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Faculty of Silviculture and Forest Engineering

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The use of geospatial technologies for forest fire hazard modeling and the analysis of contributing factors

SUMMARY

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Universitatea Transilvania din Brașov

To Mr./Ms...

Defence Committee

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No. D.015 from 21.06.2024

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The date, time, and location of the public defense of the doctoral thesis: September 4, 2024, at 11:00 AM in room SI2.

Any feedback or comments on the content of the thesis should be sent electronically in a timely manner to lorentadrian@gmail.com.

We also invite you to attend the public session for the defense of the doctoral thesis.

Thank you.

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Thesis/Summary

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LIST OF ABBREVIATIONS

JCR	Joint Research Centre
ANCPI	National Agency for Cadastre and Land Registration of Romania
ANN	Artificial Neural Network
CART	Classification and Regression Trees
CIR	Color Infrared
CI_{RE1}	Chlorophyll Index red-edge
CLC	Corine Land Cover
CORINE	Coordination of information on the environment
DJ	County Road
DN	National Road
dNBR	Differentiated Normalized Burn Ratio
$dNBR_n$	Differentiated Normalized Burn Ratio narrow
EFFIS	European Forest Fire Information System
ESA	European Space Agency
ESRI	Environmental Systems Research Institute
EVI	Enhanced Vegetation Index
FIRM	Fire Information for Resource Management System
GIS	Geographic Information System
GMT	Greenwich Mean Time
GNDVI	Green Normalized Difference Vegetation Index
GWR	Geographically Weighted Regression
BC	Combustibility Index
IGSU	General Inspectorate for Emergency Situations
INCDS	"Marin Drăcea" National Institute for Research and Development in Forestry
LiDAR	Light Detection and Ranging
MaxEnt	Maximum Entropy
MMAP	Ministry of Environment, Water and Forests
MODIS	Moderate Resolution Imaging Spectroradiometer
MSR_{RE1}	Modified Simple Ratio red-edge
MSR_{RE1n}	Modified Simple Ratio red-edge narrow
NASA	National Aeronautics and Space Administration
NBR	Normalized Burn Ratio
NBR_n	Normalized Burn Ratio narrow
NDVI	Normalized Difference Vegetation Index
$NDVI_{RE1}$	Normalized Difference Vegetation Index red-edge 1
$NDVI_{RE1n}$	Normalized Difference Vegetation Index red-edge1 narrow
NIR	Near InfraRed
RBR	Relativized Burn Ratio
RdNBR	Relative differenced Normalized Burn Ratio
RF	Random Forest
RGB	Red, Green, Blue
SAVI	Soil Adjusted Vegetation Index
SRTM	Shuttle Radar Topography Mission
SWIR	Shortwave Infrared
TPI	Topographic Position Index
TRASP	Topographic Solar Radiation Aspect Index
TWI	Topographic Wetness Index
UAT	Administrative Territorial Unit
UP	Production Unit
USGS	United States Geological Survey
VCF	Vegetation Continuous Fields
VIIRS	Visible Infrared Imaging Radiometer Suite

FORWARD

Over time, forest fires in our country have occurred with varying frequencies, intensities (burning energy), and severities (losses of organic matter resulting from burning), resulting in significant consequences such as direct economic losses, changes in social behavior and quality of life, and ecological degradation. Evaluating the risk of forest fires and their effects has thus become necessary for developing an integrated prevention and suppression policies at local, regional, and national levels. Additionally, understanding the driving forces behind forest fires and the determining factors for their ignition and spread is a constant concern for both the scientific community and practitioners, specifically the intervention personnel for this type of disaster. Although the risk of forest fires in Romania is relatively low compared to other types of disasters, despite a high probability of occurrence, there is a noticeable trend of exacerbation, evidenced by the emergence of exceptional fire seasons such as those in 2012 and 2022.

The doctoral thesis "The use of geospatial technologies for forest fire hazard modeling and the analysis of contributing factors" aims to deepen the understanding of the forest fire phenomenon in Romania by utilizing modern geospatial technologies such as remote sensing and geographic information systems (GIS) to zone fire hazard areas and identify and analyze the anthropogenic and environmental factors that contribute to their occurrence. This is intended to enhance prevention and mitigation of forest fire effects.

Achieving these objectives would not have been possible without the unwavering support of my scientific supervisor, CS I Dr. Eng. Nicolae Ovidiu Badea, a corresponding member of the Romanian Academy. I express my deepest gratitude and sincere appreciation for his efforts, generosity, support, and patience shown through his competent and constant guidance during the preparation of this doctoral thesis, as well as for his essential contribution to my professional development in the field of forest fire science.

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This list of appreciations and thanks is undoubtedly incomplete, so I extend my gratitude to all those not named here who have been by my side and supported me directly or indirectly in completing this doctoral thesis.

1. INTRODUCTION

Forest fires are a major cause of ecosystem degradation and can lead to loss of human life, economic and ecological disasters (depletion of resources, loss of biodiversity, intensification of the soil erosion process, reduction of the regeneration capacity of forests, acceleration of the desertification process in areas dry) as well as social disturbances accompanied by population migration (Heikkila et al. 2010). Recent studies show that annually more than 4 million km^2 of forest are burned globally (Lizundia-Loiola et al. 2020), also damaging the ecosystem services provided by forests. Fire is a natural process in certain ecosystems, particularly Mediterranean ones, where many plants and animals depend on fire for their survival (Kelly & Brotons, 2017), but in others such as boreal or temperate regions, fire negatively affects biodiversity, especially when natural fire regimes change suddenly (Lewis et al. 2015).

The role of scientific and technological research in the field of wildfires in general and forest fires in particular is that the tools and knowledge produced by the scientific community help international, national and regional government agencies and other organizations involved in fire management to ensure safety and resilience communities to fires, contribute to the restoration of ecosystems affected by fires and reduce their negative effects on the population, communities and the environment. A balanced fire management program will employ a range of fire response mechanisms that can be called upon for both planning and prevention as well as suppression.

Vegetation cover, its structure, composition and moisture status play a key role in the initiation and spread of fires. The characterization and mapping of these features are of crucial importance for fire risk assessment and reduction. Fire fuels can be described in terms of their chemical characteristics, flammability and physical properties, which affect the combustion process and include their quantity, size and shape, compactness and arrangement (Chiuvieco et al. 2023). Based on vertical stratification, fire fuels can be classified into ground, surface and crown fuels, each exhibiting different patterns of fire behavior (Barrows 1951).

From a methodological point of view, models have been developed using direct methods involving intensive field campaigns in which fuel properties are measured by stratified sampling according to the dominant vegetation types and its structure (herbaceous vegetation, shrub vegetation, forest, etc.) (Scott and Burgan, 2005). For surface fuels the most frequently measured parameters are: foliage load, litter load and litter depth, shrub load (up to 2 m in height) and herbaceous vegetation (live or dry). Fuel loads (weight of fuel per unit area) are determined by measuring the dry weight.

The disadvantage of this method, although considered the most accurate due to the collection of field data after stratified sampling, is that it requires a lot of effort and time to develop.

Alternatively, there is a common practice to derive vegetation fuel models (types) leading to the corresponding maps by equating combustibility indices based on existing datasets (Won et al. 2006, Sandberg et al. 2001). This approach was adopted within the "FUELMAP" project, which was implemented by the Joint Research Center of the European Union (Joint Research Center – JCR) Ispra, and provided a first approach to standardized forest fuel typologies for Europe as well as a map of the distribution of forest types in the European Union (EU) (JRC 2011). This approach consists of using geospatial datasets and remote sensing data to equate vegetation type maps with fuel types.

At the international level, research on the analysis of fire occurrence patterns based on historical events, fire risk assessment and area prioritization is gaining increasing attention and development particularly in the Mediterranean biomes of North America (Syphard et al. 2008), Mediterranean European countries (Chuvieco et al. 2010, Catry et al. 2009, Ganteaume et al. 2013), Latin America (Castro et al. 1998, González et al. 2009) or Australia (Turner et al. 2011). More recently, the dynamics and challenges of forest fires have been highlighted in regions such as Central and South America (Armenteras et al. 2016), Switzerland (Zumbrunnen et al. 2011) or the far east of Russia (Loboda et al. 2009).

Wildfire hazard zonation is often a difficult task due to the complexity of fire occurrence at multiple spatiotemporal scales (Keane and Menakis 2014). Wildfire hazard has been estimated through a variety of approaches, including predicted fire behavior (Hessburg et al. 2007), spatial distribution of fuels (Keane et al. 2010), remote sensing indices (Jurdao et al. 2012, Pan et al. 2016), topographical variables (Yool et al. 1985), expert judgment (Gonzalez et al. 2007), socio-economic variables (Koutsias et al. 2005) and fire behavior parameters (Fiedler et al. 2001). Some authors have estimated forest fire hazard by creating GIS layers with various characteristics and merged them using weighted factors to create a final forest fire hazard layer (Klaver et al. 1998).

