2020, distributed between pastures (255), agriculture (251), land and lots (157) and native forests (78).

The data for the state of Espírito Santo highlights the dangerous nature of these fires and the importance of understanding their spatial and temporal distribution, as well as the various factors that condition these events, in order to identify and classify risk areas. Consequently, this study aims to identify and develop a fire risk zoning system for the Cachoeiro de Itapemirim municipal Headquarters District (CIHD).

2. Study Area

The study area is the Cachoeiro de Itapemirim municipal Headquarters District (CIHD), located in the south of the state of Espírito Santo (ES), Brazil (BR) (Fig. 1). The total area of the municipality is 863.58 km², while the CIHD covers 211.96 km² (24.55%).

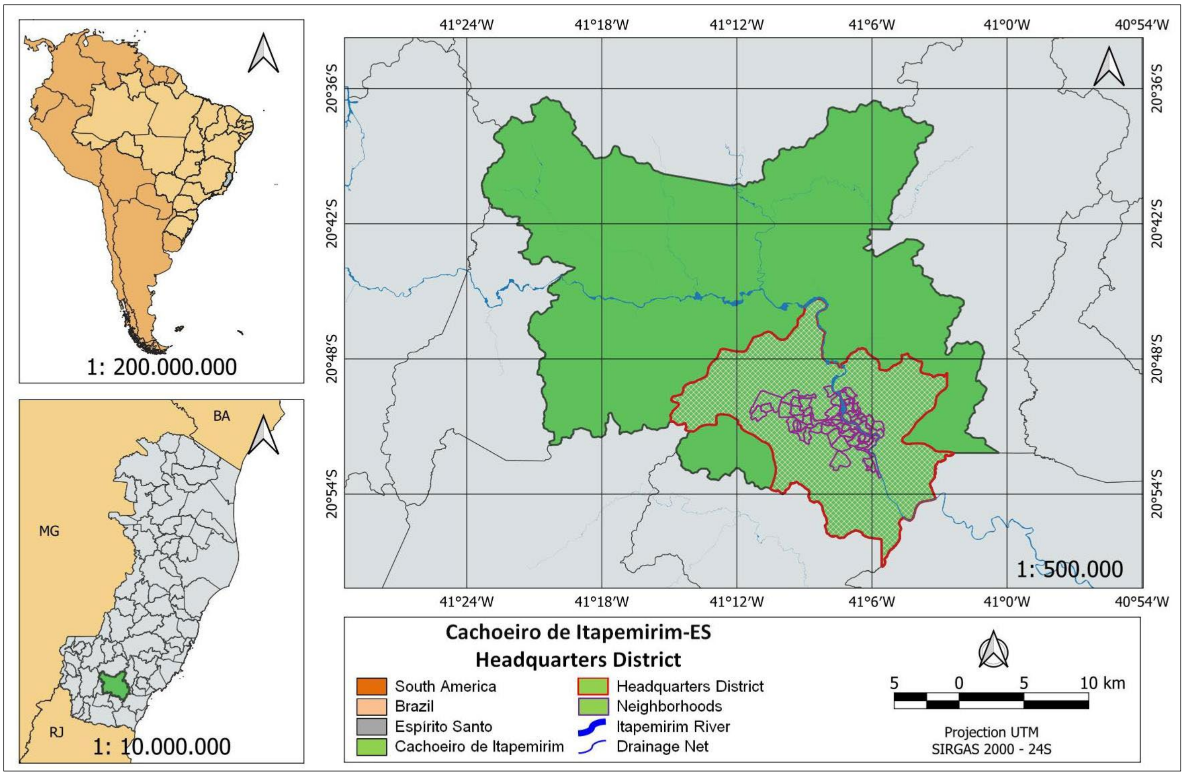

Figure 1. Location of the District of Cachoeiro de Itapemirim (ES).

According to the Capixaba Institute of Research, Technical Assistance, and Rural Extension (INCAPER, 2023), colonisation of this municipality began along the banks of the Itapemirim River in 1820, with subsistence agriculture (cassava, banana and sugarcane) being the main activity. Following the end of slavery in 1888, European immigration shaped the settlement of the interior.

From 1950 to 1970, the native forest was largely replaced by the forest-coffee-pasture cycle (Campos Júnior, 1996). During the 1980s, ornamental stone extraction and processing intensified, leading to an increase in commerce, industry and services, and to the expansion of urbanisation (Giaconi, 1998).

In terms of climate, Silva (1993) classifies it as Tropical Savannah (Aw), with intense summer rains and dry winters. The historical series from the INCAPER weather station (Figure 2) shows the highest rainfall in December (218 mm) and the lowest in July (25mm). The maximum temperature occurs in February (34.8ºC) and the minimum in July (14.4ºC).

The municipality is part of the Atlantic Tropical Domain (Sea Scarp) landscape, with mamelon coastal relief and seas of hills (Ab'Sáber, 2003). The study area is located within the morphostructural compartmentalisation of the Itapemirim Basin (1:2,000,000), which defines the central portion as the Cachoeiro Compartment, composed of hills, alternating coastal massifs, sedimentary deposits and floodplains (Peixoto-Oliveira *et al.*, 2018).

According to the mapping of native vegetation (1:250,000) by the Brazilian Institute of Geography and Statistics (IBGE, 2018), the area is part of the Atlantic Forest ecosystem, where the relief and climate contribute to formations of Dense Ombrophilous Forest (DOF - evergreen, with tall trees and dense shrub vegetation) and Semideciduous Seasonal Forest (SSF - loss of leaves due to variations in temperature and water balance).

According to INCAPER (2023), the main land use and cover classes influenced by human activity are pastures (55.2%), native forests (14.2%), coffee (6.5%), regenerating forest (5.3%), mace (3.2%) and others (15.6%).

Corroborating the importance of undertaking this work, a selection of reports and images from local media outlets illustrates several incidents of vegetation fires in the CIHD (Fig. 3). These photographic records correspond to fires that occurred in the dry months (Fig. 2) and in areas of low vegetation. According to vector data from INPE (Moderate Resolution Imaging Spectroradiometer - MODIS), 442 fire outbreaks were recorded in the CIHD between 2014 and 2024.

