Satellite Images and Spectral Vegetation Indices as Auxiliary Tools to Monitoring Fuel Availability in Areas Prone to Wildfire: Study Case in the Northern Region of Portugal

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Abstract: Remote sensing data has led to the development of spectral indices for monitoring ecosystems, land surface changes, and water quality. These indices are used in various applications, including agricultural and wildfire monitoring, to understand vegetation cycles and disturbances. Wildfire research focuses on the effects of extreme occurrences, and understanding forest ecology after severe events is crucial for evaluating forest health. Vegetation Indices (VIs) are frequently used in forest and wildfire monitoring studies to account for plant biophysical, biochemical, and physiological characteristics. Normalized Difference Vegetation Index (NDVI), Normalized Burn Ratio (NBR), Normalized Difference Infrared Index (NDII), and Plant Senescence Reflectance Index (PSRI) are indices used to assess vegetation conditions. VIs are valuable resources for monitoring post-wildfire occurrences, as they measure biophysical changes and provide comprehensive monitoring of the affected area, playing a crucial role in assessing the health of forests. Pre-wildfire vegetation conditions monitoring is also important for implementing preventative measures in critical regions to increase wildfire defense and identifying wildland fuels is crucial for improving fuel management actions. This research aims to demonstrate the effectiveness of chosen VIs and fuel models as tools to assess pre-fire conditions, enabling decision-makers to increase wildfire surveillance and landscape resilience in Vale do Sousa, Portugal's northern area. Despite limitations, this approach is valuable, especially in terms of financial or logistical constraints. Moreover, combining VIs with fuel hazard models can improve fuel reduction efforts.

1 INTRODUCTION

With the rapid development and accessibility of remote sensing data, several spectral indices have been developed to monitor ecosystems, land surface changes, and water quality (Chughtai et al., 2021; Ma et al., 2019). Spectral indices have been used in a variety of applications, including agricultural and wildfire monitoring, to better understand vegetation cycles or disturbances (Zeng et al., 2022).

A significant percentage of wildfire research focuses on the effects of extreme occurrences (Dos Santos et al., 2020). Understanding the forest ecology after severe events is crucial for evaluating forest health (Avetisyan et al., 2023). The information acquired may help stakeholders make key decisions about post-fire restoration, management, and actions. Most post wildfire assessments rely on field surveys, which are expensive, time-consuming, and limited to specific regions of the affected area (Fernandes et al., 2006).

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Vegetation indices (VIs) are frequently used in forest and wildfire monitoring studies to account for plant biophysical (detecting vegetation structure and changes), biochemical (e.g., pigments, water), and physiological (photosynthetic light use efficiency) characteristics (Zeng et al., 2022). The Normalized Difference Vegetation Index (NDVI) is one method for assessing vegetation conditions (Rouse et al., 1973). The Normalized Burn Ratio (NBR) and Differenced Normalized Burn Ratio (dNBR) are used to evaluate damage to vegetation and regeneration (Roy et al., 2006). The Plant Senescence Reflectance Index (PSRI) is used to measure chlorophyll concentration (Merzlyak et al., 1999).

VIs are a valuable resource for monitoring post-wildfire occurrences since they can measure biophysical changes, allowing for comprehensive monitoring of the affected area (Avetisyan et al., 2023). Most common VIs products are easily accessible through frameworks like Copernicus Browser, which produces NDVI, Moisture Index, and other metrics from Sentinel-2 data (ESA, 2024).

For example, NDVI can also be calculated from Landsat imagery using Google Earth Engine (Gorelick et al., 2017) or obtained as a product directly from the United States Geological Survey (U.S. Geological Survey, 2024). Other VIs can be computed using Geographic Information System (GIS) tools like QGIS, ArcGIS®, and SNAP (ESA, 2024; Esri & Environmental Systems Research Institute, 2015; QGIS Association, 2024).

VIs are calculated as a ratio of certain bands, differences, or derivatives of reflectance from sensor imagery at specific spectral wavelengths (de Almeida et al., 2020). Sentinel-2 constellation provides high-resolution images for monitoring vegetation at visible and infrared wavelengths, such as NDVI, which is calculated by combining the Near Infrared (NIR) and red bands.