Recently, the substantial development and refinement of fire risk analysis tools have resulted in software improvements, system integration, and greater data availability, all contributing to enhanced statistical analysis and GIS techniques (Mitsopoulos et al. 2016).

The most common approach to understanding spatial fire occurrence and driving forces is ***to model the distribution based on historical fire locations*** (Massada et al. 2012). Of particular importance is the fact that there needs to be a distinction between the two major stages of fire modeling: **explanatory modeling** (to test hypotheses about the role that different factors play in starting fires) and **predictive modeling** (to identify those areas that are the most prone to ignitions and where fire prevention efforts or fuel reduction treatments can be allocated).

Conceptually and methodologically, fire distribution modeling is closely related to species distribution modeling (Franklin 2010, Massada et al. 2012, Mundo et al. 2013). The basic approach is to analyze fire ignition locations (similar to species occurrence locations) in relation to suspected environmental variables in terms of their influence on the spatial distribution of fire (or species occurrence). Existing models estimate the response of fires (or species) to these predictive environmental variables. As in species distribution modeling, there are two types of ignition data that can be analyzed: *presence* (the occurrence of an ignition event at a point in space) or *abundance* (the number of ignitions per unit area). The type of data affects the choice of model type because presence data typically require a binomial response, while abundance data require a continuous response. Furthermore, although presence data are often accompanied by absence data, special modeling methods based solely on presence data have also been developed in situations where presence locations are compared to background environmental conditions ("used vs. available ") (Elith et al. 2010), as it is often impossible to identify locations where fire is not likely to occur.

There are several methods that investigate interactions between spatial variables (suspected as contributing factors) and fire occurrence. Thus, generalized linear regression models (GLM), such as **linear and logistic regression** (Catry et al. 2009, Chuvieco et al. 2010, Oliveira et al. 2012) as well as **classification and tree regression methods** (*classification and regression trees* - CART) (Amatulli et al. 2006, Archibald et al. 2009) have been widely used. These methods focus on the global picture and are characterized by stationary spatial assumptions, which is often not the case in real situations (Koutsias et al. 2010, Sá et al., 2011). According to some researchers (Archibald et al. 2009, Ganteaume and Jappiot 2013 the importance of variables explaining fire occurrence is not homogeneous across the entire area under analysis, and several methods of analysis are needed to identify local spatial factors governing the forest fire regime (Koutsias et al. 2010, Sá et al., 2011). The spatial inhomogeneity of the variables was verified by using **the geographically weighted regression method** (*Geographically Weighted Regression* - GWR) (Fotheringham et al. 2002). GWR generates a regression equation for each feature analyzed in a sample dataset as a means to address spatial variation (Guo et al. 2016). However, GWR focuses more on exploratory data analysis and interpretation than on prediction (Oliveira et al. 2014, Nunes et al. 2016).

Other advanced statistical methods that have often been used to model forest fire probability and hazard involve the use of *machine* **learning techniques**. Oliveira et al. (2012) compared the predictive ability of the two models (**linear regression and the *Random Forest technique***) to identify the main factors that explain the probability of fires occurring on a European scale. Satir et al. (2015) produced wildfire probability maps for a Mediterranean forest in Turkey by using an

artificial neural network (ANN), while Dlamini (2010) used **the automatic learning expectation-maximization** (EM) algorithm to generate a map of the fire occurrence area based on 13 biophysical and socio-economic explanatory variables using a Bayesian network (BN). Spatial patterns influencing the occurrence of human-caused fires were analyzed using K-functions and the **kernel density estimator** (Guo et al. 2015). Massada et al. (2012) compared the predictive performance, variable importance, and spatial patterns of GLM, *Random Forest*, and **maximum entropy** (MaxEnt) methods for forest fire hazard modeling and found that *Random Forest* and *MaxEnt* provided slightly higher prediction accuracies than that resulting from the application of the GLM method, given that the fitting model was similar for all three methods. Other authors have used ***fuzzy*** set theory **integrated** with a decision-making algorithm in a GIS framework to map forest fire hazard (Vadrevu et al. 2010).

In Romania, according to the "National Disaster Risk Management Plan" (IGSU 2020), the risk of forest fires is one of the highest in terms of probability of occurrence, but the level of impact is low compared to other types of risks. Analyzed unilaterally, the impact of forest fires is not similar to the impact of other types of risk and can be considered to be numerically even lower. Nevertheless, if we look at the interdependence between forests and the environment, economic and social life and the sustainable development of society, it is fair to say that forest fires have a major impact on the development of human society. However, since the year 2000 (since when there has been an increase in the frequency of years with extreme forest fires), there has been a trend towards an exacerbation of the occurrence of forest fires. Thus, the historical fires were analyzed and it was highlighted the doubling of the incidence of forest fires in Romania as well as the affected areas in the period 2006-2015 compared to the period 1956-2015 (Lorenț et al. 2018).

An important step in improving forest fire risk management was achieved within the framework of the project SIPOCA 395 "*Implementation and development of common systems and standards for the optimization of decision-making processes in the field of water and forests, the application of the system of evidence-based policies in the Ministry of Water and Forests for the systematization and simplification of legislation in the field of water and the implementation of simplified procedures to reduce the administrative burden for the business environment in the field of forestry"* implemented by INCDS "Marin Drăcea" in the period 2018-2021 in which the procedure and the Good Practice Guide no. 8 "Defense of forests against fires" were aimed at revising and updating the current Forestry Technical Norms 8 on the Prevention and extinguishing of fires in the forest fund.

Research on the application of geospatial technologies in the study of forest fires in our country is still in its early stages, but recently the topic has started to attract the Romanian scientific community. Mihai et al. (2019) evaluated the possibility of using Sentinel 2 MSI and Pleiades 1B satellite images for producing and assessing representative spectral indices in determining fire susceptibility in forests of *Pinus nigra ssp. Banatica* and *Fagus sylvatica* in an area of the Domogled – Valea Cernei National Park. Banu et al. (2014) mapped fire ignition risk based on a combined index considering variables related to exposure, altitude, slope, vegetation moisture, distance from roads and proximity to settlements. The research also covered the Domogled – Valea Cernei National Park.

2. RESEARCH AIM AND OBJECTIVES

Knowing the causes of forest fires and the main factors that determine their outbreak is an indispensable step in the development of effective policies and measures to prevent them and to help plan technical prevention measures at the regional level, increase the effectiveness and economic efficiency of forest fire interventions to extinguish vegetation fires and increase the level of preparedness of the population for such disasters. In this regard, **the aim** of the research carried out for the development of the doctoral thesis entitled "The use of geospatial technologies for the modeling of forest fire hazards and the analysis of contributing factors" is related to ***the increase in the degree of prevention and mitigation of the effects of forest fires in Romania through the***

***development of geo-spatial analysis methods to be operational in the processes of periodic evaluation according to modern and standardized procedures of the hazard of forest fires*.**

In order to achieve the aim of the research undertaken, the scientific ***objectives*** mainly refer to:

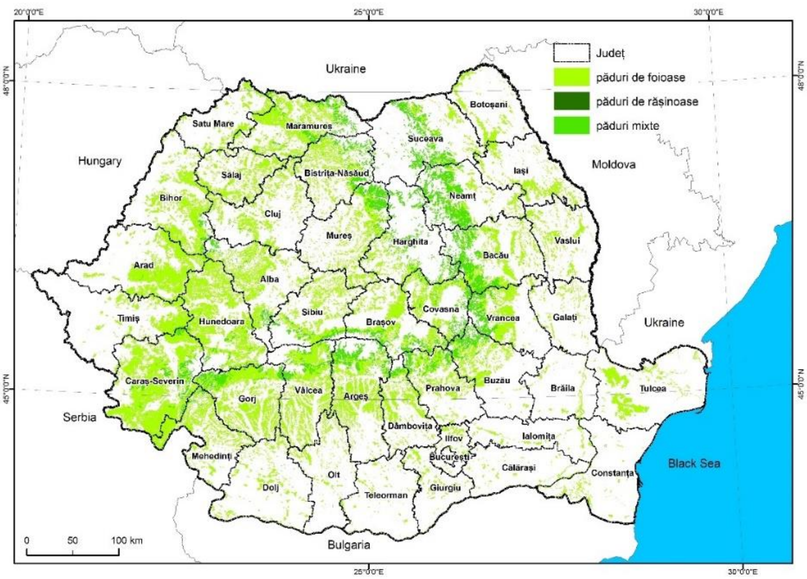
- Mapping the distribution of fuel types for the areas covered with vegetation in Romania
- Testing and validating some geo-spatial methods for forest fire hazard zonation and identification and analyzing the determining factors for their occurrence
- Development of a method for determining the area affected by the fire, based on high spatial resolution satellite images, and assessment of fire severity
- Detection and localization of forest fires and monitoring their evolution based on high temporal resolution satellite imagery.