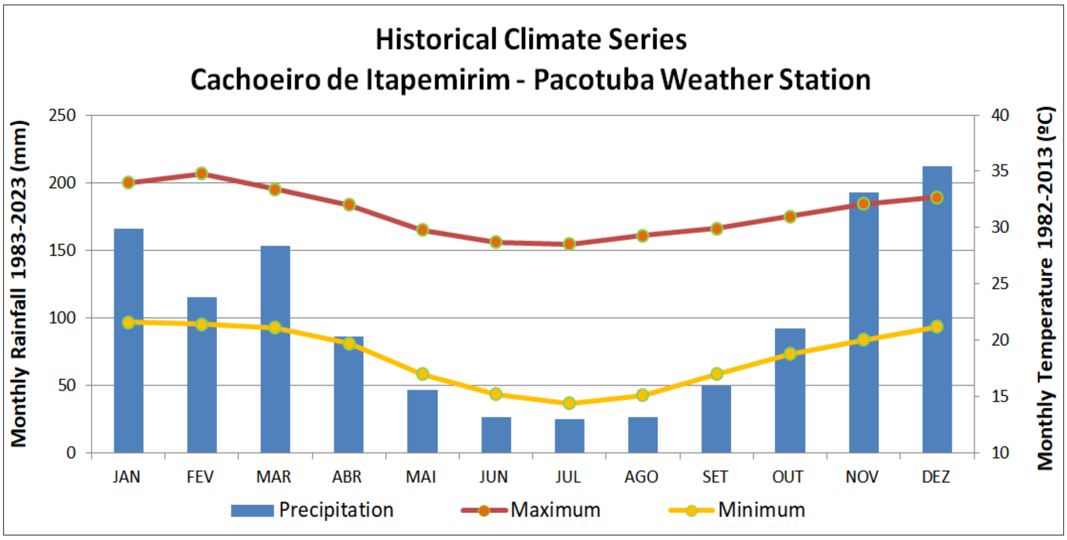

Figure 2. Monthly rainfall int the Pacotuba weather station.

Figure 3. Fire incidents by CIHD neighbourhood: (a) Aeroporto 25/06/2024, (b) Monte Belo 06/07/2024; (c) Paraiso 12/09/2024; e (d) Nossa Sr[a]. Aparecida 02/10/2024. Source: AquiNotícias (aquinoticias.com).

3. Methodology

The flowchart in Figure 4 summarises the actions taken to zone fire risks in the CIHD. A database containing the variables, data formats, scales, and the agency from which the data originated (Table 1) was set up within the Geographic Information System (GIS) environment (QGIS).

The Coordinate Reference System (CRS) used was SIRGAS 2000/UTM zone 24S. The working scale used was 1:200,000, with a spatial resolution of 50 m, as per the acceptable Root Mean Square (RMS) proposed by Santos (2010) in Equation 1.

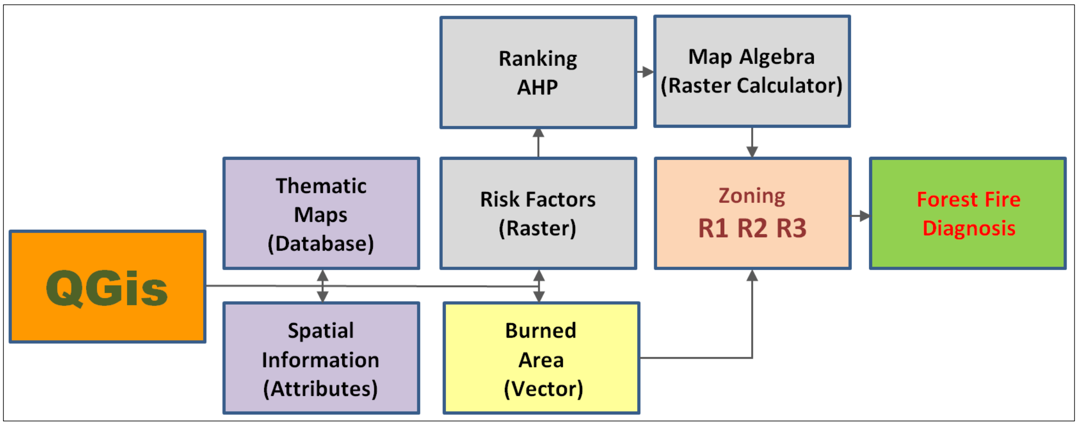

Figure 4. Flowchart of data processing steps and results.

Table 1. Cartographic data used to compose the CIHD digital database. Integrated Geospatial Base System of the State of Espírito Santo (GEOBASES), Brazilian Institute of Geography and Statistics (IBGE), City Hall of Cachoeiro de Itapemirim (PMCI), MapBiomas Brazil (MapBiomas) and National Institute for Space Research (INPE).

Digital Cartographic Data	**2,**	**Scale**	**Source**
Hypsometric curves (equidistance 20m)	Shapefile	1: 10,000	GEOBASES
Municipal and district boundaries	Shapefile	1: 600,000	GEOBASES
Dry months	Shapefile	1: 400,000	GEOBASES
Census sectors	Shapefile	1: 250,000	IBGE
Vegetation map	Shapefile	1: 250,000	IBGE
Municipal road network	Shapefile	1: 100,000	PMCI
Satellite image SENTINEL 2, pixel 10m (2022)	GeoTiff	-	MapBiomas
Burned areas 1km x 1km (MODIS)	Shapefile	-	INPE

$$RMS = \left(\frac{1/60 * DE * 0.0254}{1.64}\right) \tag{1}$$

Where:

RMS = Root Mean Square (m); and

DE = denominator of the numerical scale.

In order to make the data compatible (scale and spatial resolution) and eliminate possible geometric disagreements between the original data, the following post-processing steps (Fig. 5) were carried out: (i) definition of the average scale of the mapping data (1:350,000); (ii) conversion of vectors to Raster with a resolution of 100 m according to Equation 1; (iii) conversion of Raster to vectors (polygon) with smoothing of arcs; (iv) conversion to Raster with a refined resolution of 50 m; and (v) selection of data for geometric adjustment (Build Virtual Raster), which generates final data with aligned pixels.

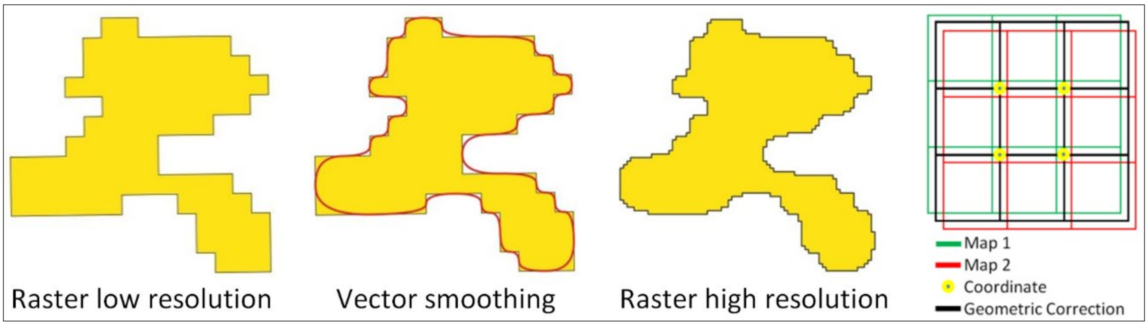

Figure 5. Adequacy of resolution and scale.