With a rising rate of severe weather events associated with climate change, VIs also play an important role as reliable tools for assessing the health of forests (Lee et al., 2024). As an example, the forest in Portugal's northern region is particularly vulnerable to severe wildfires, which are becoming increasingly regular in this region (Marques et al., 2017; San-Miguel-Ayanz et al., 2017; Teodoro & Duarte, 2013).

As mentioned before, post-wildfire event monitoring is crucial for forest management and decision-making processes. However, studying vegetation before a fire occurs is just as important as assessing post-fire conditions, physical features, and climate data for the affected area (Lee et al., 2024). When stakeholders monitor pre-wildfire vegetation conditions, they can implement preventative measures in critical regions to increase wildfire defense. VIs are helpful to evaluate the condition of vegetation in terms of greenness (NDVI), humidity (Normalized Difference Formulation Index - NDII), and senescence (PSRI) (Bento-Gonçalves et al., 2019b; Hardisky et al., 1983; Merzlyak et al., 1999).

Wildfire behavior and impacts have a connection to the type of vegetation and its attributes; in the words of Fernandes et al., (2006), describing wildland fuels is crucial in order to improve fuel management actions. This means that it is essential to classify the study area's land use and land cover (LULC) in order to identify vegetation cover type and structure, as well as classify them according to their fire hazard potential. When combined NDVI, PSRI and NDII to identify fuel availability, with other information, such as fuel hazard potential, they may assist in identifying areas where fuel management should be prioritized (Bento-Gonçalves et al., 2017).

The main objective of the present research is to demonstrate the effectiveness of the chosen VIs as a tool to assess pre-fire vegetation conditions. To assess fuel availability, a vegetation fuel hazard model developed for Portugal by Fernandes et al., (2006) was considered. Enabling decision-makers to take action to increase wildfire surveillance and landscape resilience in Vale do Sousa, Portugal's northern area, principally in critical areas such as the Wildland Urban Interface.

2 MATERIALS AND METHODS

2.1 Study Area

The research area (Figure 1), a forested area with about 29k ha, Vale do Sousa, which is situated in northern Portugal, encompasses two Forest Intervention Zones (ZIFs): Entre-Douro-e-Sousa and Castelo de Paiva. Extreme fires have taking place in the Vale do Sousa woodland area over the past few years (Pavani-Biju et al., 2024). Large wildfires occurred in 2017, burning more than 5000 hectares and causing major environmental and financial impacts (ICNF, 2017).

Vale do Sousa has also a large rural area, with Eucalyptus (*Eucalyptus globulus* Labill) as the dominating tree species, followed by Maritime Pine (*Pinus pinaster* A.), small areas of other deciduous oak such as cork oak (*Quercus suber* L.), and pedunculate oak (*Quercus robur* L.), and riparian areas.

