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ORIGINAL ARTICLE – Conservation of Nature

Burning Susceptibility Modeling to Reduce Wildfire Impacts: A GIS and Multivariate Statistics Approach

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Abstract

Forest burning susceptibility mapping is a tool to mitigate wildfires, with several methods to develop them. This study aimed to compare the Analytic Hierarchy Process (AHP), Multiple Linear Regression (MLR), and Random Forest (RF) methods for mapping. Several variables were used to generate the maps. For MLR and RF methods, fire frequency between 1990 and 2010 was used as the response variable in the models. To validate the methods (AHP, MLR and RF), fire data between 2011 and 2018 were used in four stages. RF was the best method employed. Correct and incorrect values for this method were 74% and 26% and AUC 0.66. The sensitivity and specificity for the highest risk class were 31% and 96%. The low sensitivity values can be attributed to the randomness attributed to anthropic fire. The high specificity values point to a good separation of the higher risk class compared to the others.

Keywords: Analytic Hierarchy Process, Burn Frequency, Fuzzy Logic, Portugal, Random Forest.

1. INTRODUCTION AND OBJECTIVES

In Mediterranean Europe, the frequency and size of forest fires have increased dramatically in recent decades (San-Miguel-Ayanz et al., 2013; Francos et al., 2018). Among the affected countries, Portugal is the worst hit by forest fires (Tonini et al., 2017), including some notable events, such as those in the central region, in 2017, which caused 113 deaths, and the one in Castelo Branco, in 2019, which resulted in dozens of injuries. Also, the report of the *Instituto da Conservação da Natureza e das Florestas* (ICNF) explains that, for the past 10 years, nearly 132,049 hectares of forests and shrublands in Portugal were burned per year, which constitutes about 2.87% of the total area of these classes (i.e., forests and shrublands) (DGTERRITÓRIO, 2019a; ICNF, 2019a). Besides, the north region of Portugal has a high fire frequency, compared to the rest of the country (Parente et al., 2018; ICNF, 2019b).

Wildfires are responsible for numerous environmental impacts, being able to shape the landscape and change the habitat, flora and fauna structures, reducing the forest and other natural environments area (Aximoff & Rodrigues, 2011; Camargo et al., 2018). In addition to environmental damage, fires are a social and economic threat (Jafari Goldarag et al., 2016; Kayet et al., 2020), as they endanger the population property and contribute to CO_2 and air pollutant emissions, which impacts the air quality and reduces the productivity of the ecosystems (Torres et al., 2018; Sannigrahi et al., 2020; Yin et al., 2020). Several studies indicate that global climate change can be a driving factor for the increased occurrence and severity of fires (Bedia et al., 2014; Eugenio et al., 2016; Da Silva Junior et al., 2020; Stephens et al., 2020). However, most fires are caused by human factors, such as incendiary fire, debris burning, smoking, campfire, railroad, children, and equipment use (Grala et al., 2017). Due to this human behavior factor, in addition to factors such as climate, topography, species composition, and soil type (Harris & Taylor, 2017; Keyser & Leroy Westerling, 2017; Whitman et al., 2018; Mitsopoulos et al., 2019), identifying areas of high and low risk is not always a trivial task.

Several tools are used to prevent the occurrence and mitigate the negative impacts of the fires, such as the forest burning susceptibility maps, often generated from historical data of fire occurrence (Ferreira et al., 2015; Guglietta et al., 2015; Parente & Pereira, 2016; Rodrigues et al., 2020). These maps can be generated from different methodologies (Pan et al., 2016; Akinola & Adegoke, 2019; Mota et al., 2019; Abedi Gheshlaghi et al., 2020; Tonini et al., 2020), such as statistical methods (Bui et al., 2016; Gholamnia et al., 2020) and hierarchical methods (Eugenio et al., 2016). However, there is no universal method for all situations, since their effectiveness varies according to the region and the spatial data resolution available for analysis. Thus, understanding the dynamics of the factors affecting BS is extremely important for the process of decision-making regarding fire prevention and management (Duarte & Teodoro, 2016; Pourtaghi et al., 2016; Pourghasemi et al., 2020).

Several methodologies are used to evaluate the BS map accuracy. The Area under the curve (AUC) method is one of the most used (Pourghasemi et al., 2016; Abedi Gheshlaghi et al., 2020; Razavi-Termeh et al., 2020; Rodrigues et al., 2020). It assesses BS into "correct" and "incorrect" classification, while other methods work on the relationship between the burned area and BS classes (Eskandari, 2017; Leuenberger et al., 2018; Gigović et al., 2019;). Not so widely used in BS studies, sensitivity analysis is another validation method widely used in model validation in other areas of science (Albano et al., 2019; Arabameri et al., 2019; De Araújo Carvalho et al., 2020; Lee et al., 2020).