Three main groups of fire risk factors were defined based on a review of the literature: physical factors (relief orientation and slope, and months without rain), biological factors (land use and cover) and socioeconomic factors (population density, buildings and roads). The thematic representations were:

- Natural vegetation: forest fires can have various impacts depending on the ecosystem. While fires are essential processes in plant communities with adapted species, in non-adapted ecosystems, they can have negative impacts (Ramalho *et al*., 2024). Based on the mapping of natural vegetation, vegetation flammability values were assigned according to Setzer *et al*. (2019) for Dense Ombrophilous Forest (1.5) and Semideciduous Seasonal Forest (1.7).
- Topography: orientation and slope are related to changes in the microclimate, which can influence the potential for fire ignition and spread. Slope plays an important role in fire spread, which is faster in sloping areas and slower in flat areas (Chuvieco and Congalton, 1989). The orientation of the relief dictates the length of exposure to solar energy (incidence and duration), which affects plant physiology and surface temperature (Silva, 2020). A Digital Elevation Model (DEM) was generated by interpolating the contour lines (r.surf.contour). The slope map (analysis) was reclassified into 5 categories: softly rolling (0º-5º), rolling (5º-15º), strongly rolling (15º-25º), sloping (25º-35º) and steeply sloping (>35º). The relief orientation (aspect) was reclassified into 6 categories: flat, dark (south, southeast and southwest), semi-dark (east), semi-illuminated (northeast), illuminated (west and northwest) and full sun (north). The slope and relief orientation categories were used by Juvanhol *et al*. (2015).
- Months without rain: the atmospheric conditions of a region can be altered by variations in climatic elements (temperature, precipitation, humidity, wind and atmospheric pressure), favouring the occurrence of forest fires (Schumacher and Dick, 2018; Lamat *et al*., 2021). Regions with humid climates require more energy (heat) for fire ignition and plant combustion. Long periods of low rainfall lead to decreased water retention by vegetation and organic soil cover (leaf litter), favouring the occurrence of fires (Ramalho *et al*., 2024). In this study, additional climatic variables that may influence forest fires were excluded due to the unavailability of historical observation and mapping data. The CIHD study identified three classifications of months without rain: rainy (2.5), rainy-dry (4.5) and dry (6.0).
- Land use and cover: the flammability of vegetation can be related to its composition, stage of development and type of agricultural management. Forests present a lower risk of fire due to the conservation of moisture and reduced wind circulation brought about by plant densification (Ramalho *et al*., 2024). Areas given over to agriculture, livestock, mace production and vegetation recovery are more vulnerable due to their exposure to climatic variations (solar radiation, humidity and atmospheric circulation) (Setzer *et al*., 2019; Demir and Akay, 2024). Photointerpretation procedures, supervised classification (Reclassify Table), vector conversion and individualised risk classification (attributes) were applied to the SENTINEL 2 images. The related methodologies used were those of Mambile *et al.* (2025) and Murta Júnior and Oliveira (2024).

- Population density: shows the population distribution according to the number of individuals per metric unit adopted (Souza *et al*., 2021). A higher number of individuals increases the risk of fires due to increased traffic, altered landscapes and the generation of waste (industrial and domestic). The population (inhabitants) and area (hectare unit) values for each census tract were divided by the respective attributes (field calculator).
- Proximity to homes: the edges of urban areas are more at risk of vegetation fires due to the proximity of people. Burning garbage and undergrowth on plots is a common practice and can aggravate fires due to inadequate fire control (Juvanhol *et al*., 2015). The edges of urban areas were grouped into 5 classes: the starting area (isolated buildings, urbanisation and water bodies on the edge of urban boundaries) and 4 buffer classes (<500 m, 500-1,000 m, 1,000-1,500 m and >1,500 m). The starting area (lowest risk) aims to avoid any spatial overestimation of the most high-risk class (<500m) within the urbanised area, as it does not contain vegetation at higher risk of fire, according to Pirovani *et al.* (2012).
- Proximity to roads: roads may constitute a fire risk when they are close to vegetated areas, depending on the materials transported and emissions produced (Oliveira *et al*., 2020). There are both side roads and paved roads in this region, connecting urban, rural and industrial areas. Two categories of road influence were adopted: the first based on a buffer (<150 m) and the second based on the overlap with the study area (>150 m), as per Chuvieco and Congalton (1989).

To classify the importance of the risk factors, values were assigned to each thematic subdivision of the maps in vector format. A ranking scale of 0 to 5 was utilised for vegetation fire risk, as shown in Table 2.

Table 2. Classification of fire risk factors. Source: Juvanhol et al. *(2015) and Murta Júnior e Oliveira (2024).*

Susceptibility	Ranking	Explanation
None	0	No possibility.
Very Low	1	Proximity of risk elements.
Low	2	Combined risk elements.
Moderate	3	Intermediate condition.
High	4	Proximity between risk elements and human activities.
Very High	5	Combined risk elements and human activities.

Table 3 shows the ranking of the factors that contribute to fires in the CIHD, according to Risk Group (physical, biological and socioeconomic), Variable (vectors), Thematic Class and Ranking (value inserted in “attributes”).

The hierarchical ordering and assignment of weights to the risk variables were organised using GIS (specifically, Easy AHP). The Analytic Hierarchy Process (AHP) method was employed, which involves establishing a hierarchy of importance, ordering the information in a matrix and conducting pairwise comparisons (Saaty, 1977). According to Demir and Akay (2024), AHP studies of forest fires include various spatial factors that can initiate and/or potentiate such events. To avoid subjectivity, the data representing these factors must be judged and ordered according to their importance in the context of the event. The matrix ordering generates a pairwise comparison of the risk factors, followed by the elimination of subjectivity by assigning weights.

Table 3. Ranking of the factors. Source: adapted from Juvanhol et al. *(2015).*

Risk Group	Variable	Thematic Class	Area Km²	Area %	Ranking
Physical	Relief Gradient (RD)	Softly rolling	63.19	29.81	1
		Rolling	90.85	42.86	2
		Strongly rolling	39.66	18.71	3
		Sloping	13.27	6.26	4
		Steeply sloping	5.00	2.36	5
	Relief |Orientation (RO)	Flat	0.23	0.11	1
		Dark	46.27	21.83	1
		Semi-dark	59.73	28.18	2
		Semi-illuminated	31.75	14.98	3
		Illuminated	49.01	23.12	4
		Full sun	24.97	11.78	5
	Months Without Rain (MWR)	Rainy	4.71	2.22	3
		Rainy-dry	28.95	13.66	4
		Dry	178.30	84.12	5
Biological	Native Forest (NF)	DOF	122.70	57.89	1.5
		SSF	89.26	42.11	1.7
	Land Use and Cover (UC)	Agriculture	116.41	54.92	5
		Intermediate vegetation	25.29	11.93	4
		Isolated buildings	1.85	0.87	2
		Rock vegetation	1.12	0.53	2
		Urban area	29.52	13.93	1
		Forest	35.68	16.83	1
		Water body	2.11	0.99	0
Socioeconomic	Population Density (inhabitants/hectare) (PD)	0 – 1	179.19	84.54	2
		1 – 10	10.45	4.93	3
		10 – 30	4.73	2.23	4
		> 30	17.59	8,30	5
	Proximity to Homes (PH)	Starting area	31.86	15.03	1
		< 500 m	86.71	40.91	5
		500 – 1000 m	43.41	20.48	4
		1000 – 1500 m	24.33	11.48	3
		> 1500 m	25.65	12.10	2
	Proximity to Roads (PR)	< 150m	52.10	24.58	5
		> 150m	159.86	75.42	1

Judgments can vary by importance, with 1 (equal importance) and 9 (absolute importance of one criterion over another) as shown in Table 4. Validation is obtained from the Consistency Ratio (CR), which must be less than 1.0 or 10%.