Achieving these objectives contributes to the deepening and development of knowledge regarding the spatial distribution of forest fires in Romania, the determining causes and their impact for knowing the influence of the most important geospatial parameters that lead to their occurrence in the region.

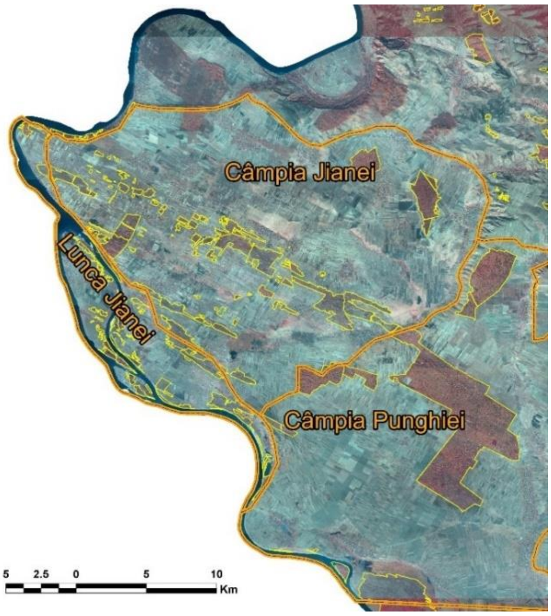
3. RESEARCH METHOD AND MATERIAL

3.1 Research Location

The research carried out in order to map the distribution of fuel types, to identify and analyze the factors favoring forest fires as well as to zone the hazard were located all over Romania and the determination of the areas affected by fires based on satellite images and the tracking of their propagation over time was carried out in the municipalities of Jiana and Pătulele in Mehedinți County, in forest bodies managed by Renașterea Pădurii Forest District and Vînju Mare Forest District (Figure 3.1).



a)



b)

Figure 3.1. Research location: a) Romanian territory - for the mapping of vegetable fuels and hazard analysis and b) a forested area within municipalities of Jiana and Pătulele in Mehedinți County

3.2 Mapping the distribution of fuel types for the areas covered with vegetation in Romania

In the framework of the research carried out on the occasion of the development of the doctoral thesis, the mapping of fuel types was performed using the indirect mapping method, based on geospatial data sets covering the entire territory of Romania according to which plant species / communities are associated with fuels described in terms of vegetation types (e.g. grass, shrubs and trees) and properties (e.g. height, density, mixture), and finally fuel types are mapped using different image analysis techniques (Tănase & Gitas, 2008).

Following the analysis of the existing European fuel type classification systems such as FUELMAP or ArcFuel (Toukiloglou et al. 2013), it was found that they can be adapted and customized for the Romanian territory. Thus, the main fuel groups were taken: grasslands, shrubs, transition zones between shrubs and trees, coniferous forests, deciduous forests, mixed forests, aquatic vegetation, agro -forestry land and the groups and types of fuel were identified specific to Romania. The fuel groups representing the non-forest vegetation were established among the land cover classes from which the fire can spread in the areas covered with forest, therefore, they were extracted from the lands covered with shrub vegetation, grass vegetation or transition zones between shrubs and forest.

By classifying litter types specific to forest ecosystems based on their distinct combustibility properties, a map of surface (litter) fuel types for forested areas can be obtained. This is a simplified and expeditious method but which, nevertheless, provides an additional level of information when using fire propagation models, since ecosystem types are grouped according to pyrotechnic characteristics that influence the speed and mode of spread of a surface fire.

In this respect, already elaborated studies, which were based on the direct method, i.e. direct field measurements, were used to classify ecosystems into combustibility groups according to litter. The first study considered was that of Dimitrakopoulos (2002) who made a classification of the Mediterranean vegetation of Greece into fuel types. This work, although it approaches an ecosystem complex with significant differences from that in our country, provides important details regarding the types of fuels in pine and quercine stands. For completion, the study developed by Scott and Burgan (2005) was also used, who developed a new set of combustibility models for modeling fire behavior for North American vegetation, as well as scientific information on forest fire risk management that provides a detailed description of the forest fires produced in Suceava county in the period 1990-2009 (Burlui, 2013), especially on the mode of manifestation of litter fires depending on the composition of the stand.

Following the consultation of these scientific studies, it was determined that surface forest fires have specificities determined by the type of litter existing in the stand, these being grouped into five main classes: resinous litter, xerophytic quevercine litter (downy oak, grayish oak), litter of mesophytic quercinea (oak, sessile oak), litter of other deciduous species. For their mapping, the Forest Map of Romania based on forest ecosystem types (Doniță et al. 2008). The grouping of ecosystem types into fuel classes was carried out in the polygon vector layer containing the distribution of forest ecosystem types, after which the conversion from vector to raster with a resolution of 30 m was carried out.

Next, each type of forest fuel was subdivided according to the percentage of tree cover, knowing that areas with dense vegetation have more fuel matter than sparse ones, and therefore vegetation density is one of the important physical properties of the fuel.

The MODerate-resolution Imaging Spectroradiometer (MODIS), Collection 6, Vegetation Continuous Fields (VCF) product known as MOD44B was used for this purpose. The product provides global estimates at sub-pixel level with 250 ma resolution of percent tree cover that is derived based on emissivity and reflectance data recorded by the MODIS satellite instrument. These data are produced every 1 year. The 2020 data was downloaded for the present analysis.

Fuel groups representing non-forest vegetation (ie land covered with shrub vegetation, herbaceous vegetation or transition zones between shrub and forest) were extracted from the Corine Land Cover 2018 dataset.

In the end, 20 types of fuels were obtained and the map of their distribution at the national level was made. Each fuel type is at the same time a fuel model as it represents "an identifiable association of combustibility elements belonging to distinctive species: shape, size, continuity, which will exhibit a characteristic fire behavior under defined burning conditions" (Merrill and Alexander, 1987).

3.3 Determining the hazard of forest fires and analyzing their contributing factors

For fire distribution modeling the most widely used approach consists of analyzing historical fire events to identify fire ignition locations in relation to suspected variables that influence the spatial distribution of fires. Existing models estimate fire response to these predictive variables. Therefore, the first stage of the research was the creation of a geo-spatial database in which to integrate the data sets that will feed the statistical models tested later.

The database of forest fires registered in Romania in the period 2006-2018 was used as the dependent variable. This contains detailed records on forest fires and were obtained for the period 2006-2015 from the National Forestry Authority (RNP) ROMSILVA for the state-owned forests and for the privately owned forests managed by the RNP, and for the period 2011-2018 were obtained centralized fire records by the Ministry of Environment, Water and Forests (MMAP) for the entire national forest fund. The database contains a number of 4,220 fires that were geolocated based on georeferenced landscaping maps, given that the original records did not contain the geographic coordinates of the fires, their location being recorded by specifying the landscaping units affected by the fire. The tabular records include information about *the location of the fire, the affected area, the duration of the fire, information about the intervention forces* mobilized to extinguish it (forest engineers, firefighters, police and gendarmes, respectively citizens), *damage produced* (partial data), *the cause of production* (according to the EFFIS nomenclature) as well as *information regarding the geographical area* (eg: plain, hill, mountain, etc.), the nature of the forest (e.g.: resinous, deciduous, mixed, plantation, etc.) and the type of fire (eg: litter, litter and canopy).

The most common approach to understanding spatial fire occurrence and driving forces is *to model the distribution based on historical fire locations* (Massada et al. 2012). The research tested two predictive models to identify those areas that are most prone to ignition and where fire prevention efforts or fuel reduction treatments can be allocated. Two predictive methods (**Random Forest and logistic regression)** were tested that allow the spatial representation of areas prone to fires, respectively *hazard zonation*, simultaneously highlighting the factors that most influence the occurrence of forest fires. The analysis was therefore carried out at the raster level, on the entire study territory (i.e. the territory of Romania).

Random forest (RF) is a non-parametric model derived from classification and regression trees (CART) that establishes multiple decision trees, using a randomly selected subset of samples and training variables (Belgiu and Drăguț, 2016). RF consists of a combination of trees, where each tree is generated by *bootstrap samples,* leaving about a third of the total sample for validation (out-*of-the -bag predictions*). Each split of the tree is determined using a random subset of predictors at each node. The final result is the average of the results of all trees. This method has been applied in ecological studies (Cutler et al. 2007), where it provided both high precision and high ability to model complex interactions between variables. Additionally, since it uses *out-of- the -bag samples* (observations independent of those used to grow the tree) to calculate error variance and variable importance, no test data or cross-validation is required. However, the method behaves as a ``black box'' as individual trees cannot be examined separately and does not calculate regression coefficients or confidence intervals (Cutler et al. 2007). However, it allows the calculation of the importance of the variables which can be compared with other regression techniques (Oliveira et al. 2012).