The present research aimed to verify the possibility of modeling and validating maps of BS, using land cover/use, topographic and climatic variables by applying different methods, with the aid of historical fire data. Thus, in this study, three different approaches were used to map the BS in the vegetated areas of Northern Portugal, which were subsequently compared with the aid of different validation methods. Finally, it was also evaluated whether the BS classes can be used as guidelines for decision-making in the control and management of fires, prioritizing the greatest BS areas.

2. MATERIALS AND METHODS

2.1. Study area

The study was conducted in the north region of Portugal, which comprises the districts of Viana do Castelo, Braga, Porto, Vila Real and Bragança. With approximately 21,278 km², the area is mainly covered by forest stands and shrublands (Figure 1) and has an estimated population of 3,575,338 inhabitants (INE, 2020a). The climate is characterized as Mediterranean with Atlantic influence, with climate types Csa (temperate with hot and dry summer) and Csb (temperate with dry or temperate summer), according to Köppen–Geiger Climate (Fernandes et al., 2020). The altitude ranges from sea level to 1527 m. The average temperature in the region is 13.8 °C, with minimum and maximum values of 7.9 °C and 19.7 °C, respectively (INE, 2020b).

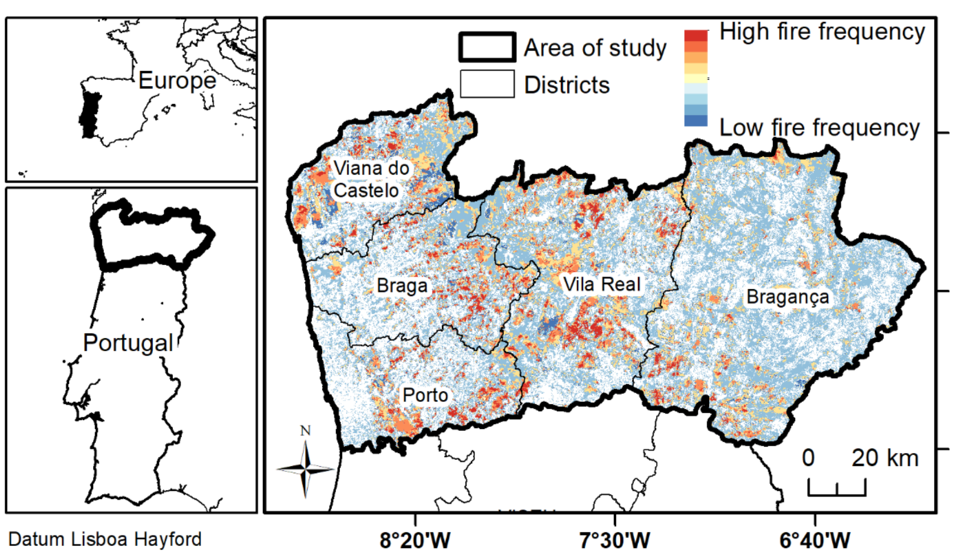

Figure 1. Study area and frequency of fires from 1990 to 2018 (ICNF, 2019a).

2.2. The datasets

The data used to map the BS includes the history of the burned area, acquired from the ICNF (ICNF, 2019b); land use/cover of 2010 and 2018, for the study modeling and validation, respectively; roads and topography, obtained from the *Direção-Geral do Território* (DGTerritório) (DGTERRITÓRIO, 2003, 2017, 2019a); and historical temperature and precipitation data from the *Sistema Nacional de Informação de Recursos Hídricos* (SNIRH) (SNIRH, 2020). The land cover maps were developed from 25 cm resolution images, generalized to 1 ha cells, according to technical specifications (DGTERRITÓRIO, 2018, 2019b).

2.2.1. Historical fire data

Polygons of fire between 1990 and 2018 (Figure 1) derived from a dataset with a resolution of 100 m were used (ICNF, 2019b). Afterwise, the fire frequency from 1990 to 2010 was calculated for modeling BS by the Multilinear Regression (MLR) and Random Forest (RF) methods, while the frequency from 2011 to 2018 was calculated for validating the results of the BS maps.

2.2.2. Variables related to the land use/cover

From land use/cover (LU/LC) data, it was generated, for 2010 and 2018, the Euclidean distance, up to a limit of 2 km, of the classes: urban areas (URB), agriculture (AGR) and water bodies (DWB) The first two were interpreted as anthropic influence regions directly related to the BS. The distance from water bodies (DWB), started from the premise that vegetation closer to water are benefited by higher humidity in the soil, being less fire prone (Busico et al., 2019). The vegetated areas were classified into five classes (VGT), which weight were defined as: hardwoods (0.59), conifers (0.57), eucalyptus (0.39), agroforestry systems (0.34) and shrublands (2.52) (Carmo et al., 2011).