Based on a review of the literature, including regional studies (Juvanhol *et al.*, 2015; Setzer *et al.*, 2019; Almeida *et al.*, 2022; Juvanhol *et al.*, 2023), the fire risk factors were ranked by importance for inclusion in the matrix. This ranking used a continuous scale (1-7) with the inclusion of intermediate values (2-6), to enhance the precision of the assessments between factors. This approach reduces the risk of overestimating any given factor when analysing the information (ranking and judgment). As a result, the final outcome reflects a more integrated contribution from multiple risks (Chuvieco and Congalton, 1989; Oliveira *et al*., 2020; Lamat *et al*., 2021; Jones *et al*., 2025).

Table 4. Paired comparison scale. Adapted from Saaty (1977).

Values	Mutual Importance	Explanation
1	Equal importance	Equal contribution of two factors
3	Minor importance	Slightly favours one of the factors
5	Essential importance	Essentially favours one of the factors
7	Strong importance	Strongly favours one of the factors
9	Extreme importance	Very strongly favours one of the factors
2, 4, 6 & 8	Intermediate between judgments	Compromise between two factors
1/9	Extremely less important than	-
1/7	Very strongly less important than	-
1/5	Strongly less important than	-
1/3	Moderately less important than	-

Physical factors are at the top of the matrix, followed by biological factors in the middle and socioeconomic factors at the bottom. The matrix hierarchy used shows combined risks based on the degree of proximity or capacity for human intervention in the environment. It is assumed that vegetation cover is naturally susceptible to fires. However, in the current context, fire histories indicate that human presence and intervention are precursors for the recurrence of these events, as they enhance the potential for ignition and spread of fire by altering natural landscapes and increasing fuels in environment (Shumacher and Dick, 2018; Silva, 2020; Almeida *et al*., 2022; FAO, 2023; Demir and Akay, 2024).

The variables assigned the lowest weights in the matrix are the relief gradient, noting that there have been no significant changes associated with a gain in slope (1) and exposure to solar radiation (2).The months without rain (3) represent the influence of atmospheric conditions, while biological factors are assigned an intermediate weight (3-4) given that human factors start fires but climate and relief can accelerate their spread. The highest weights are attributed to population density (4-5), proximity to houses (5-6) and roads (6-7), due to the increased potential risk created by the mobility of people and vehicles (Chuvieco and Congalton, 1989; Juvanhol *et al*., 2015; Murta Júnior and Oliveira, 2024).

Table 5 shows the hierarchy of the factors included in the first model (R1) with an acceptable CR (0.012). Only the natural variables (the physical variables and the native forest) were included, indicating their significance in contributing to forest fire risk.

The next model (R2) included the biological and socioeconomic factors in the matrix hierarchy (Table 6). The increase in the number of factors (7) resulted in a dilution of the weights and an increase in the CR (0.020), which remained acceptable.

The third model (R3) included the Months Without Rain (MWR), which resulted in the reordering of 7 factors and increased the dilution of the weights compared to the previous zonings (Table 7). The CR value (0.025) remained acceptable.

Table 5. Hierarchy of factors (R1). The names of the variables are explained in Table 3.

Factor	RD	RO	MWR	NF	Weight
RD	1	1/2	1/3	1/4	0.096
RO	2	1	1/2	1/3	0.161
MWR	3	2	1	1/2	0.277
NF	4	3	2	1	0.466
Consistency Ratio					**0.012**

Table 6. Hierarchy of factors (R2). The names of the variables are explained in Table 3.

Factor	RD	RO	UC	PD	PH	PR	Weight
RD	**1**	1/2	1/3	1/4	1/5	1/6	0.044
RO	2	**1**	1/2	1/3	1/4	1/5	0.066
UC	3	2	**1**	1/2	1/3	1/4	0.102
PD	4	3	2	**1**	1/2	1/3	0.160
PH	5	4	3	2	**1**	1/2	0.249
PR	6	5	4	3	2	**1**	0.379
Consistency Ratio							**0.020**

Table 7. Hierarchy of factors (R3). The names of the variables are explained in Table 3.

Factor	*RD*	*RO*	*MWR*	*UC*	*PD*	*PH*	*PR*	*Weight*
RD	***1***	*1/2*	*1/3*	*1/4*	*1/5*	*1/6*	*1/7*	*0.032*
RO	*2*	***1***	*1/2*	*1/3*	*1/4*	*1/5*	*1/6*	*0.046*
MWR	*3*	*2*	***1***	*1/2*	*1/3*	*1/4*	*1/5*	*0.070*
UC	*4*	*3*	*2*	***1***	*1/2*	*1/3*	*1/4*	*0.106*
PD	*5*	*4*	*3*	*2*	***1***	*1/2*	*1/3*	*0.159*
PH	*6*	*5*	*4*	*3*	*2*	***1***	*1/2*	*0.238*
PR	*7*	*6*	*5*	*4*	*3*	*2*	***1***	*0.350*
Consistency Ratio								***0.025***

Three fire risk models were generated using the map algebra method (Raster Calculator). For each proposed model (R1, R2 and R3), the variables were multiplied by the respective weight obtained by AHP (Tables 5, 6 and 7) and the factors were summed according to Equation 2.

$$R = (FA*P1) + (FB*P2) + (FC*P3) + (FD*P4) + (FE*P5) \tag{2}$$

Where:

R: Risk of forest fire;

F: Risk factor;

A, B, C, D and E: variables (Table 3); and

P: Weight assigned to the risk factor.

The analysis of the study area consisted of reclassifying and measuring (Report Layer Raster) the zoning. The thematic classification of risks included in Table 2 is shown as follows: <1 (blue); 1-2 (olive green); 2-3 (green); 3-4 (beige); 4-5 (orange); and ≥5 (red).

The next step was to organise a 5-year historical series (2020-2024) of burned area mapping data (Libonati *et al.*, 2015). This data comes from a Brazilian-Portuguese initiative—the Brazilian Fire-Land-Atmosphere System (BrFLAS)—that uses remote sensing to monitor vegetation fires. The data is obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS 1km resolution) and is provided by INPE in shapefile format in 1 km x 1 km quadrants (AQ1km).

Merging the data from the historical series of burned areas (BA) involved first excluding overlapping polygons (merge) and then cutting out the study area (recut), thereby ensuring spatial consistency between the final burned area and the CI boundaries.

In order to identify the conformity between the zoning data and the historical series of burned areas, a comparison was made between the two. Based on the BA data, cut-outs were made over R2 and R3, followed by an assessment of the zoning classes within the boundaries of the areas affected by fires (Zhao *et al*., 2024; Jones *et al*., 2025).

4. Results

The CIHD forest fire risk zoning used the mapping of variables, whose spatial distribution values can be seen in Table 3 and Figure 6.