Logistic regression modeling is used to determine a dichotomous variable Y from a set of independent predictor variables by estimating the probability of the event occurring. The main working assumption of a logistic regression model is the linear relationship between the natural logarithm of the odds of the binary outcome (Y takes the values 1 and 0) and the independent variables. In contrast to other multivariate statistical methods, no assumption of multivariate normality needs to be proven.

Logistic regressions can be useful for classifying remote sensing data, especially when the independent variables do not follow a normal distribution. The main requirement in implementing the logistic regression model in the classification process is to express the classification problem in a binary dichotomous manner, ie to analyze the classification categories two at a time. The logistic regression equation is expressed as follows:

$$p_i = P(z_k(x_i) | Y = 1) = \frac{\exp\left(\beta_o + \sum_{k=1}^{K} \beta_k z_k(x_i)\right)}{1 + \exp\left(\beta_o + \sum_{k=1}^{K} \beta_k z_k(x_i)\right)} \quad (3.1)$$

where,

- pi represents the probability of a fire occurring in cell i,

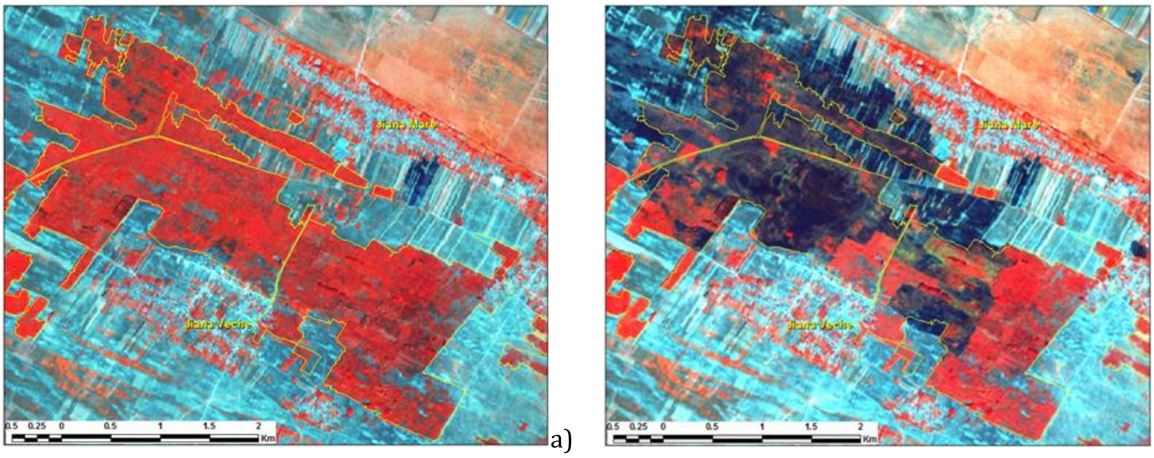
- βo, βk are regression coefficients determined for the weighting of explanatory variables xi.

3.4 Assessment of post-fire effects based on high spatial resolution satellite images and products

The research area is located in southwest Romania, in Mehedinți county (Figure 1), being mainly covered by black locust forests installed on the river dunes in the high terrace of the Danube, where the forests alternate with cultivated or uncultivated agricultural land. Under conditions of prolonged drought and strong winds, from August to September 2021, these repeated stubble burning fires spread into nearby forests, resulting in thousands of hectares of agricultural fields and forests affected to varying degrees.

Satellite imagery from Sentinel 2 satellites equipped with *a push-broom* sensor - *MultiSpectral Imager* (MSI), a 13-band multispectral imager with a 290 km wide bandwidth (left-right of nadir), was used to assess the post-fire effects. The spatial resolution is different for the 13 bands, ranging from 10 m for bands 2,3,4 and 8 (visible and NIR), 20 m for bands 5,6,7,8a,11 and 12 (red edge and SWIR bands) and 60 m for bands 1, 9, and 10 (atmospheric correction bands).

To assess the degree of post-fire damage to stands, a forest fire severity estimation methodology was adopted using images recorded before, during and after fire events. In addition, aerial orthoimages made by the National Agency for Cadaster and Land Registration of Romania (ANCPI) were used in natural color (RGB) and color infrared (CIR), captured in 2015 with an ADS80 camera with a spatial resolution of 0.5 m, together with ultra-high resolution orthoimages obtained by processing RGB aerial images captured with a DJI Mavic 2 Enterprise drone Dual, about a month after the fire events. The Sentinel 2 images were downloaded from the Copernicus Open Access Hub portal (https://scihub.copernicus.eu/dhus/#/home). A total of 9 S2 images with L2A processing level (bottom - of - atmosphere orthorectified images) were obtained and used in the study, covering the period between August 1 and September 11, 2021, when the more forest fires. All images were grouped into bands (except bands B1, B9 and B10), cropped for the study area and reprojected to the Stereographic 1970 projection. Two images were selected for rapid evaluation, one before the fire series (2021-08 -01) and another after the fires ended (2021-08-11) (Figure 3.2). A total of 9 Sentinel 2 images recorded on: 01/08/2021, 04/08/2021, 06/08/2021, 11/08/2021, 19/08/2021, 24/08/2021, 03/09/2021, 08/09/2021 have been downloaded.



a) b)

Figure 3.2. Sentinel 2 images of the study area: 2021-08-01 (a) before fire events, 2021-08-11 (b) after fire events. Color combination: RGB = B8, B3, B2. Yellow line - forest boundaries (Jiana forest body, Mehedinți county)

Forest fire incident reports were obtained from the Ministry of Environment, Water and Forests (MMAP). In total, 11 forest fire events were recorded in August 2021 in the study area, affecting a total of 611.85 hectares of forest. Forest management and associated maps were used to provide information on stand characteristics and to delineate management units affected by fires.

In order to establish the degree of damage to the stands, a severity scale was developed to systematize and standardize the way of evaluating it according to the effects visible on the ground and on aerial images on the stand, stratified by stand age and canopy cover index. Thus, after the preliminary mapping of the severity of the fires based on the satellite images, a field trip was carried out (in the Jiana and Pătulele forest bodies) to check if the automatically created severity classes correspond to the real impact of the fires. For this purpose, 40 locations with different degrees of severity and different characteristics in terms of crown height and cover were identified on the severity map. Field data collection took place in October 2021, one month after the forest fires occurred.

Burn severity represents the degree or extent of environmental change caused by the fire. Change can be represented by single or multiple biophysical variables on a continuous scale from none to major changes. For the field estimation of fire severity, 5 severity classes were considered, similar to those proposed by Key CH and Benson NC, 2006: *unaffected stand, low, medium-low, medium-high* and *high severity.* Fire severity was visually assessed in the field for the four layers: understory, grass and low shrubs, tall shrubs and young trees (< 10m H) and mature trees (> 10m H), assigning a value between 0 (unaffected) and 4 (high severity). Therefore, the 40 representative sample areas of square shape (20x20 m) were placed in the field (Figure 3.3). The severity classes were adapted to the specifics of the black locust forests in the study region and are presented in Table 3.1.

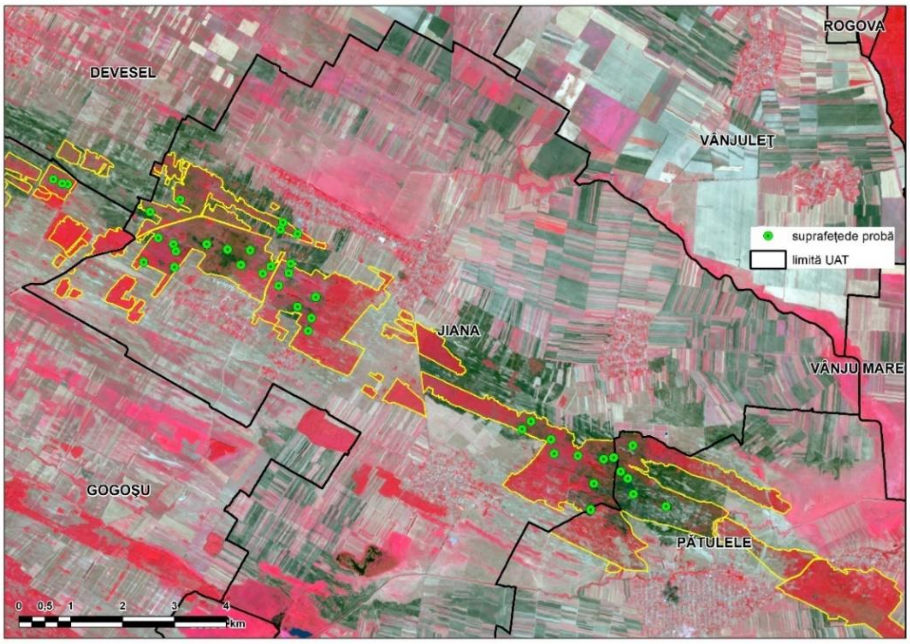


Figure 3.3 Location of test areas for estimating the severity of wildfires

Table 3.1. Criteria for estimating wildfire severity

Severity	**Field classification criteria**
low	• unaffected soil • litter and seedbed up to 1m affected • apparently unaffected plantations • short (young) forest stand with unaffected foliage • tall (mature) forest stand with blackened tree trunks up to 0.5 m
moderately reduced	• partially affected soil • litter, shrub layer and seed affected • visibly affected plantations • short (young) forest stand with unaffected foliage • tall (mature) forest stand with blackened trunks up to 1 m