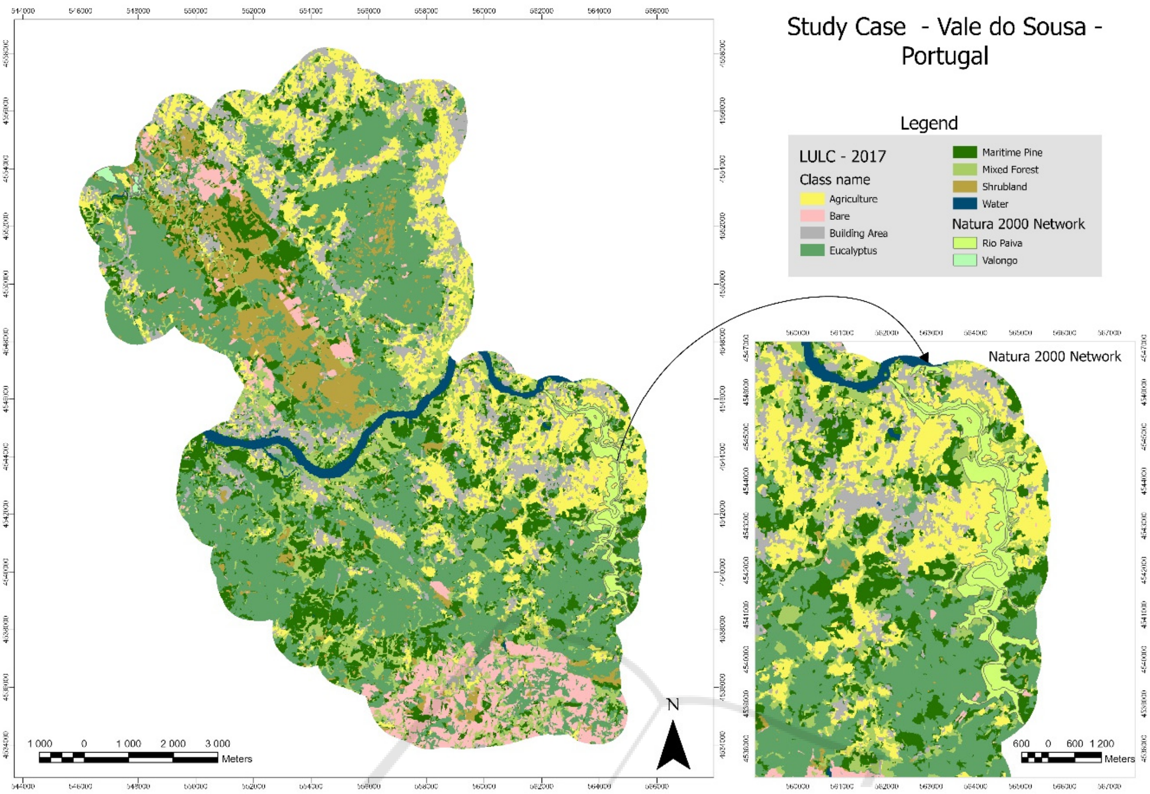

Figure 1: Study area Vale do Sousa.

However, the study area includes small portions of the NATURA 2000 Network, a network of protected areas that covers Europe's most valuable and vulnerable landscapes and spans 27 European Union Member States and in order to protect this area, crucial actions need to be taken to mitigate large wildfires harmful effects (CEE, 1992).

2.2 Data Acquisition and Analysis

For this study, images from Sentinel-2 between 2017 and 2018 were obtained at Copernicus Browser (table 1), based on the closest date the wildfire started, with less than 5% cloud cover. First, images were pre-processed from Level-1C (Top of Atmosphere – TOA) to Level-2A (Bottom of Atmosphere - BOA) resulting in orthorectified surface reflectance images, at SNAP using the algorithm SEN2COR (ESA, 2024). After, VIs were produced for September and October of 2017 in order to evaluate pre-fire vegetation conditions.

Table 1: Sentinel-2 images collected for 2017 and 2018.

Sentinel Images	Date Wildfire started
September 02^{nd}, 2017	September 02^{nd}, 2017
October 12^{th}, 2017	October $15^{th,}$ of 2017

Furthermore, leaf-on multispectral images from July 2017 and July 2018 were classified using Machine Learning (ML), Support Vector Machine in ArcGIS Pro® to determine changes between 2017 and 2018. To train the classifier 200 samples were collected for each class were collected from the thematic map of Land Use and Occupation (COS) of Portugal, from 2015 and 2018. The same spatial information were adapted to establish the accuracy assessment points.

The COS is the most widely used national reference cartography for land use issues. It is a vector product updated every three years that represents 83 thematic classes with a minimum cartographic unit of 1 hectare based on the visual interpretation of orthophoto maps. There are five temporally consistent editions available (1995, 2007, 2010, 2015, and 2018), with an accuracy higher than 85% (SNIG, 2022).The sampling approach used was random points. Approximately 500 points were generated from the image. Further, the confusion matrix and accuracy assessment were calculated. Accuracy ranges from 0 to 1, with 1 representing 100% accuracy, and the Kappa statistic indicate the overall accuracy of the classification. (McCoy & Johnston, 2001).The landscape classes chosen to perform the classification comprised agriculture, bare land, building area, eucalyptus, maritime pine, mixed forest (which includes riparian and non-riparian), and shrubland. Additionally, the classified data from 2017 was utilized to classify fuel types and hazards (Table 2). According to the Portuguese custom fuel model(Fernandes et al., 2006; Fernandes & Loureiro, 2021), fuel hazard values range from 1 (very low) to 5 (very high). Vegetated areas were classified on a scale of 2 to 5 because the fuel model runs from 1 to 4. To encompass additional land cover types in the classification, such as water, barren land, houses, and agriculture, were assigned 1 because they are not considered wildfire fuel.

Table 2: Sentinel-2 images collected for 2017 and 2018.