2.2.3. Roads

The road network was used to determine the Euclidean distance from roads (ROD) for the study area, with a maximum distance of 2 km established as their area of influence in the BS.

2.2.4. Topography

The slope (SLP), its aspect orientation (ASP) and the elevation (ELV) were generated from 10 m contour lines. The weights of the ASP were classified into five classes which weights were defined as: flat (0.55), north (1.04), east (1.03), south (0.85) and west (0.95) (Carmo et al., 2011). These variables have a strong influence on the ignition and spread of fires (Catry et al., 2009; Li et al., 2014; Sivrikaya et al., 2014; Çolak & Sunar, 2020).

2.2.5. Temperature and precipitation

Temperature (TMP) and precipitation (PCP) were obtained from meteorological stations (SNIRH, 2020) for the dry period of the hydrological year of Portugal (May – September), using the mean temperature and accumulated precipitation from available dataset, furtherly interpolated for the study area applying ordinary kriging adopting the inverse distance squared method. For precipitation, 220 hydrometric stations, distributed in the study area and for temperature, data from 13 stations were used. Despite the low sampling, the weather stations with temperature data are well distributed in the study area and considered sufficient for the thermo-climate characterization on a regional scale. For the modeling, a period from 1990 to 2010 was used, while for the validation, historical data from 1990 to 2018 were used.

2.3. Burning susceptibility mapping

2.3.1. Fuzzy logic and Analytical Hierarchy Process (AHP)

The Fuzzy logic was used for data reclassification (Zadeh, 1965), which generated gradual associations of pixels or segments to one or more classes (Abedi Gheshlaghi et al., 2020). In other words, the variables were spread to a scale from 0 to 255, through a linear association. The reclassification of each continuous variable was based on its implications for burning. So, the higher the TMP, SLP and DWB the greater the BS (Verde & Zezere, 2010; Carmo et al., 2011; Busico et al., 2019), while for PCP, AGR and ROD, it has an inverse relationship, that is, lower values imply a greater BS (Duarte & Teodoro, 2016; Eugenio et al., 2016; Sakellariou et al., 2019). The ELV was reclassified according to Verde & Zêzere (2010), where burning probability increases up to an altitude of 1300 m, and reduces to higher elevations. VGT was classified according to section 2.2.2, and later stretched linearly to the same scale (0 to 255).

Then, the Analytical Hierarchy Process (AHP) methodology was applied, which consists of valuing the importance of one factor relative to the others and obtaining a final weight for each of the parameters (Saaty, 1977). Then, the scale of importance was defined based on the literature (Moreira et al., 2009; Parente et al., 2018; Busico et al., 2019). The consistency of the execution was analyzed using the Consistency Ratio (CR), according to Equation (1).

$$\mathrm{CR} = \mathrm{CI}/\mathrm{RI} \tag{1}$$

where, CR: Consistency Ratio, CI = Consistency Index, RI: Random Index.

Based on these factors, all input layers were combined according to their respective weights, thus generating a final map.

2.3.2. Multiple Linear Regression (MLR)

In the multilinear regression analysis, a linear model was adjusted to estimate the BS (Equation 2), using a least-squares approach for multiple regression. The frequency calculated between the years 1990 and 2010 was set as the response variable in the models, as described in section 2.2.1. The F-test was automatically made by the software.

$$\mathrm{Y} = \beta_0 + \beta_1 \times \mathrm{x}_1 + \beta_2 \times \mathrm{x}_2 + \ldots + \beta_\mathrm{n} \times \mathrm{x}_\mathrm{n} + \varepsilon \tag{2}$$

Where: Y = response variable (frequency of fires); β_0 = intercept; β_1 = model parameters; x_1 = explanatory variables; ε = Random error associated with the model.

Further details of the method can be found in Clark & Hosking (1986) and Kleinbaum et al. (1988).

2.3.3. Random Forest

The algorithm based on decision trees Random Forest (Breiman, 2001) was the third method to generate the BS maps. This method is based on several decision trees from random selection with variable and observation replacement (bootstrap). This process is repeated several times to generate a decision tree that makes non-biased predictions. More details on how this method works can be found in Breiman (2001). The sampling was carried out in a stratified manner, according to the number of fires that occurred (Table 1). The algorithm was trained using the fire frequency values generated from the historical data of fires between 1990 and 2010, as a response variable. The number of decision trees was set at 500 and, for the number of variables randomly sampled in each "node" (mtry), values of 2, 3, and 4 were tested. The best model was selected based on the correlation coefficient between the predicted and observed values in the validation. The data were separated into 5 groups, and one was removed at each interaction for validation (5 -fold cross-validation). The training and validation of the algorithm were conducted using the Caret package (Kuhn, 2019) present in the R software system, version 3.6.2 (R CORE TEAM, 2018).