moderate-high	• carbonized soil organic layer • carbonized litter, shrub layer and seed • charred plantations, possible return only after receipt • short (young) forest stand with partially dry or burnt foliage • tall (mature) forest stand with blackened trunks up to 2 m
high	• organic layer of soil turned into ash • the litter, the shrub layer and the seed turned into ash • plantations reduced to ashes • short (young) forest stand with dry or burnt foliage, charred trunks • tall (mature) forest stand with blackened trunks over 2 m, partially dry or burnt foliage

At the office stage, it was taken into account that the trees reflect electromagnetic radiation in the green and near-infrared spectrum, so the lower they are, the higher the degree of damage. Taking into account the texture of the image, which was visually analyzed, the stands were also classified as bare land, plantations, young stand and mature stand as well as the coverage index was estimated. Three types of stand types were considered (plantation, young stand below 10 m height, mature stand above 10 m height), their vulnerability to surface fires being inversely proportional to the height and 4 categories of cover index size (no canopy, low 0.1-0.3, medium 0.4-0.6 and high 0.7-1.0), these being necessary for correcting the severity.

3.5 Processing of satellite images

The original georeferenced images are those provided by ESA, in UTM map projection on the WGS84 ellipsoid. In order to overlay them with the geospatial data used in Romania, it was necessary to reproject them in the 1970 Stereographic map projection. Thus, the multispectral files were created in which the files with the original spectral bands are inserted and *the JPEG 2000* format was switched to *the TIFF* format. Also, the images used were cropped from the original tile to match the area of the study area. All these operations were performed with the object programming available in the ArcGIS system, using *ModelBuilder* (Figure 3.4).

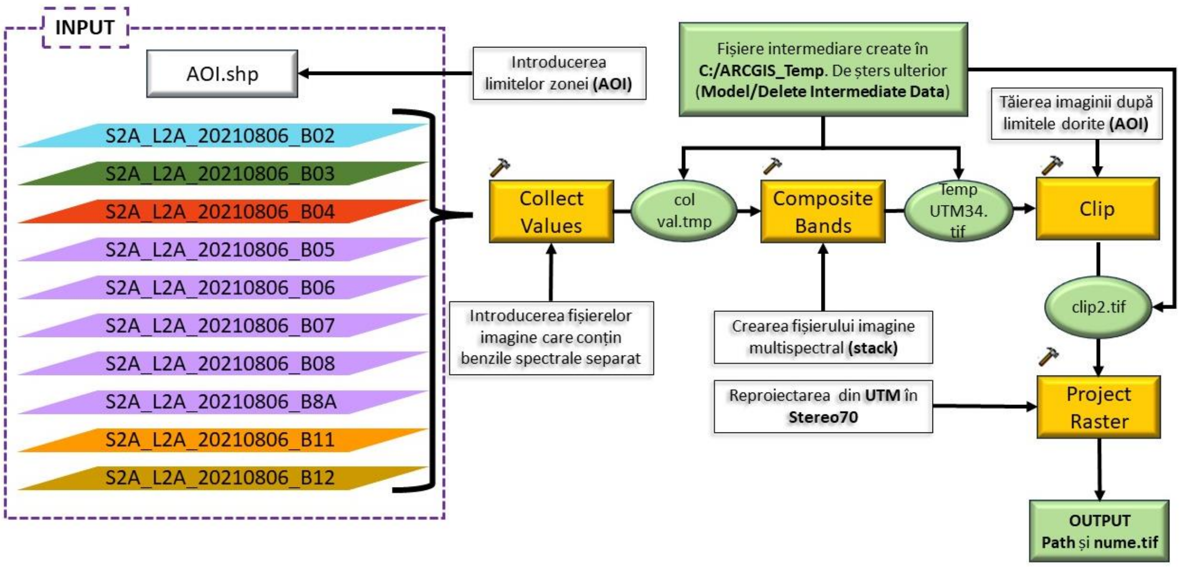


Figure 3.4. The Sentinel 2 Automated Imagery Preprocessing (MSI) model in the ArcGIS system

Establishing spectral indices for determining the area affected by forest fires and their severity

Several indices that can be used to determine the areas affected by forest fires and to assess the severity of the effects have been retained from the literature. Thus, the indices recorded by Mallinis et al. (2017) were tested as being susceptible for highlighting the areas affected by fires, being adapted to the spectral bands of the MSI sensor on the Sentinel 2 satellites (Table 3.2).

Table 3.2. Spectral indices used to assess the effects of forest fires (adapted from Mallinis et al., 2017)

Spectral index	Swapping	Calculation formula
Normalized Burn Ratio	NBR	$\frac{Band8 - Band12}{Band8 + Band12}$
Normalized Burn Ratio narrow	NBR_n	$\frac{Band8A - Band12}{Band8A + Band12}$
Normalized Difference Vegetation Index	NDVI	$\frac{Band8 - Band4}{Band8 + Band4}$
Green Normalized Difference Vegetation Index	GNDVI	$\frac{Band5 - Band3}{Band5 + Band3}$
Normalized Difference Vegetation Red-edge index 1	$NDVI_{RE1}$	$\frac{Band8 - Band5}{Band8 + Band5}$
Normalized Difference Vegetation Index red-edge1 narrow	$NDVI_{RE1\,n}$	$\frac{Band8A - Band5}{Band8A + Band5}$
Chlorophyll Index red-edge	CI_{RE1}	$\frac{Band7}{Band5} - 1$
Modified Simple Ratio red-edge	MSR_{RE1}	$\frac{\left(\frac{Band8}{Band5}\right) - 1}{\sqrt{\left(\frac{Band8}{Band5}\right) + 1}}$
Modified Simple Ratio red-edge narrow	$MSR_{RE1\,n}$	$\frac{\left(\frac{Band8A}{Band5}\right) - 1}{\sqrt{\left(\frac{Band8A}{Band5}\right) + 1}}$

In addition to these indices, which are calculated for a specific image (monotemporal indices), bitemporal indices were established, using two images, one before the event (in this case fire) and one after the event (Table 3.3).

Table 3.3. Bitemporal spectral indices used to assess the effects of forest fires (adapted from Mallinis et al, 2017)

Spectral index	Swapping	Calculation formula
Differenced Normalized Burn Ratio	dNBR	preferNBR - postfireNBR
Differenced Normalized Burn Ratio narrow	$dNBR_n$	$preferNBR_n - postfireNBR_n$
Relative differenced Normalized Burn Ratio	RdNBR	$\frac{dNBR}{\sqrt{\left\lvert\frac{prefireNBR}{1000}\right\rvert}}$
Relativized Burn Ratio	RBR	$\frac{dNBR}{PrefireNBR + 1{,}001}$

The difference between NDVI can also be used:

$dNDVI = {}_{Pre\text{-}fire}NDVI - {}_{Post\text{-}fire}NDVI$

or between any other indexes.

Determination of indices for the detection of burned forest areas

Determining the severity level of the fire

In order to determine the severity level (degree of damage) of vegetation following the fire, severity steps were determined according to the United States Geological Survey (USGS) based on the values of the *Differenced Normalized Normalized Burn Ratio*, dNBR (Key and Benson, 2006; Lutes et al., 2006) (Table 3.4).

Table 3.4. Severity levels based on dNBR index (adapted from USGS)

Severity level	dNBR values
unaffected	-0.100 - +0.099
Low severity	+0.100 - +0.269
Medium-high severity	+0.270 - +0.439
Medium-high severity	+0.440 - +0.659
High severity	+0.660 - +1.300

The images were processed using the ERDAS system, specialized for image processing, in which, with the object programming system called *Modeler, the model for calculating Normalized Burn Ratio (NBR) index was developed, adapted for Sentinel 2 images.*

For each index used, such a scheme was defined and the corresponding formula was introduced.