Fuel Types – LULC classes	Fuel Models	Fire Hazard
Building; Water; Agriculture; Bare	1	Very Low
Mixed Forest – Riparian and Non-Riparian	2	Low
Maritime Pine Stands	3	Moderate
Shrubland – Small Vegetation	4	High
Eucalyptus Stands	5	Very High

The VIs were estimated using the ArcGIS Pro® indices tool, using pre-fire satellite images. In this case, only the largest forest fires that occurred in 2017, designated as Burned Area 1 (BA1), which occurred in September and Burned Area 2 (BA2), which occurred in October (Table 1), were considered in this analysis. Since both events are classified as extreme wildfires because they covered more than 100 hectares, BA1 has 5,433 hectares, while BA2 has 666,3 hectares.

First, the NDVI was computed (1). Its values vary from -1 to 1. Values near 0 represent bare, rocks, sand, and snow. Low positive scores (0.2-0.4) are associated with shrubs and grassland. Values greater than 0.4 imply live green vegetation (Rouse et al., 1973).

$$NDVI = \frac{(Band\ 8 - Band\ 3)}{(Band\ 8 + Band\ 3)} \quad (1)$$

The NDII (2) is sensitive to variations in the water content of the plant canopy (Hardisky et al., 1983). The value rises as water content rises. NDII measurements can range from -1 to 1, with green vegetation often falling between 0.02 and 0.6.

$$NDII = \frac{(Band\ 8 - Band\ 11)}{(Band\ 8 + Band\ 11)} \quad (2)$$

The PSRI (3) assesses plant senescence (Merzlyak et al., 1999). PSRI values, like NDVI, range from -1 to 1. Although values ranging from -0.1 to 0.2 suggest healthy vegetation, values greater than 0.2 imply senescence and values less than -0.1 are associated with other landscape characteristics such as water and buildings.

$$PSRI = \frac{(Band\ 2 - Band 4)}{(Band\ 6)} \quad (3)$$

While higher NDVI values suggest greater greenness, PSRI indicates significant senescence. To measure fuel availability, a composite using ArcGIS Pro® composite band tool, of the three VIs was used. To use PSRI in conjunction with NDVI and NDII, it was multiplied by -1. Converting positive senescence numbers to negative values. The compositions were then sliced based on wildfire fuel availability, which ranged from 1 to 5, based on what was reported by Bento-Gonçalves et al., (2019a). Where 1 represents very low, 2 represents low, 3 represents moderate, 4 represents high, and 5 represents extremely high wildfire fuel source.

Vector data containing polygons from burned regions BA1 and BA2 were obtained from the Portuguese National Authority for Nature Conservation (ICNF) and compared to VIs and wildfire fuels data. This was conducted to see if the spatial information generated corresponds to the perimeter of the burned regions in official data. The classified image from 2017 was then compared to 2018 data to determine the percentage change following the occurrence of these extreme events.

3 RESULTS AND DISCUSSION

VIs were estimated for the two greatest burned areas (BA1 and BA2) in Vale do Sousa before wildfire occurrence. In terms of vegetation conditions for BA1, the NDVI values (figure 2) range from -0.06 to 0.60, with a mean of 0.16 and a standard deviation of ±0.11. It is considered healthy vegetation when NDVI values are higher than 0.40, and the average value likely implies that the area is probably primarily covered by shrubland. This class covers roughly 318,84 ha, accounting for 48% of the total area.

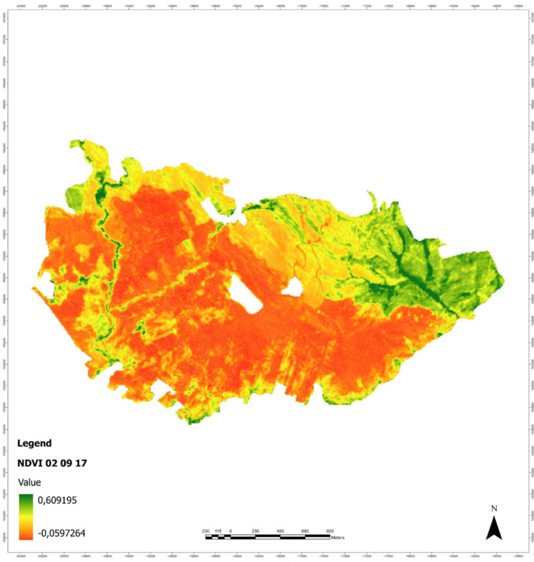

Figure 2: NDVI of BA1.