Table 1. Number of pixels of the vegetated area in the study area in which fires occurred 0, 1, 2 - 3, 4 - 5 and more than 5 times, and number of pixels of each class used to train the Random Forest algorithm.

	Total Area	Sample (n)
Free-fire pixels	689,088	13,782
Pixels with 1 fire	215,055	4,301
Pixels with 2 or 3 fires	100,501	2,010
Pixels with 4 or 5 fires	35,555	711
Pixels with more than 5 fires	17,680	354
Total pixels	1,057,879	21,158

2.4. Validation and assessment of burning susceptibility map quality

Validation was conducted using data from fires that occurred between 2011 and 2018 to verify the efficiency of the methods for years not used during modeling. It was carried out in two parts.

In the first validation part, the BS maps generated by each method were reclassified into "High BS" and "Low BS", thus splitting the estimated risk values of the methods in half. The map from this classification was crossed with the total burned area in the years from 2011 to 2018. For each intersection, we defined as: "Correct" the areas that did not burn and were considered as Low BS and the burned area considered "High BS"; and "Incorrect" the burned area considered low BS and the area that did not burn considered "High BS". Furthermore, we calculated the Area Under the Curve (AUC) (Equation 4) as a summary of the Receiver Operating Characteristic (ROC) (Bradley, 1997). The AUC can be interpreted as the probability that a randomly picked burned area will be classified as "High BS" compared to an unburned area. Values below 0.6 can be considered as unsuitable; values between 0.6 and 0.7 indicate poor performance; between 0.7 and 0.8, moderate; between 0.8 and 0.9, good performance; and between 0.9 and 1.0 means excellent performance (Tien Bui et al., 2018; Shang et al., 2020).

$$\mathrm{AUC} = \frac{\frac{\mathrm{TP}}{(\mathrm{TP}-\mathrm{FN})} - \frac{\mathrm{FP}}{(\mathrm{FP}+\mathrm{TN})} + 1}{2} \tag{4}$$

Where: AUC = area under the curve. TP = burned areas classified as "High BS" (true positive); FN = burned areas not classified as "High BS" (false negative); FP = areas classified as "High BS" that did not burn (false positive); TN = areas that did not burn and were classified as "Low BS" (true negative).

In the second validation part, the BS values estimated were reclassified into five classes: very low, low, medium, high and very high. Likewise, the fire frequency map, from 2011 to 2018, was reclassified and used as a basis for comparison, using the "natural breaks" option of the ArcMap reclassify function, in which breaks are defined to create groups with similar values and maximizes the differences between classes. We also calculated the proportion of burned area to the total area of each class.

Furthermore, we calculated the classification sensitivity and specificity for the BS class "Very high". The sensitivity is the percentage of high-risk areas correctly (Equation 5) while the specificity indicates the proportion of areas that were correctly not classified as "Very high" (Equation 6). This calculation was carried out to identify if the methods parsimoniously classified the "High BS" areas.

$$\text{Sensivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100 \tag{5}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \times 100 \tag{6}$$

Where: TP = number of cells correctly classified as "Very high" BS (true positive); FN = number of cells that should be classified as "Very high" but were not (false negative); TN = number of cells out of the "Very high" BS class that were correctly classified (true negative); FP = number of cells that were wrongly classified as "Very high" BS (false positive).

The best method for mapping BS was defined according to the performance in the two validation steps. The workflow of the methodology is presented in Figure 2.