To increase the accuracy of the fire effects map based on the dNBR index , a digital map of crown cover and tree height was produced based on aerial color infrared (CIR) imagery with 0.5 m spatial resolution captured in 2015. The classes were delimited by manual vectorization, and crown cover degrees and heights were visually established by photo-interpretation.

For tree height, three classes were considered, namely plantations (artificial culture of young trees, with the crown still developing), short trees (height below 10 m) and tall trees (height above 10 m). The classes were established after finding in the field that the vulnerability to fires is inversely proportional to the height of the trees. Four categories were established for the degree of crown coverage: no canopy, low 0.1-0.3, medium 0.4-0.6, and high 0.7-1.0. Trees with low canopy cover appear to be more severely affected than in reality on satellite images.

In stands with a lower degree of coverage (such as black locust stands) the herbaceous cover developed more, providing more fuel for burning, being seconded by a greater air/space visibility of the burned soil. In dense stands, which cover the ground well (the case of stands of Quercinea species), the herbaceous cover and shrubs are poorly developed, so that the surface fire is fueled only by the litter and the leafy canopy can hide the real severity.

A particular case are plantations that are very vulnerable because of their low age, large amounts of fuel (tall, dry grass), no canopy and exposed burned soil, so the severity estimated on aerial or satellite imagery is usually overestimated.

The presence or absence of foliage unaffected by the fire is the factor that causes the severity estimate based on aerial/satellite imagery to be different from the ground reality. This makes the estimate closer to reality during leaf-off periods in the case of deciduous trees. A correction key for the severity estimated on aerial/satellite images based on the above criteria was thus proposed (Table 3.5).

Table 3.5. Severity correction key estimated from satellite/aerial imagery

Tree type + trend (↑↓)	**Coverage index + trend**	**Estimated severity aerial/satellite images**	**Correction**	**Terrain severity**
Empty Land ↑	No stand ↑	high	-	-
Plantation ↑	No canopy ↑	low	↑	medium-low
		medium-low	↑	medium-high
		medium-high	↑	high
		high	↑↓	high
Stands with heights of the trees below 10 m ↑	low 0.1-0.3 ↑	low	↓	low
		medium-low	↓	low
		medium-high	↓	medium-low
		high	↓	medium-high
	medium 0.4-0.6 ↑↓	low	↑↓	low
		medium-low	↑↓	medium-low
		medium-high	↑↓	medium-high
		high	↑↓	high
	high 0.7-1.0 ↓	low	↑	medium-low
		medium-low	↑	medium-high
		medium-high	↑	high
		high	↑	high
Stands with heights of the trees over 10 m ↓	low 0.1-0.3 ↑	low	↓	low
		medium-low	↓	low
		medium-high	↓	medium-low
		high	↓	medium-high
	medium 0.4-0.6 ↑↓	low	↓↑	low
		medium-low	↓	low
		medium-high	↓	medium-low
		high	↓	medium-high
	high 0.7-1.0 ↓	low	↑↓	low
		medium-low	↑↓	medium-low
		medium-high	↑↓	medium-high
		high	↑↓	high

3.6 Detecting and locating forest fires and tracking their evolution based on high temporal resolution satellite images

The research was carried out in a wooded area located within municipalities of Jiana and Pătulele in Mehedinți county (Figure 4.1). Thus, the data on the forest fires produced in August 2021 were obtained from the Renașterea Pădurii Forest District and the Vînju Mare Forest District, which are the ones that administer the forest fund from the Jiana and Pătulele forest bodies, respectively. At the same time, tabular electronic records were used, which summarize the fire reports for the year 2021 provided by MMAP (Table 3.6).

Table 3.6. Centralization of forest fires registered in the Jiana and Pătulele forest bodies during 04-14.08.2021 (according to the fire reports drawn up by the forest departments and the synthetic centralizer of fires from 2021 provided by MMAP)

Forest District	Production Unit	Forest unit	Composition	Age (years)	Affected area (ha)	Type fire	Date and time	
							Start	Stop
Renașterea Pădurii	UP II Burila	89-242%	10 SC	10; 12	160.0	litter	04.08. 2021 15:10	06.08. 2021 12:00
Vînju Mare	IX Burila Mare	82	10 SC	12	4.0	litter	04.08. 2021 17:00	04.08. 2021 22:00
Vînju Mare	IX Burila Mare	38A-C, 39, 46AC, 50	10 SC	2; 22	43,41	litter	04.08. 2021 17:00	04.08. 2021 21:30
Renașterea Pădurii	XXIV Mehedints	292%-300%	10 SC	6; 30	80.0	litter	06.08. 2021 12:30	07.08. 2021 6:00
Vînju Mare	IX Burila Mare	84A	10 SC	15	10.0	litter	07.08. 2021 12:00	07.08. 2021 22:15
Greengold Vest SRL	XV	21-30, 37, 38%	HARDWOOD	21-30; 37; 38	173.3	litter	09.08. 2021 14:15	10.08. 2021 -
Vînju Mare	IX Burila Mare	84	10 SC	15	3.24	litter	09.08. 2021 10:45	09.08. 2021 14:00
Renașterea Pădurii	XXIV Mehedinți	2, 3, 31, 32	10 SC	6; 20	70.0	litter	11.08. 2021 13:40	11.08. 2021 14:00
Renașterea Pădurii	XXIV Mehedinți II Burila	4%-15%, 7%, 8%	10 SC	6; 20	55.0	litter	11.08. 2021 16:20	11.08. 2021 19:20
Renașterea Pădurii	I Gogosu	101	Plantation SC	6; 10	8.0	litter	13.08. 2021 14:00	13.08. 2021 15:00
Renașterea Pădurii	XXIV Mehedinți	6%, 8%	10 SC	6; 10	5.0	litter	14.08. 2021 14:00	14.08. 2021 15:40

In total they were reported **11 forest fires** produced in a 10-day interval from August and September 2021, which affected a total area of 611.85 ha. The fires were surface fires, affecting the litter, herbaceous vegetation, undergrowth, dead wood on the ground and mainly, trees and black locust plantations. The reported cause of the fires was spread from agricultural land for 10 of the fires and stubble burning for 1 fire, respectively.

Sentinel 2 satellite images available on the Copernicus platform (https://scihub.copernicus.eu/) were used to locate the fires and follow their evolution, as well as two images recorded by satellites from the PlanetScope Doves constellation, were used to localize the fires and to follow their evolution. The PlanetScope Dove satellite images are taken in 4 spectral bands (3 bands in the visible spectrum and one band in the near-infrared spectrum), the daily revisit time at nadir is 8:30 GMT (11:30 local time, daylight saving time). Satellite fire location data from MODIS and VIIRS sensors downloaded from the EFFIS platform were also used.

To achieve the research objective, 9 Sentinel 2 satellite images were downloaded (for the days of 01.08.2021, 04.08.2021, 06.08.2021, 11.08.2021, 19.08.2021, 24.08.2021, 03.09.2021 and 08.09. 2021), as well as MODIS and VIIRS vector data, representing active point-type fires as well as the extent of polygon-type burned areas derived from MODIS imagery, obtained from the EFFIS platform for the entire month of August, in *shapefile format* in ETRS89 projection*.*

4. RESULTS

4.1 Mapping the distribution of fuel types for areas covered with vegetation in Romania

For the national mapping of vegetation fuel types, a series of geospatial datasets were combined. The Forest Map of Romania based on forest ecosystem types (scale 1:100,000) (Doniță et al. 2008) was used for the distribution of forest fuels, the Corine Land Cover 2018 database was used for non-forest vegetation fuels, and the MOD44B product derived from MODIS satellite images was used to extract forest vegetation density.

Classification of forest vegetation in relation to the nature of the litter layer

For the mapping of Romanian forests by types of fuels in relation to the type of litter type, Forest Map of Romania based on forest ecosystem types was used, in which forests are classified into 140 types of ecosystems which in turn are grouped into 12 groups. Thus, 5 relevant types of litter were identified: *beech litter, conifers litter, mesophyte oaks litter, xerophytic oaks litter*, *litter of other deciduous species*.

By equating the groups of forests with the 5 types of litter considered relevant for the separation of fuel types, the Map of the distribution of types of surface fuels (litter) in Romania was created (Figure 4.1).

Classification of forest vegetation in relation to its density (percentage of tree cover)

To describe the density of forest vegetation, the percentage values in the MOD44B layer representing the percentages of tree cover were grouped into three value ranges and were interpreted as follows: "isolated trees" (the coverage percentage of their crowns occupies less than 10% of area), "open forests" (percentage of crown cover of existing trees occupies between 10 and 40% of the area) and "dense forests" (percentage of crown cover occupies more than 40% of the area). The percentage ranges adopted are those also used in the ArcFuel classification system (Toukiloglou et al. 2008) and the map of forest vegetation density distribution was thus obtained (Figure 4.2).