However, the area contains Eucalyptus, Maritime Pine, and Mixed Forest stands, which is why the NDVI maximum value is 0.60.

The humidity index, NDII (figure 3), ranges from 0.41 to 0.38, with a mean of -0.07 and a standard deviation of ±0.09. As can be observed, moisture content in September had a negative mean, and the lowest values are below what is considered healthy green vegetation (between 0.02 and 0.6), showing that the vegetation of area BA1 was suffering from water stress.

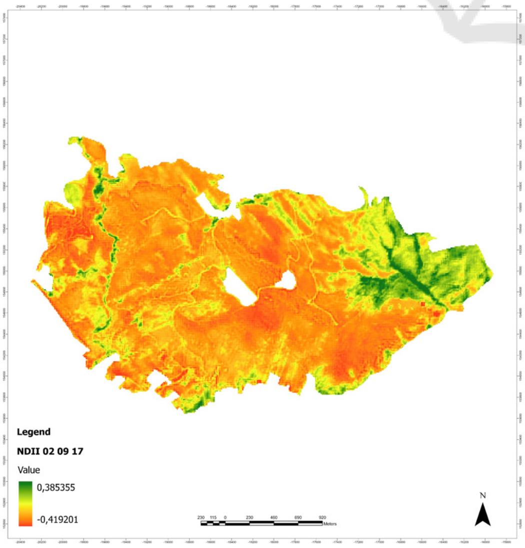

Figure 3: NDII of BA1

Regarding PSRI (figure 4), which was multiplied by -1 as described in Bento-Gonçalves et al., (2019a), negative values now signify senescence, and positive values represent healthy vegetation. This was done to create a composition that would evaluate wildfire fuel availability for both areas of interest. PSRI scores vary from -0.51 to 0.06, with an average of -0.08 and a standard deviation of ±0.034.

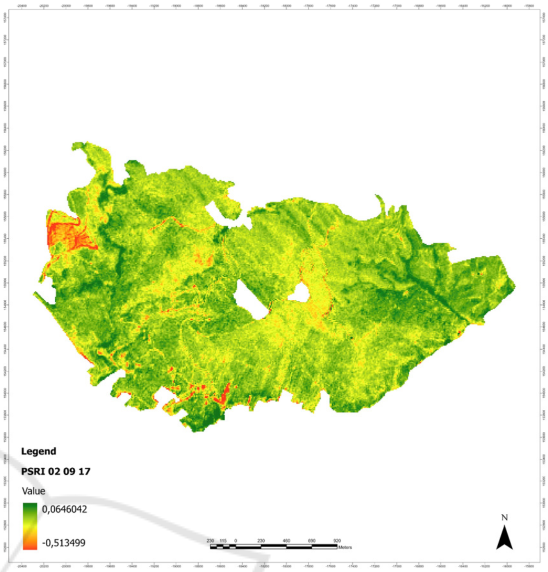

Figure 4: PSRI of BA1.

This indicates that the majority of the vegetation in region BA1 falls between the values considered as healthy green vegetation. While a minor portion exceeds the threshold for healthy vegetation, ranging from -0.21 to -0.51.

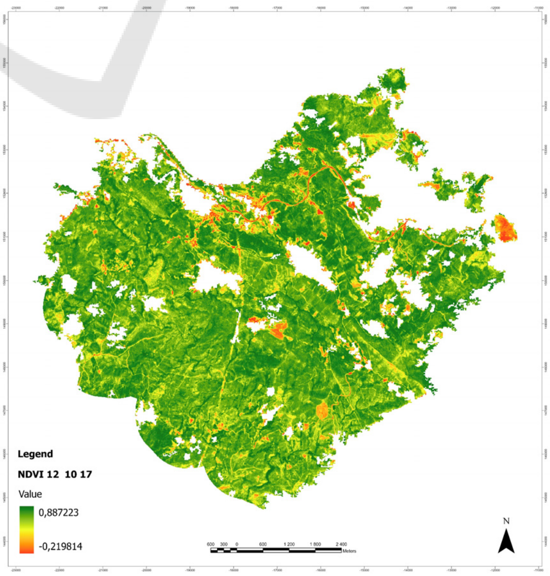

Figure 5: NDVI of BA2.