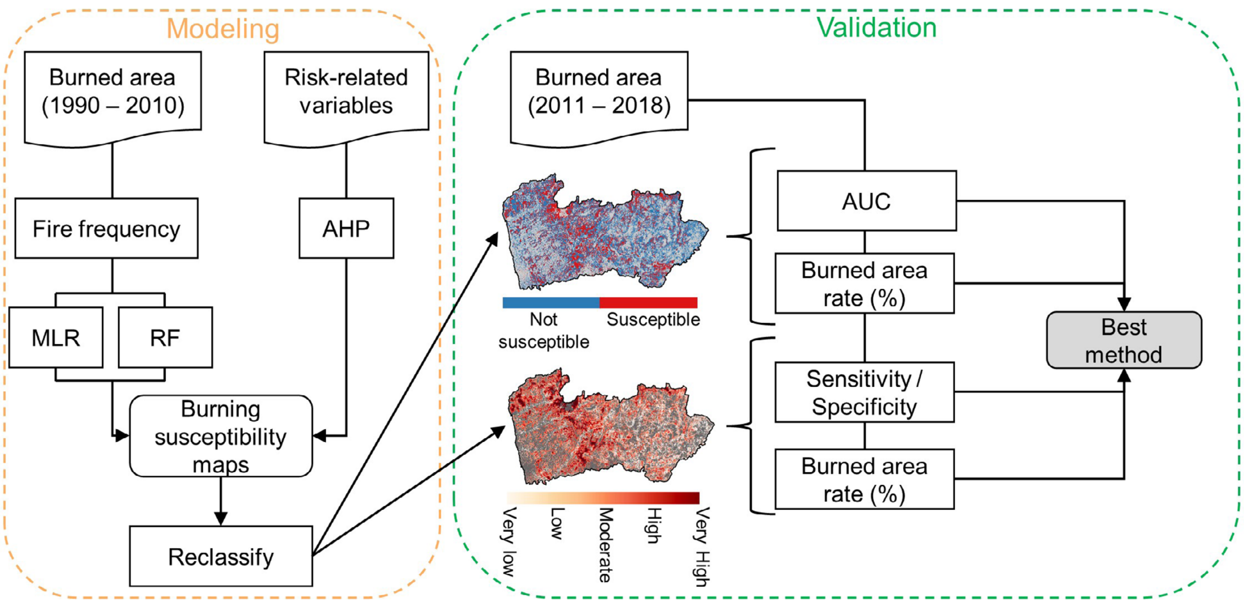

Figure 2. Flowchart of the methodology used to model burning susceptibility using the Analytic Hierarchy Process (AHP), Multiple Linear Regression (MLR) and Random Forest (RF) methods for northern Portugal.

3. RESULTS

The parameters used to generate the BS maps using the AHP, MLR and RF found using the fire frequency data are presented in Tables 2 and 3. The CR calculated for the AHP method was 0.01, which is less than the threshold (0.1) (Kayet et al., 2020), so the consistency is acceptable (Table 2). The methods MLR and RF presented correlation coefficient (r), equal to 0.34 and 0.62, respectively (Table 3). The MLR presented a f-value of 13691.59668 with 10 degrees of freedom of the regression and 1065441 of residuals, being higher than the critical f-value for 0.05 significance level (1.830713), which means the model is significant.

Table 2. Pairwise comparison of factors for Forest Burning susceptibility and their respective parameters for the Analytical Hierarchy Process (AHP) for modeling burning susceptibility areas.

Parameter	VEG	URB	SLP	ASP	PCP	TMP	ELV	AGR	DWB	ROD	Weight
VEG	1	1	2	3	4	4	4	5	5	5	0.2295
URB	1	1	2	3	4	4	4	5	5	5	0.2295
SLP	1/2	1/2	1	2	3	3	3	4	4	4	0.1534
ASP	1/3	1/3	1/2	1	2	2	2	3	3	3	0.0999
PCP	1/4	1/4	1/3	1/2	1	1	1	3	3	3	0.0603
TMP	1/4	1/4	1/3	1/2	1	1	1	2	2	2	0.0603
ELV	1/4	1/4	1/3	1/2	1/2	1	1	2	2	2	0.0603
AGR	1/5	1/5	1/4	1/3	1/3	1/2	1/2	1	1	1	0.0356
DWB	1/5	1/5	1/4	1/3	1/3	1/2	1/2	1	1	1	0.0356
ROD	1/5	1/5	1/4	1/3	1/3	1/2	1/2	1	1	1	0.0356

Table 3. Parameters associated with the Multiple Linear Regression (MLR) and Random Forest (RF) methods for modeling burning susceptibility areas. r = correlation coefficient.

Method	Parameters	r
MLR	$0.037292 + 8.8E-3 \times VEG - 5E-6 \times URB + 4.5E-4 \times SLP + 6.4E-5 \times ASP + 6E-6 \times PCP - 2.9E-3 \times TMP - 1.4E-5 \times ELV + 2.4E-5 \times AGR + 1E-5 \times DWB + 6E-6 \times ROD$	0.33744
RF	n = 500; mtry = 4	0.62122

The RF method had the highest area considered as "Correct" and (Table 4). Figure 3 shows the distribution of the "Correct" and "Incorrect" classification on the study area, illustrating the higher precision of the RF method. All the methods presented AUC near 0.6, with RF also standing out with the highest value (0.66).

For the second validation part, the maps presented different characteristics (Figure 4). In general, the AHP method presented a greater area in the classes of greater risk, compared to MLR and RF. The AHP also had "High" and "Very high" classes more distributed in the study area, whereas in MLR and RF, these classes were mainly found in the west part of the study area.

Table 4. Proportion of "Correct" and "Incorrect" classification and area under the curve (AUC) for the burning susceptibility maps generated using the Analytic Hierarchy Process (AHP), Multiple Linear Regression (MLR) and Random Forest (RF) methodologies. "Correct" = Burned areas classified as "High burning susceptibility" or unburned areas classified as "Low risk"; "Incorrect" = Unburned areas classified as "High burning susceptibility" or burned areas classified as "Low burning susceptibility".