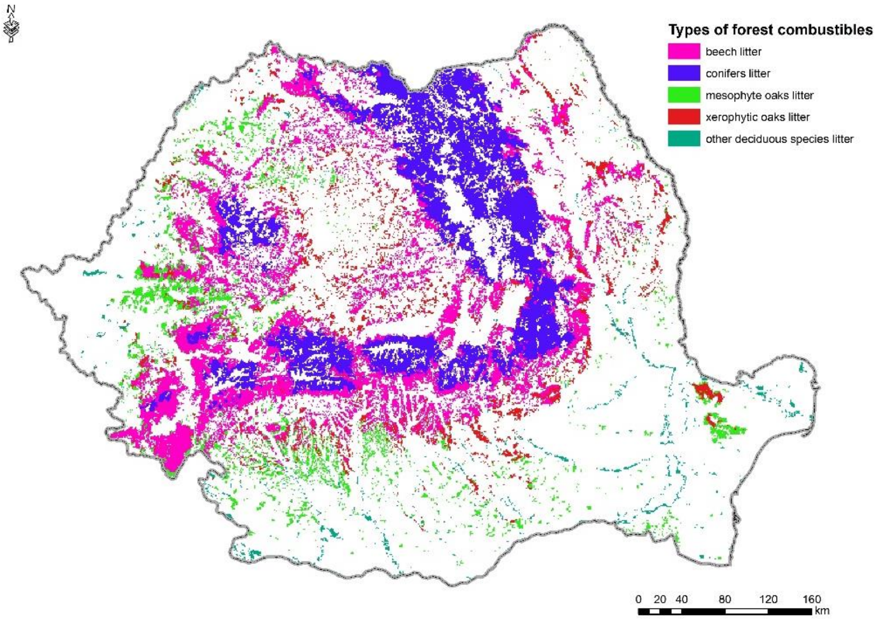


Figure 4.1. Map of types of surface fuels (litter) for forest ecosystems in Romania

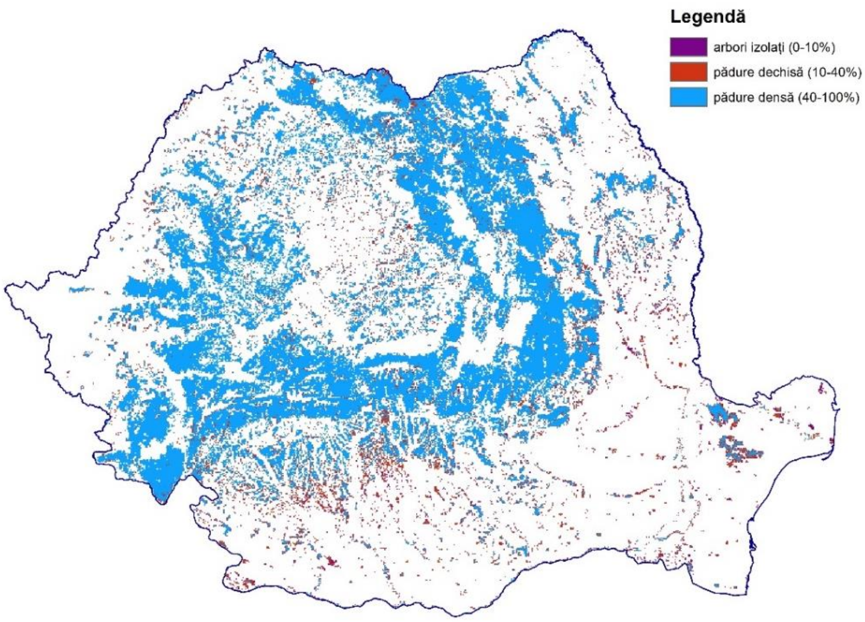


Figure 4.2. Forest vegetation density distribution map for Romania obtained based on MOD44B data (percent tree cover)

Meadows and pastures

The main classes of vegetation fuel from the grassland group were extracted from the Corine Land Cover (CLC) 2018 dataset, and the following land cover types were included in this fuel group:

- *Pastures, meadows and other permanent grasslands under agricultural use* (code CLC-231), which include permanent grasslands characterized by agricultural use or strong human disturbance. Floral composition is dominated by graminacea and influenced by human activity. They are usually used for grazing (pastures) or mechanical harvesting of grass–meadows.

- *Natural grassland* (code CLC-321), which include lands of low productivity, covered with grass, where human influence is absent or of moderate intensity. They are often located in areas with rugged, uneven terrain, with steep slopes, frequently including rocky areas or portions covered by other types of (semi-natural) vegetation.

- *Land principally occupied by agriculture, with significant areas of natural vegetation* (code CLC-243), consisting of areas mainly occupied by agriculture, interspersed with significant natural or semi-natural areas (including forests, shrubs, wetlands, water bodies, mineral outcrops) in a mosaic spatial pattern.

Shrubs

In this group was included *the subalpine shrubby vegetation* (code CLC-322) which, in the case of our country, includes mountain thickets with juniper, dwarf mountain pine, and other short, dwarf or prostrate shrubby plant associations with species of the genus Rhododendron, Vaccinium, etc.

Transition zones between shrubs and forest

In this group, transitional shrubland areas (code CLC-324) were included, which comprise transitional shrub and herbaceous vegetation, occasionally with scattered trees. These can represent areas of degraded forests undergoing recolonization or areas of natural succession, areas represented by the natural development of forest formations composed of deciduous or coniferous trees, with herbaceous vegetation and scattered trees. The transition process can also be represented by natural succession on abandoned agricultural lands, forest regeneration following destructive events (e.g., storms, windthrows, avalanches, landslides, and collapses), forest degradation caused by natural or anthropogenic stress factors (e.g., drought, pollution), reforestation after logging, etc.

Based on these considerations, the groups and types of vegetation fuels used for creating their distribution map were identified for the national territory (Table 4.1).

Table 4.1. Types of vegetation fuels selected for creating the national distribution map of fuel types at national level

Fuel group	Type of fuels	Data source
Forests	1. Beech litter/isolated trees	Forest Map of Romania based on forest ecosystem types MOD44B 2020
	2. Beech litter/open forest	
	3. Beech litter/dense forest	
	4. Resinous litter/insulated trees	
	5. Resinous litter/open forest	
	6. Resinous litter/dense forest	
	7. Xerophytic oaks litter/isolated trees	
	8. Xerophytic oaks litter /open forest	
	9. Xerophytic oaks litter /dense forest	
	10. Mesophytic oaks litter /isolated trees	
	11. Mesophytic oaks litter /open forest	
	12. Mesophyte oaks litter /dense forest	
	13. Deciduous litter/isolated trees	
	14. Deciduous litter/open forests	
	15. Deciduous litter/dense forests	
Meadows and pastures	16. Pastures, meadows and other permanent grasslands under agricultural use	Corine Land Cover 2018
	17. Natural grassland	

Fuel group	Type of fuels	Data source
	18. Predominantly agricultural lands mixed with natural vegetation	
Shrubs	19. Subalpine shrubby vegetation	Corine Land Cover 2018
Transition zones between shrubs and forest	20. Transitional woodland/shrub	Corine Land Cover 2018