Area BA2 is substantially larger than BA1, covering around 5,433 hectares. The NDVI (Figure 5) suggests that the vegetation is photosynthetically active, as the values range from -0.21 to 0.88, with a mean of 0.68 and a standard deviation of ±0.12. The forested impacted area is mostly covered by Eucalyptus, followed by Maritime Pine stands, and small regions of mixed forest. The high average value is most likely owing to the region's substantial forested land.

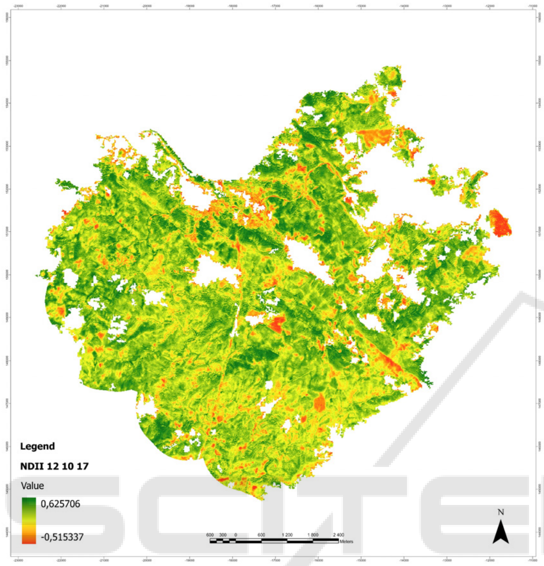

Figure 6: NDII of BA2.

The NDII (figure 6) minimum value is -0.51, and the maximum value is 0.62, with a mean of 0.22 and a standard deviation of ±0.14. This indicates that most of the vegetation's humidity was closer to the threshold of what is considered water stress than healthy vegetation. Furthermore, a wildfire occurred in October of 2017, when the weather was dry and hot, which is unusual for this month (IPMA, 2017). All of these elements most likely contributed to the escalation of these events, which had ramifications for Vale do Sousa's social, economic, and environmental conditions.

Regarding the VI senescence (figure 7), the PSRI's minimum value is -0.93, indicating extreme senescence in some portion of the wooded area, the highest value, which indicates healthy vegetation of 0.40. Although the negative mean value of -0.12 with a standard deviation of ±0.06, is within what is considered healthy vegetation, demonstrates the effect of the high negative values on the mean, changing the distribution of the data.

With this information, it was possible to compute the fuel availability for both areas (Bento-Gonçalves et al., 2019a). As shown in Figure 7, the fuel ranges from very low to moderate in BA1 and very low to very high in BA2. Nonetheless, only classes above 2 were considered wildfire fuel, implying that, while both areas are primarily covered by class 1, there are small patches of class 2 and 3 in BA1, and areas classified from 2 to 5 in BA2, indicating that fuel was available in both areas.

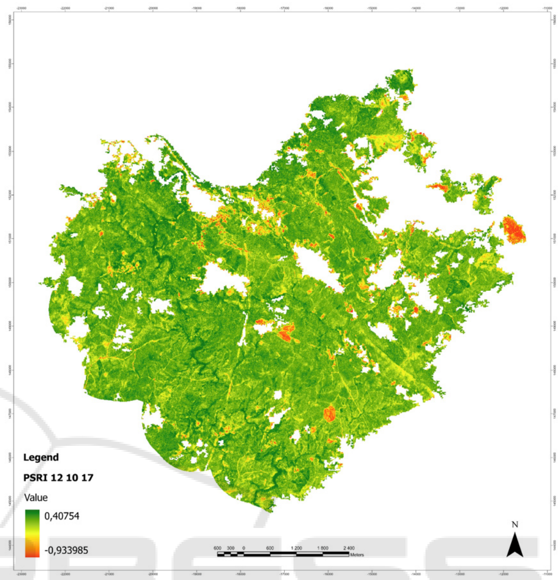

Figure 7: PSRI of BA2.

The ML method used to perform the classification of the selected scenes of 2017 and 2018 was Support Vector Machine, followed by the computation of a confusion matrix and accuracy assessment. The classification was evaluated using the Kappa Index, which is greater than 0,8, indicating high accuracy of the classification. Image from 2017 was classified to identify the fuel type (Fernandes et al., 2006) and, as a result, fuel hazards maps were created for both areas, is also shown in Figure 7.