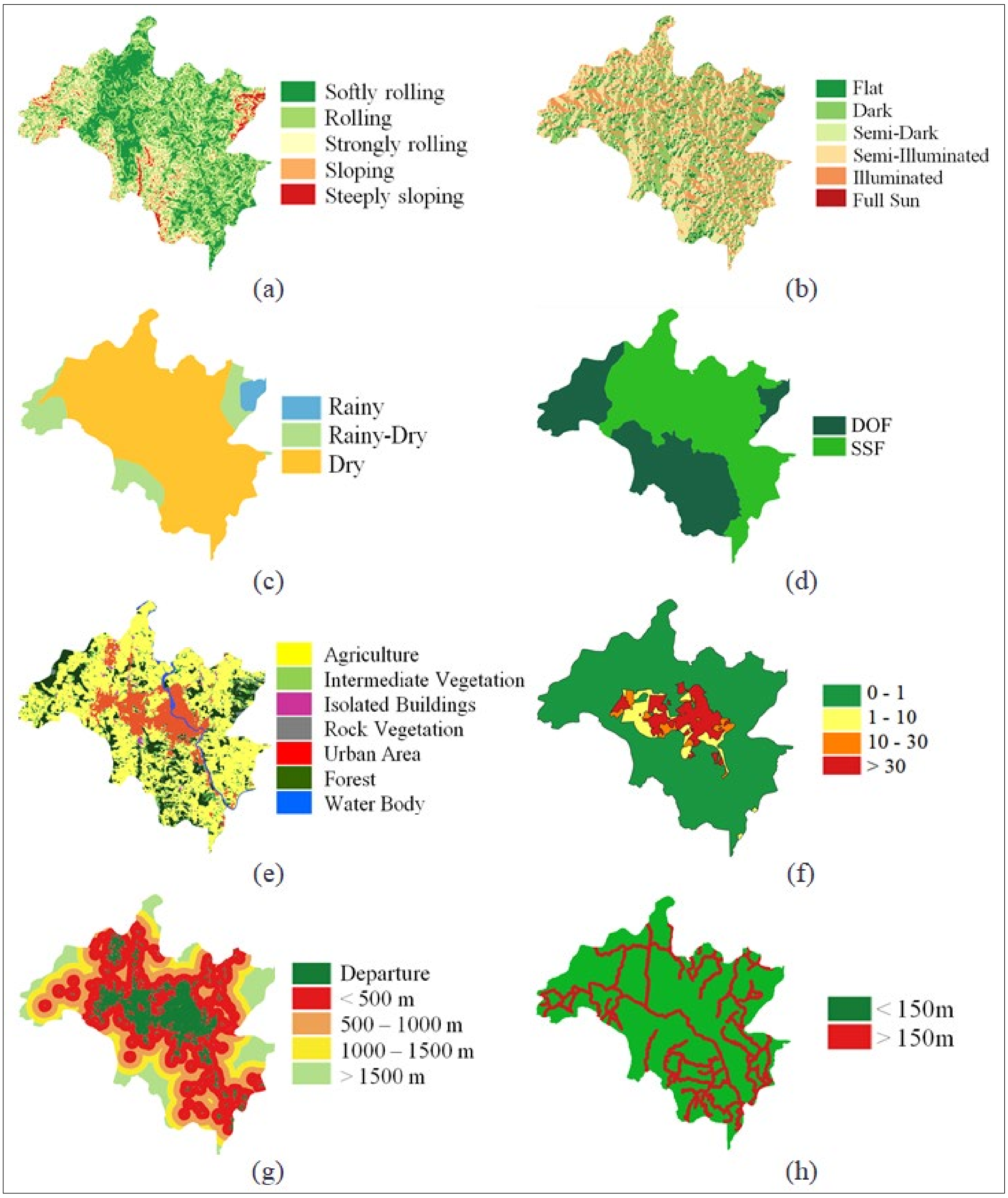

Figure 6. Spatialisation of the factors that influence the occurrence of forest fires: (a) relief slope; (b) relief orientation; (c) months without rain; (d) native vegetation; (e) land use and cover; (f) population density; (g) distances from urbanised areas and (h) distance from roads.

With regard to the relief gradient (5-a), rolling (42.86%) and gently rolling (29.82%) terrain predominate, indicating that more than 72.68% of the area is subject to lower fire risks due to the influence of the relief.

The distribution of the strongly rolling terrain (18.71%) indicates a significant amount of transition between risk categories, and together with the sloping (6.26%) and steeply sloping (2.36%) terrain, represents 27.33% of the area. Relief orientation (5-b) indicates a predominance of semi-dark relief (28.19%), followed by illuminated (23.12%) and semi-illuminated (21.83%). Areas of full sun account for 11.78%. Dark (14.98%) and flat (0.11%) relief are the least common. Oliveira *et al.* (2020) identified high declivity and a predominantly westerly relief orientation as high-risk factors for vegetation fires. The speed of fire spread can double on slopes above 10º and quadruple when above 20º.

In the spatialisation of the dry months (5-c), the dry classification (84.12%) predominates, while the rainy-dry classification (13.66%) occurs in scattered stretches and the rainy classification (2.22%) applies only to a small, isolated area. The native vegetation (4-d) is made up of 3 (three) fragments of Dense Ombrophilous Forest (57.89%) and a strip of Semideciduous Seasonal Forest (42.11%). Jones *et al.* (2025) observed that pine forests (dry areas) increase the potential for fires by providing fuel, while areas of deciduous vegetation (moisture conservation on the soil surface) act as firebreaks.

In terms of land use and cover (5-e), the highest occurrence is in agricultural and pastoral terrain (54.92%), primarily comprising pastures and other areas of low vegetation, which are more physiologically vulnerable to climatic variations. This is followed by forests (16.83%) and urban areas (13.93%). Intermediate vegetation (11.93%) consists of agricultural areas with low plant spacing, deforestation and areas under recovery. Isolated buildings (0.87%) consist of small clusters of buildings or areas under construction, including stretches of soil exposed by cutting slopes and earthworks. The rock vegetation category (0.52%) was defined by identifying and combining vegetation with rocky outcrops. According to Ramalho et al. (2024) the importance of forest ecosystems in stopping fires has only recently been recognised, as their ability to fulfil this role has been diminished as human activities have advanced.

Among the population density classes evaluated in terms of inhabitants/hectare (Figure 4-f), the highest fire occurrence was in areas of 0-1 (84.54%), which corresponds to areas classified as rural in the IBGE census sectors. This was followed by the >30 (8.30%) class, 1-10 (4.93%), and 10-30 (2.23%), all in urbanised areas. In order to compare population and vegetation cover, Pirovani *et al.* (2012) assessed green area indices (GAI) in the municipality, identifying an index (35.04 m²/inhabitant) well above the minimum value indicated (15 m²/inhabitant). However, urban tree planting can be found in small fragments in the central area. The absence of green areas in urban environments can result in phenomena related to rising temperatures and thermal discomfort, such as heat islands.