Method	Correct (%)	Incorrect (%)	AUC
AHP	65	35	0.57
MLR	66	34	0.63
RF	74	26	0.66

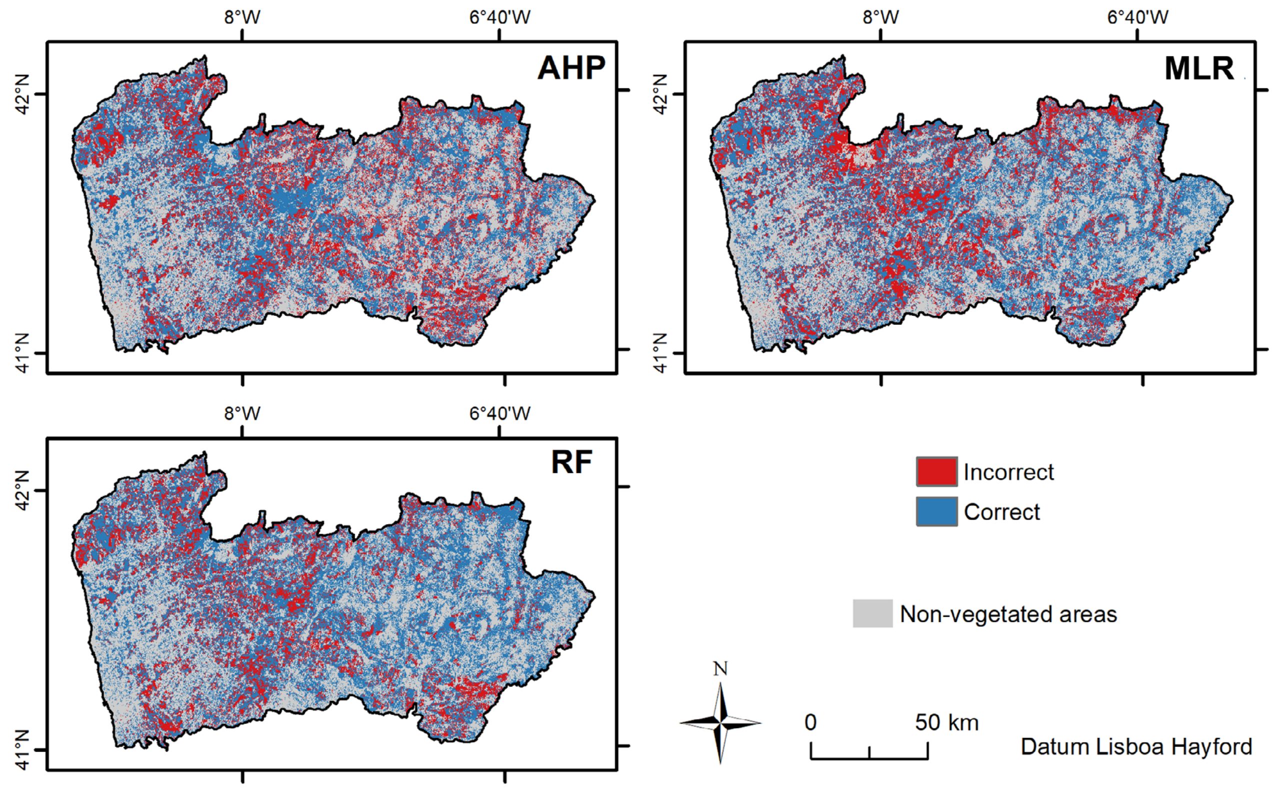

Figure 3. Map of the regions correctly and incorrectly classified for the first validation part based on the burning susceptibility maps generated using Analytic Hierarchy Process (AHP), Multiple Linear Regression (MLR) and Random Forest (RF) for the north of Portugal. "Correct" = Burned areas classified as "High burning susceptibility" or unburned areas classified as "Low risk"; "Incorrect" = Unburned areas classified as "High burning susceptibility" or burned areas classified as "Low burning susceptibility".