Aside from water stress, senescence, and vegetation health, wildfires are also affected by climate, slope and fuel hazards. Because fuel hazard influences fire spread and magnitude. As can be seen, a large section of BA1 is classified as 4 (High), with 214 ha classified as 5 (very high). Demonstrating how forest cover types can have an important influence on these events. It is worth mentioning that for this study, the vegetation structure was not evaluated. Classes 3–5 are related to Maritime Pine, shrubland, and Eucalyptus. Maritime Pine was classified as 3 (moderate) because it has fewer stands than Eucalyptus. Shrub was classed as 4 (High) because the area with this classification is quite close to the

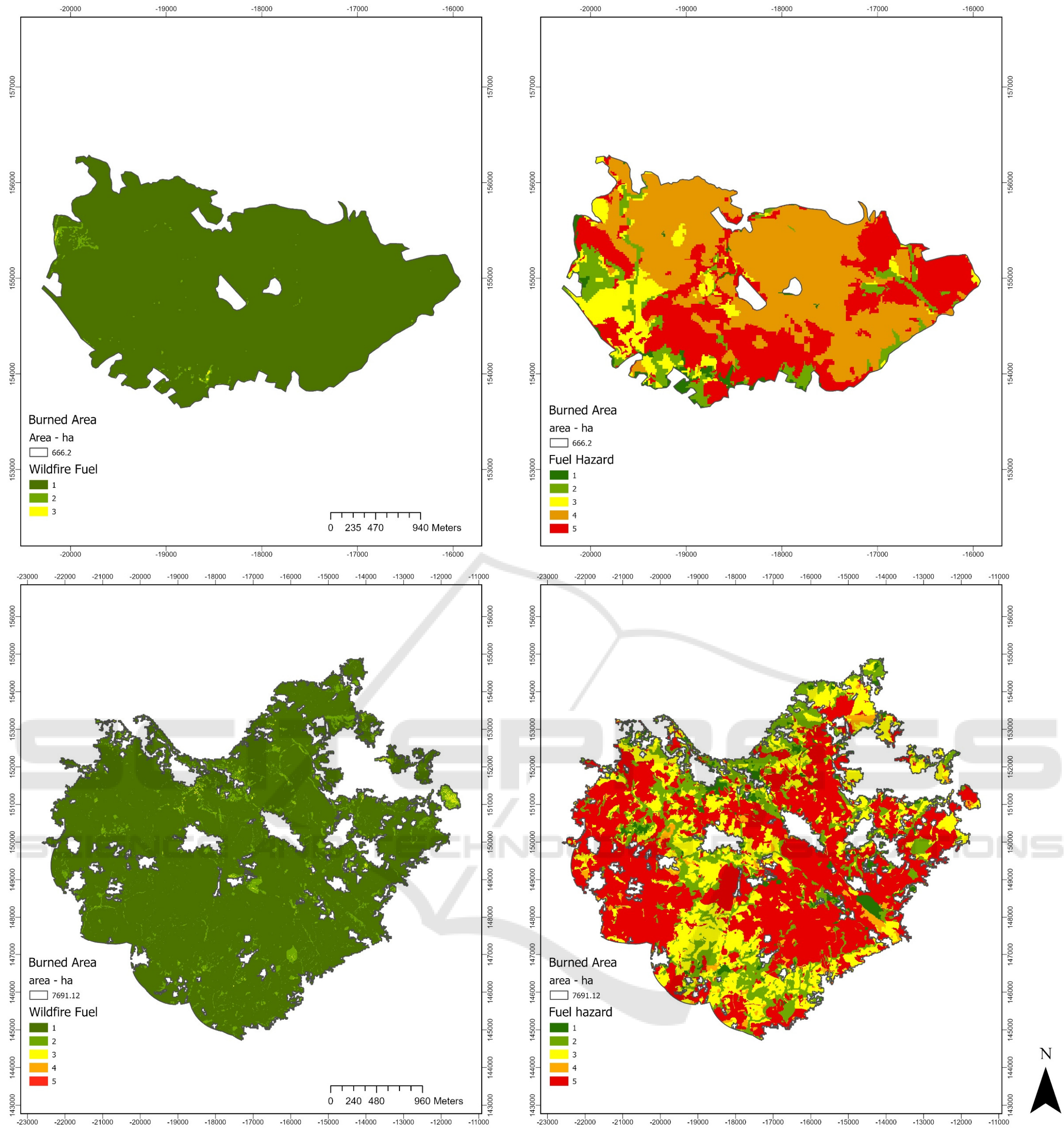

Figure 8: Wildfire fuel and Fuel hazard maps of 2017.