With regard to proximity to homes (4-g) the largest class was the buffer closest to the edges of urban areas (<500 m; 40.91%). This was followed by 500-1,000 m (20.49%), >1,500 m (12.10%) and 1,000-1,500 m (11.48%). The procedure of creating a buffer (150 m) from roads and highways (4-h) resulted in a risk area of proximity (24.58%) and surroundings (75.42%). Murta Júnior and Oliveira (2024) explained the influence of the proximity of urbanisation and roads on the risks of vegetation fires in the municipality of Itinga (Brazil/MG), where they identified that the areas at highest risk correspond to those with a combination of occupational and anthropic activities (roads, urbanisation and agriculture).

Map algebra procedures enabled the generation of three fire risk models: R1 (a), R2 (b), and R3 (c), as shown in Figure 7. The spatial distribution of the risk levels is shown in Table 8. In the model based on natural factors (R1), the most dominant level is "low risk" (79.98%), followed by "moderate risk" (18.97%) and "very low risk" (0.12%). The "no risk" level (0.92%) corresponds to water bodies in all the models. When added together, the areas with lower risk levels account for 81.03% of the total. The values obtained from this zoning indicate that a significant part of this area, under natural conditions, is not very susceptible to vegetation fires.

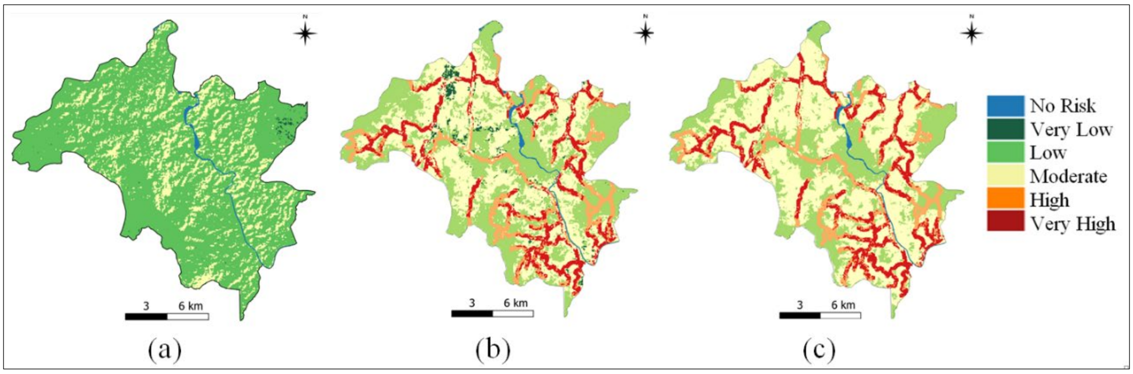

Figure 7. Thematic representation of forest fire risk zoning in the study area for each model: (a) R1; (b) R2 e (C) R3.

Table 8. Levels of fire risk in models R1, R2 and R3.

Level	R1			R2			R3			R3–R2
	(km²)	(%)	(%)	(km²)	(%)	(%)	(km²)	(%)	(%)	(km²)
No risk	1.95	0.92	-	1.95	0.92	-	1.95	0.92	-	1.95
Very Low	0.26	0.12	-	3.53	1.67	-	0.00	0.00	-	-3.53
Low	169.53	79.98	81.03	79.71	37.61	40.19	58.65	27.67	28.59	-21.06
Moderate	40.22	18.97	-	79.78	37.64	-	102.05	48.15	-	22.27
High	0.00	0.00	-	22.59	10.66	-	22.02	10.39	-	-0.57
Very High	0.00	0.00	18.97	24.40	11.51	59.81	27.29	12.88	71.41	2.89
Total	**211.96**	**100**	**100**	**211.96**	**100**	**100**	**211.96**	**100**	**100**	**-**

In the second model (R2), which includes biological and socioeconomic factors, “moderate risk” was the most common (37.64%), followed closely by “low” (37.61%). Next are “very high” (11.51%), “high” (10.66%) and “very low” (1.67%). When combined, the lower risk levels account for 40.19% of the total area, while the higher risk levels account for 59.81%. The highest risk levels are concentrated around the roads: high (red) and very high (orange). The combined risk factor of pasture areas in proximity to the edges of urbanised areas generated a moderate risk (yellow). The low (light green) and very low (dark green) risk areas are found in urban settings and native forests, as expected due to the procedure adopted to avoid overestimating values within urban areas. When compared to the model based solely on natural factors (R1), this model highlights the significant role of human activities in influencing the risk of vegetation fires.

The R3 model, which takes into account the months without rain, shows a more complex scenario due to the inclusion of the climate factor. “Moderate risk” is the most common (48.15%), accounting for almost half of the study area. “Low risk” (27.67%) is in second place, followed by “very high risk” (12.88%) and “high risk” (10.39%). The “very low” risk level does not occur in this model. When combining risk levels, this model shows greater disparity, with the top three lower-level classes accounting for 28.59% and the highest risk levels accounting for 71.41% of the district. The areas of very high risk (red) are increasing and remain close to the roads. The areas of moderate risk (yellow) align with the spatialisation of the drought areas in months without rain, increasing the risk factor in stretches of pasture and forest. The spatialisation of fire risks by combined anthropogenic factors shows the high potential risk in these areas in both models (R2 and R3), highlighting the increased risk around roads.

Figure 8 shows how the risk levels behave when the area values (km²) of the R3 model are subtracted from those of the R2 model. The “no risk” level remains inert (1.95 km²), which is to be expected as these are water bodies. The levels that saw their areas reduced were “low risk” (-3.53 km²) and “high risk” (-0.57 km²), while the levels that saw their areas increased were “moderate risk” (22.27 km²) and “very high risk” (2.89 km²).

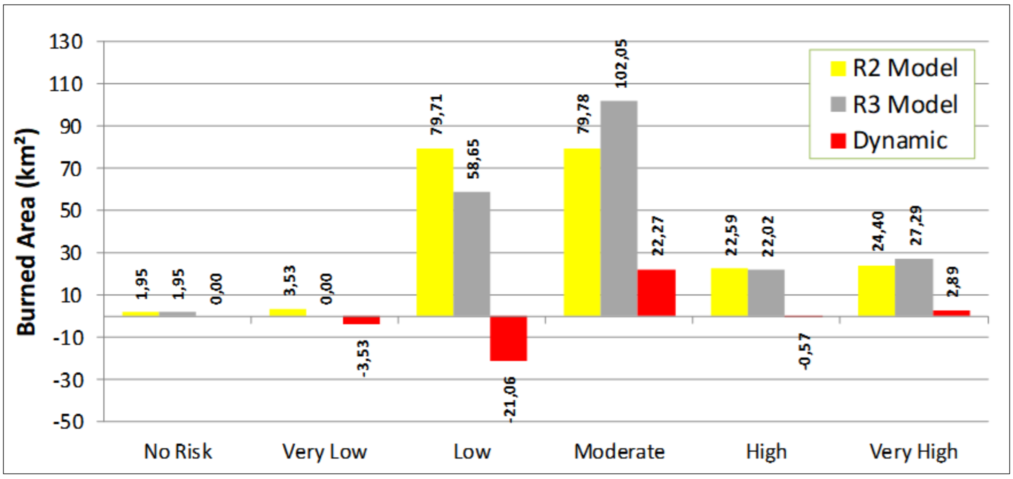

Figure 8. Comparison of values between R2 and R3.