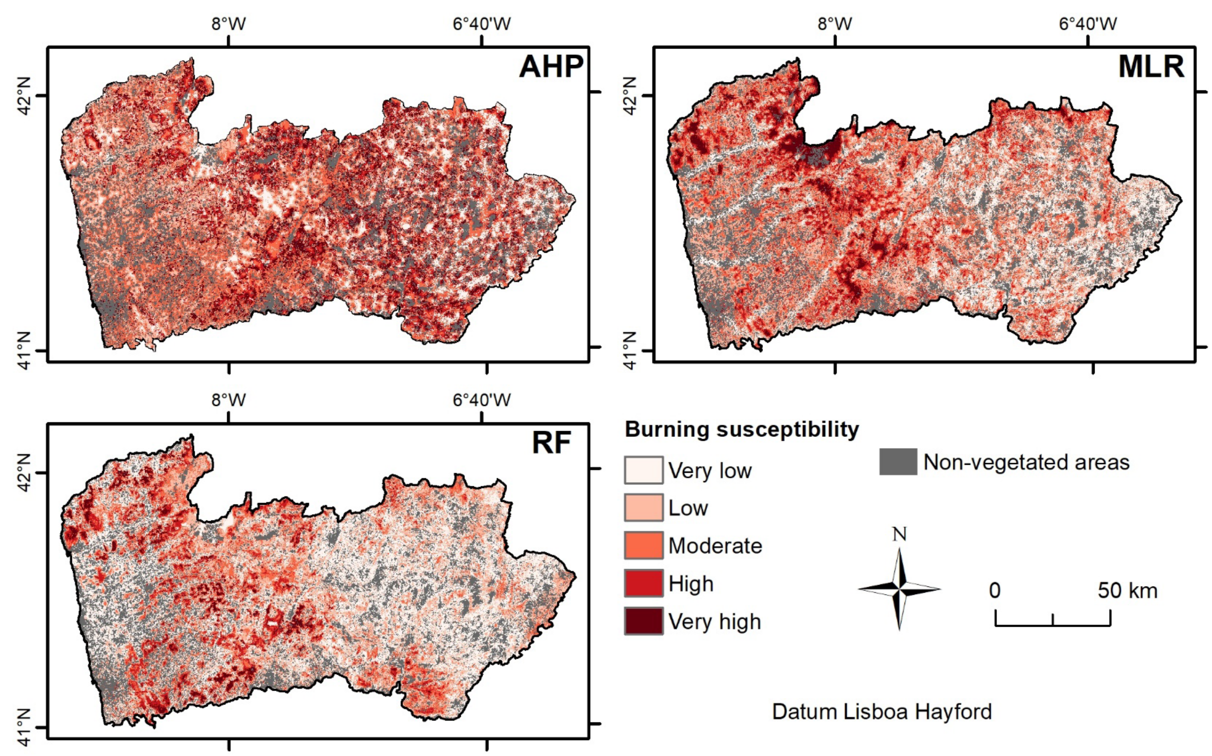

Figure 4. Burning susceptibility map using the Analytic Hierarchy Process (AHP), Multiple Linear Regression (MLR) and Random Forest (RF) for the northern region of Portugal.

RF and MLR were more consistent regarding the relative burned area per class (Figure 5). The burned area grows, following the increased susceptibility for RF and MLR, fact not observed for AHP. More than 60% of the total area classified as "Very high" BS by RF was burned (Figure 5) between 2011 and 2018.

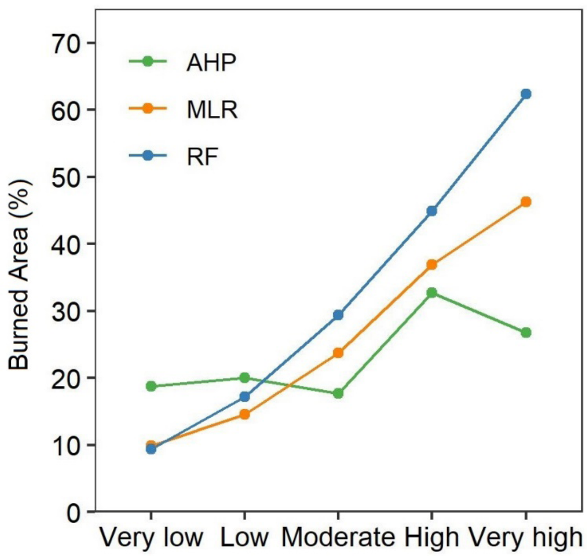

Figure 5. Relative burned area from 2011 to 2018 by burning susceptibility class defined by the Analytic Hierarchy Process (AHP), Multiple Linear Regression (MLR) and Random Forest (RF) methods using data from previous years (1990-2010).

All the methods presented relatively high specificity (> 85%) and low (< 31%) sensitivity for classifying the "Very high" BS class. The RF method presented the highest values for both sensitivity and specificity - 31% and 96%, respectively (Table 5). Despite having a similar specificity value (94%), MLR presented low sensitivity.