above-listed tree species' stands. According to (Fernandes et al., 2006), the subcover can affect the spread and fire hazard. Eucalyptus covers a larger area in BA2, accounting for 52% of the entire area. Maritime pine represents 23.4% of the total area. When looking at VIs, it is easy to see lower or extreme values of the forest's biophysical state. The significant fuel availability and hazards in the study area most likely contributed to the large fire. From 2017 to 2018, the change in landcover type of BA1 reveals a 35% decline in Eucalyptus and 52.5% in maritime pine stands. These percentages reflect the conversion of those categories to bare and shrubland cover types in 2018.

There were no eucalyptus losses in the case of BA2, but the same did not occur to maritime pine stands. According to the changes observed between 2017 and 2018, the eucalyptus area had an increase of 1%. Whereas maritime pine lost nearly 90% of its area. However, this loss may be due not only to wildfire effects but also to harvesting, as Eucalyptus plantations have increased in recent years in the study area. It is worth noting that bare land and shrubland cover types have also increased. They accounted for barely 3% in 2017, but almost 30% in 2018.

As illustrated, all of these factors may influence extreme wildfire outbreaks. Although fuel availability with extreme value only accounts for a small percentage of the region of interest, when combined with VIs and fuel hazard score, it revealed that those locations were prone to wildfires before they occurred, both PSRI and fuel hazard classes had higher values. When these remote sensing products are combined, they can be valuable in pre-fire management actions by identifying where precautions should be taken to reduce losses caused by wildfires, as shown in the change analysis.

One weakness of this study is the classification of fuel hazards. Because forest structure was not included in this study. In this manner, the Portuguese fuel model was modified to be used with the classified image. Classes were clustered, which could affect hazardous classification, as the structure becomes more important to fire behavior than tree species (Fernandes et al., 2006). It is critical to determine the structural types of the stands (closed, low, or tall; open, low, or tall) if the objective is to develop a fuel hazard model alongside VIs and fuel availability.

Despite this limitation, the primary goal of this study was to identify available remote sensing-derived products as support tools for fuel monitoring and management throughout the wildfire season. Since both wildfires occurred in areas where VIs indicated great senescence, low water content and less greenness, fuel availability could be identified in the study region. With fuel availability classified as low to medium in BA1, and low to very high in BA2.

The modified fuel hazards model for both locations identified vast areas classified as high or extremely high. It was possible to demonstrate that the remote sensing-derived data information is reliable in detecting alterations in forest biophysical properties. Furthermore, this information could potentially be employed as an auxiliary tool or as information when carrying out the most effective fire control measures in order to manage fuel loading while decreasing fire severity and fulfil forest fire management objectives.

4 CONCLUSIONS

Monitoring forest fire fuels is critical for implementing best practices management approaches to mitigate wildfire threats to forest ecosystems, population health, and financial losses. With the availability of a variety of satellite constellations, such as Sentinel-2, VIs may be used as additional tools to monitor fuel loading and hazards, hence reducing the severity of wildfires.

Data is available and accessible across a variety of platforms, and VIs resulting from remote sensing imagery can be computed through different GIS tools. Furthermore, decision-makers could employ these spatial data to support forest fire prevention activities.

Despite its limitations, this approach remains a significant resource, particularly in locations where fieldwork is not feasible owing to financial or logistical constraints. The attempts to reduce wildfire fuel could be improved by looking at VIs along with fuel hazard models and other management actions, suggesting which regions need to be investigated when selecting where the efforts to reduce fuels should be invested.

Further studies should be performed to verify additional burned areas from previous years utilizing alternative satellite constellations such as Landsat. In addition, other VIs should be explored to verify the forest's biophysical composition. Although LiDAR data was not used in this study, it is still an important remote sensing data as it may provide information about the structure of the forest in less time and assess understory fuels.

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