Comparing the R2 and R3 risk level zonings allows us to infer the importance of including the climatic factor (dry months) in the analysis for the CIHD, as doing so produces a reduction in areas of lower fire risk and an increase in areas more susceptible to vegetation burning.

Figure 9 contains maps showing both the total burned area and the historical series (2020-2024) provided by INPE. The fire risk levels within the total burnt area are shown in Table 9. The smallest burnt area was recorded in July 2020 (1.15 km²), followed by May and July 2021 (3.45 km²). There was an increase in 2022 between the months of July and September, totalling 29.59 km². In 2023, fires were recorded in July (10.37 km³). The largest burned area was recorded in 2024 between the months of June and September, totalling 5604 km².

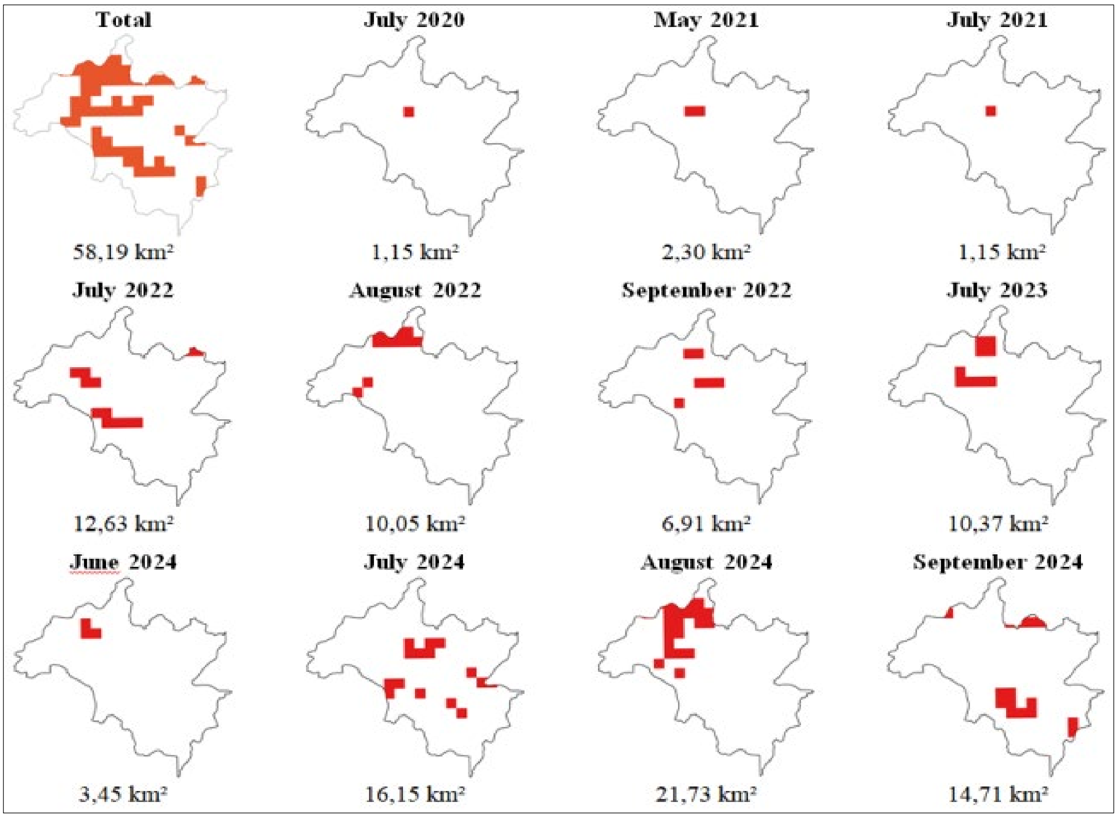

Figure 9. Temporal evolution of the burned area.

Table 9. Behaviour of the fire risk models (R2 and R3) within the boundaries of the total burned area.

Level	R2			R3		
	(km²)	(%)	(%)	(km²)	(%)	(%)
None	0.30	0.52	-	0.30	0.52	-
Very Low	2.32	0.54	-	0.00	0.00	-
Low	13.38	20.66	27.50	10.02	17.22	17.73
Moderate	28.91	53.82	-	34.00	58.42	-
High	4.97	7.15	-	4.52	7.77	-
Very High	8.33	17.31	72.50	9.36	16.08	82.26
Total	58.19	100	100	58.19	100	100

A common factor among all the vegetation fire mappings is the occurrences of fires in July, which corresponds to the driest period according to INCAPER rainfall data (Fig. 2). By combining and eliminating any overlaps between the burned areas, a polygon of 58.19 km² was obtained, which corresponds to 27.45% of the area.

In the BA x R2 overlap, the highest occurrence is in the “moderate risk” level (53.82%), which accounts for more than half of the area from the historical records of vegetation fires. This is followed by the “low” (20.66%), “very high” (17.31%) and “high” (7.15%) levels. The “very low” risk level (0.54%) has the lowest occurrence in the historical series. Combining the groups indicates a low occurrence in the lower risk levels (27.50%) and a high occurrence in the higher risk levels (72.50%).

In the R3 model, occurrences in the “very low” risk level are zero (0.0%). “Moderate risk” was the most common (58.42%), followed by “low risk” (17.73%), “very high” (16.08%) and “high” (7.77%). The lowest risk levels combined account for 17.73% of the area, while the highest risk levels combined account for 82.26% of the burnt area.

5. Discussion

5.1. Fire risks in the study area

The CIHD, as a unit, can be considered highly susceptible to forest fires. The high percentage of area accounted for by low fire risk values in the R1 model (81.03%) can be attributed to its representation of original conditions, with a predominance of native forests. The absence of anthropogenic intervention allows forests to perform their environmental functions (controlling humidity, temperature and atmospheric circulation), reducing the risk of fire ignition and spread. The combination of factors that increase the risk of fire (physical, biological and socioeconomic) contributed significantly to the increase in high-risk levels in the R2 (59.81%) and R3 (71.41%) models.

Moro and Oliveira (2023) studied fire data (1,260 points) from the southern region of the state of Espírito Santo between 2017 and 2020, with 970 locations in the municipality of Cachoeiro de Itapemirim alone. The data revealed that the distribution of fire types was 54.64% vegetation, 43.95% in urban areas and 1.41% not classified. The authors found that the combined presence of geographical and occupational factors contributes to the recurrence of fires in the south of the state, which corroborates the high-risk potential for forest fires identified in the CIHD.

Based on the values identified for slope distribution and relief orientation, the CIHD can be considered to have a high solar incidence. The prevailing climatic and hydrological conditions can induce long periods of drought (up to 6 months), a phenomenon reflected in the water stress and fragility of the region’s vegetation. As noted in the existing literature, these specific relief, climate and vegetation conditions can increase the incidence of ignition points and accelerate the spread of fire (Oliveira *et al.*, 2020; Souza *et al.*, 2021; Almeida *et al.*, 2022; Demir and Akay, 2024).