Table 5. Sensitivity and specificity for classifying "Very high" BS areas using the Analytic Hierarchy Process (AHP), Multiple Linear Regression (MLR) and Random Forest (RF) methods

Method	Sensitivity (%)	Specificity (%)
AHP	29	85
MLR	15	94
RF	31	96

4. DISCUSSION

In this study, we evaluated three BS mapping methods using fire frequency data from the north region of Portugal. The RF method presented the best performance in both validation steps. Recent studies have also demonstrated the efficiency of this method for fire risk and hazard mapping using different data sources and at different scales (Leuenberger et al., 2018; Gigović et al., 2019; Gholamnia et al., 2020; Shang et al., 2020; Tonini et al., 2020). This method is probably favored by its characteristics of building several decision trees during the training process by having high tolerance to outliers and noisy data (Oliveira et al., 2012; Rodrigues & De La Riva, 2014; Su et al., 2018). As modeling involves several intricate errors, and those might also present self-correlation, the other tested methods might not incorporate all the necessary data complexity. Another RF advantage is the fact that it does not depend on prior knowledge of how each factor affects fire, as this is defined during the training process. This might facilitate its application, since the factors that most affect fire ignition can vary according to the region (Eugenio et al., 2016; Ma et al., 2020).

It is known that the primary goal of fire susceptibility studies is locating areas of greater susceptibility for fire management and suppression (Turkman et al., 2014), which makes it imperative focusing the methods predicting susceptible areas to the detriment of low-risk areas, assisting the correct distribution of efforts for fire control. The AHP and MLR methods had similar accuracy in the two classes susceptibility classification (i.e., High BS and Low BS). The AUC index classifies the AHP as inadequate, while the MLR and RF presented poor performance (Ngoc Thach et al., 2018; Tien Bui et al., 2018). The best method (RF) used in this study presented an AUC value of 0.66, which is below the values found by other studies (Pourtaghi et al., 2016; Gholamnia et al., 2020; Rodrigues et al., 2020). The methods of low suitability can be explained by several factors. It is known, for example, that warmer and drier areas are more prone to fires (Sousa et al., 2015; Pourghasemi et al., 2016; Tosic et al., 2019; Živanović et al., 2020), because they accelerate fuel moisture content reduction (Keyser & Leroy Westerling, 2017). However, in our study area, such behavior was not observed, which reveals the low significance of these factors for BS mapping. Also, the anthropic factors randomness, as well as their low detail, may have reduced the efficiency of the methods, since the fire frequency is highly related to human action (Ganteaume et al., 2013; Oliveira et al., 2017; Elia et al., 2019). Nevertheless, the use of future data (2011-2018) for validation compared to those used for modeling (1990-2010) may also have reduced precision in the BS prediction.

In the BS maps, the RF efficiency is more evident, mainly when assessing the relative burned area per class, where more than 60% of the area classified as "Very high" BS has burned. Another study found similar results, where approximately 40% of the highest susceptibility class burned (Leuenberger et al., 2018). The low sensitivity values can be related to the short period used to validate the maps (2011 to 2018), since the burned areas may not be enough to validate. In this period, areas where the fire was more frequent burned four times. Furthermore, methods such as the RF might perform better when applied to the range of the dataset used for training, and some of the variables such as temperature and precipitation might have changed from one dataset (1990 – 2010) to the other (2011 – 2018). It is worth noting that the specificity values were relatively high for all methods (> 85%), especially for RF (96%). This assessment, associated with the high values of the relative burned area, indicates that the BS map generated from fire frequency data is helpful in the segmenting areas from low to high BS.

The framework used here can be replicated for different regions, considering the characteristics of each method. The AHP has the advantage of not requiring the fire frequency data. However, this issue can be overcome given the availability of orbital data and constant monitoring of fire hotspots (Bernier et al., 2016; Adab, 2017; Aini et al., 2019). This is especially important for regions where fire data is difficult to access or resources are insufficient for collection, which can be observed mainly in developing countries with large territorial extensions (Lim et al., 2019), like Brazil (Caúla et al., 2015; Da Silva Junior et al., 2020).

This study focused on BS mapping by incorporating variables related to the susceptibility of burning. Further studies may consider each element separately since they can target different prevention strategies and that there is more uncertainty regarding the ignition probability as it is related to the random factor attributed to anthropic activities (Bui et al., 2016). It is also possible to separate urban areas and vegetation into more specific classes for more representative models. Besides that, unavailable temperature or precipitation data on some stations might have interfered on the accuracy of the models.

The framework implemented here can be used in the development of local BS maps to facilitate decision making (Vallejo-Villalta et al., 2019; Ma et al., 2020). In addition, it is important to evaluate the methods quality in segmenting very high BS areas, as the under-detection can leave areas that need attention out of the planning, while over-detection can make it difficult to assign the available resources. We expect that this study will contribute to the improvement of BS mapping methodologies and favor regional mitigation planning strategies to reduce the negative impacts caused by fires.

5. CONCLUSIONS

The RF method presented the best performance, incorporating the variability and interactions of the variables that affect BS. This method had high specificity for mapping "Very high" BS areas, showing to be adequate to elaborate BS maps at different times. This method can contribute to the improvement of BS mapping at similar scales (~ 100m) and assist professionals and researchers in decision-making regarding regionally applied mitigation actions.

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