The land use and cover categories point to the significant influence of human intervention on fires. Agricultural activities occupy more than half of the area (54.92%), followed by urbanisation (13.93%). The extent of forested areas is relatively limited (16.83%), largely due to historical destruction, and this increases the area's water and environmental fragility. Therefore, increasing preserved forest areas offers a viable alternative for creating natural barriers to the spread of fire, helping to conserve moisture, and mitigating high temperatures (Juvanhol *et al.,* 2015; Ramalho *et al.*, 2024).

The distribution of the population reveals higher concentrations in the urbanised areas and lower concentrations in the rural areas of the CIHD. It is important to reflect on two aspects: (i) urbanised and populated areas may represent a lower risk of forest fires due to the lower occurrence of vegetated areas, commonly limited to parks and allotments; and (ii) rural areas with a low population represent a higher risk of forest fires due to the extensive areas of diverse vegetation. Thus, the edges of urban areas are considered transition zones between these factors (urban and rural), in which the proximity of vegetated areas, urban facilities and the movement of people combine. Ferreira (2021) considers these variables to be the main components of the urban-rural interface. This is a recent concept in forest fire studies, but it demonstrates how rural and urban landscapes merge and enhance fuel generation.

The enhanced risk in the vicinity of urban areas does not eliminate the risk of fires within them, but it accounts for their lower potential for spreading fire due to the distance between vegetated areas, which are commonly surrounded by buildings. Almeida *et al*. (2022) identified a generic typology (low vegetation) of urban vegetation fires and occurrences in the months with favourable climatic variables (low rainfall/humidity and high temperature).

It should also be noted that small patches of vegetation and urbanisation may be omitted at certain scales. Murta Júnior and Oliveira (2024) considered the urban area to be of low susceptibility to vegetation fires and excluded small communities in rural areas, as these did not represent significant changes to the results.

The spatialisation of roads can cover different environments and encourage the movement of people and vehicles, compromising the integrity of vegetation. Chuvieco and Congalton (1989) gave greater weight to road surroundings (150 m) because they deemed them to be a higher risk factor. Demir and Akay (2024) found a significant reduction in the risk of forest fires in a region with a Mediterranean climate (Mersin, Turkey) as the distance between road surroundings increased (<100 m = 0.51 and >400 m = 0.04).

The adoption of inspection measures, prevention (firebreaks), control responses (fire brigades) and infrastructure (access roads) in areas at risk of forest fires is both important and necessary. These actions and resources have proven to be effective in preventing and controlling forest fires, but in many cases, they are not properly implemented as recommended by the respective regulations due to the various investments required (Murta Júnior Oliveira, 2024).

5.2. Zoning procedures

Conducting a study based on forest fire risk zoning is a complex undertaking, requiring the identification and representation of various geographical factors that contribute to the likelihood of these incidents. Data integration and processing models can be used depending on the research objective(s), generating different results. The CIHD's fire risk study is supported by other studies that have focused on zoning and comparing fire history.

The results obtained by Tahri *et al*. (2024) are similar to those obtained by the CIHD fire risk zoning. These authors used the AHP method combined with Neural Networks to model 20 parameters related to forest fires in the Czech Republic. The weighting procedure gave greater relevance to the land use and cover map (33%) due to the combination of various factors influencing fire frequency and control, followed by distance from roads (22%) and population density (14%). The other factors accounted for less than 10%.

Mambile *et al*. (2025) used procedures similar to those of the CIHD study to integrate data for modelling vegetation fires on Mount Kilimanjaro (Tanzania). The highest risk rates were associated with stressed vegetation, low humidity and deforestation for the introduction of agriculture. The authors addressed some of the limitations of zoning models, such as the non-availability of historical data and the absence of a comprehensive approach that factors in human interventions and other elements contributing to forest fires.

Lamat *et al*. (2021) used the AHP method to zone forest fires in the Ri-Bhoi district (India), analysing the correlation between original fire records from the MODIS satellite and the final products obtained by processing georeferenced data. After classifying the risks into 4 categories, the fire susceptibility was distributed as "very high" (32.86%), "high" (23.82%), "moderate" (27.39%) and "low" (15.93%). Stretches with higher rainfall had a reduced risk due to the higher moisture content and physiological growth of vegetation, which reduced the spread of fire.

Demir and Akay (2024) obtained consistent results by comparing the risk map (AHP) and the fire history between 2003 and 2022 (562 fires), achieving 74% accuracy using the curve method. They found that 71.71% of historical outbreaks occurred in high and very high-risk areas.

Zhao *et al*. (2024) linked the recurrence and increase of burned areas to surface climate impacts (energy conservation and warming) and the post-fire recovery of boreal and temperate forests in the Northern Hemisphere (predominance of species with greater resilience). The assessment of the burned area points to possible recurrences of forest fire events. Including the climate factor in the equation shows that periods without rainfall should be viewed with caution, as the fragility of the vegetation at these times increases the risk of forest fires.

5.3. Considerations with regard to spatialised information and integration methods

The unavailability of observation data (mainly on climate and land use) is a reality in many countries, which makes it difficult to develop consistent spatial analyses. Data on meteorological events and landscape changes are of great importance for forest fire studies, as various factors can influence and enhance these events (Libonati *et al*., 2015).

The procedures used to overlay and cross spatial data in a computer environment (vector, matrix or image) are considered significant advances in the context of geotechnologies. The AHP method is a viable alternative for studies based on overlaying spatial data (Tahri *et al*., 2024).

However, in the CIHD study, several limitations associated with this method were noted, namely: (i) it does not allow the impacts of the spatial and/or temporal dynamics of the variables involved in a single process to be represented; (ii) the inclusion of many variables in the same process can lengthen the matrix and compromise the integration between the factors; and (iii) the hierarchical ordering of the factors must adopt external options that eliminate the subjectivity of the decision stage (review of literature, Ad Hoc. Leopold matrix, etc.).

In order to overcome the aforementioned limitations of complex analyses (gaps in historical series, stationarity issues and model subjectivity), different techniques for processing and integrating variables have been used in forest fire studies. Several of these experiments, even those still in the experimental phase, have shown that significant progress can be made with the use of data processing and integration models, such as regression models, decision trees, artificial neural networks and machine learning (Oliveira *et al*., 2020; Juvanhol *et al*., 2023; Tahri *et al*., 2024; Zhao *et al*., 2024).

6. Conclusions

Forest fire risk zoning was conducted for the Cachoeiro de Itapemirim municipality Headquarters District (CIHD) in Espírito Santo, Brazil. The findings indicate that human occupation and prolonged periods without rainfall increase the occurrence of fires, thereby heightening the risks to both the population and the environment.

GIS tools enabled the thematic representation of spatial variables and the generation of models to analyse the interaction of fire risk factors. The methodological model used - the Analytic Hierarchy Process (AHP) - proved to be an effective tool for supporting decision-making, as it allowed for the ranking and hierarchical structuring of variables.

Taking a holistic view of the decision-making process, forest fire risk zoning is a recommended approach, particularly when it incorporates human and climatic factors that affect the ignition and spread of fires. It is hoped that this study will contribute to the advancement of research into forest fire risk.

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