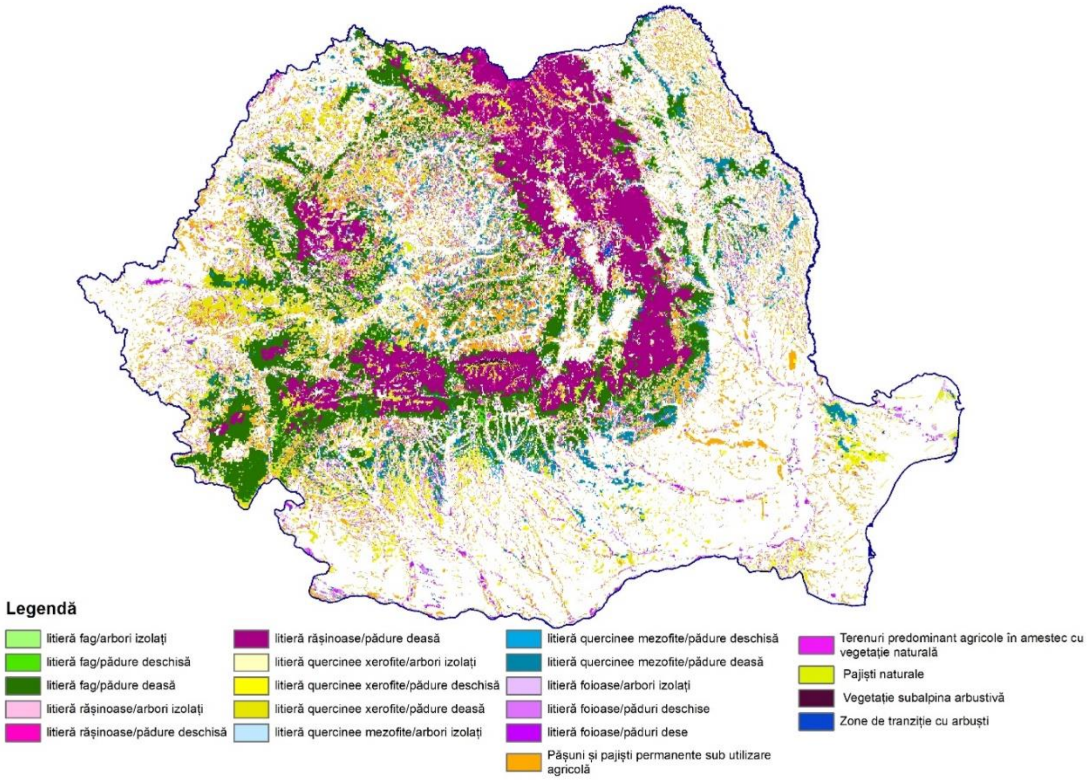


Figure 4.3. Map of the distribution of types of vegetable fuels at the national level

Finally, all these vegetation layers representing fuel classes were aggregated into a single raster layer with 20 classes of fuel types with the resolution of 30 m, and the map of fuel types at the national level was elaborated (Figure 4.3).

To create the distribution map of forest species based on the combustibility index, the combustibility indices (CI) for the main tree and shrub species in Romania's forests (Adam, 2006) were used, taking into account wood density, burning rate, and calorific value. Due to their resin content and lower wood density, conifers have a higher combustibility than deciduous trees.

For equating the combustibility indices at the ecosystem type level, the Forest Map of Romania based on forest ecosystem types was also used this time (Table 4.2).

Table 4.2. Indices of combustibility at the ecosystem type level for forests in Romania

Ecosystem type	IC	Ecosystem type	IC
Mixed Turkey oak-beech forests	7	Narrow-leaved ash forests (downy ash in southern Romania)	2
Mixed sweet chestnut and other broad-leaved forests	5	Riparian downy ash forests	2
Mixed Turkey oak/Hungarian oak-sessile oak forests	7	Mixed ash-pedunculate oak-with and/or black poplar forests	2
Mixed Turkey oak-sessile oak forests with hornbeam and manna ash	7	Hungarian oak forests with *Carex praecox*	7
Mixed Turkey oak-silver lime-hornbeam forests	7	Hungarian oak forests with eastern hornbeam and manna ash	7
Mixed Hungarian oak-pedunculate oak forests	7	Hungarian oak forests with *Glechoma hirsuta*	7
Mixed Turkey oak-Hungarian oak-pedunculate oak-beech-silver lime forests	7	Acidophilous sessile oak forests	7
Mixed Turkey oak-Hungarian oak and beech forests	7	Sessile oak forests with *Carex pilosa*	7
Mixed Turkey oak-Hungarian oak-sessile oak-pedunculate oak-hornbeam forests	7	Sessile oak forests with hornbeam	7
Mixed Turkey oak-sessile oak-beech forests	7	Sessile oak forests with eastern hornbeam and manna ash	7
Mixed Turkey oak-sessile oak-hornbeam forests	7	Sessile oak forests with Turkey oak and eastern hornbeam	7
Mixed Turkey oak-sessile oak-pedunculate oak forests	7	Sessile oak forests with Cornel dogwood	7
Acidophilous beech-sessile oak forests	2	Sessile oak forests with manna ash	7
Mixed beech-sessile oak-silver lime forests	2	Sessile oak forests with Poa angustifolia-*Carex praecox*	7
Mixed beech-silver fir-hornbeam forests	2	Sessile oak forests with silver lime/European ash	7
Mixed beech-sweet chestnut forests	2	Neutrophile sessile oak forests	7
Neutrophile mixed beech-sessile oak hornbeam forests	2	Mixed sessile oak-pedunculate oak-hornbeam forests	7
Mixed beech-sessile oak-small-leaved lime-hornbeam forests	2	Mixed sessile oak-pedunculate oak forests with *Poa angustifolia-Carex praecox*	7
Mixed beech-sessile oak-silver fir forests	2	Low altitude European larch forests	8
Mixed beech-sessile oak-pedunculate oak forests	2	European larch and/or European larch and Norway spruce forests on limestone	8
Mixed beech-sessile oak-small leaved lime forests	2	Mixed Norway spruce-silver fir forests on limestone	6
Mixed beech-manna ash/eastern hornbeam forests	2	Mixed Norway spruce-beech forests on limestone	6
Mixed Hungarian oak-pedunculate oak forests	7	Acidophilous mixed Norway spruce-silver fir-beech forests	6
Mixed sessile oak-small-leaved lime-hornbeam forests	7	Mixed Norway spruce-beech-silver fir forests on limestone	6
Mixed sessile oak-silver lime-eastern hornbeam forests	7	Low acidophilous mixed Norway spruce-silver fir-beech forests	6
Mixed sessile oak-small-leaved lime-hornbeam forests	7	Acidophilous Norway spruce and silver fir forests	6
Mixed sessile oak-Turkey oak-silver lime-eastern hornbeam forests	7	Low acidophilous Norway spruce and silver fir forests	6

Ecosystem type	IC	Ecosystem type	IC
Mixed sessile oak-beech-eastern hornbeam forests	7	Acidophilous Norway spruce-beech forests	6
Mixed beech-Norway spruce-silver fir-sessile oak/hornbeam/beech forests	6	Low acidophilous Norway spruce-beech forests	6
Mixed Scots pine and broad-leaved forests	8	Norway spruce forests with *Hylocomium ssp*	6
Mixed grey oak-silver lime-hornbeam-sessile forests	7	Norway spruce forests with *Luzula sylvatica*	6
Mixed grey oak-downy oak forests	7	Norway spruce forests with *Oxalis acetosella*	6
Mixed grey oak-silver lime-eastern hornbeam forests	7	Norway spruce forests with *Vaccinium myrtillus*	6
Mixed grey oak-Turkey oak-downy oak-Hungarian oak forests	7	Norway spruce forests on limestone	6
Mixed grey oak/downy oak/sessile oak-Hungarian oak forests	7	Norway spruce forests with *Sphagnum ssp.*	6
Mixed pedunculate oak-silver lime-hornbeam forests	7	Banat black pine forests	8
Mixed grey oak-downy oak/ sessile oak-Hungarian oak forests	7	Scots pine forests with *Luzula luzuloides-Rubus hirtus*	8
Mixed pedunculate oak-sessile oak forests with Tartarian maple	7	Scots pine forests with Vaccinium myrtillus	8
Grey alder forests	2	Acidophilous Scots pine forests on siliceous rocky slopes	8
Black alder forests	2	Hybrid poplar	2
Swampy black alder woods	2	Mountain pine bog woods with *Sphagnum sp.*	8
Acidophilous silver fir forests	6	Black locust	2
Silver fir forests with *Pleurozium ssp.*	6	Black locust and Hybrid poplar	2
Silver fir forests on limestone	6	Black locust and Saint lucie cherry	2
Low acidophilous silver fir forests	6	Black locust, Saint lucie cherry, Small leaved elm	2
Tamarisk shrubs	5	Black locust, Grey oak, European ash	2
Arolla pine and/or European larch and Norway spruce woods with Vaccinium myrtillus	8	Black locust, Grey oak, Scots pine and/or black pine, Small leaved elm and Saint lucie cherry	2
Turkey oak forests with *Festuca heterophylla*	7	Grey oak	7
Turkey oak forests with *Glechoma hirsuta*	7	Grey oak	7
Steppe Turkey oak forest	7	Grey oak and Ash species	7
Mixed Turkey oak-Hungarian oak forests with *Carex praecox*	7	Grey oak forests with Tartarian maple	7
Mixed Turkey oak-Hungarian oak forests with eastern hornbeam and manna ash	7	Grey oak forests with eastern hornbeam and manna ash	7
Mixed Turkey oak-Hungarian oak forests with *Glechoma hirsuta*	7	Danube Delta mixed grey oak-ash-poplar species forests	7
Acidophilous beech forests with Scots pine	2	Pedunculate oak forests with Tartarian maple	7
Acidophilous hilly beech forests	2	Pedunculate oak forests with *Asarum europeum*	7
Mixed hilly beech forests	2	Pedunculate oak forests with hornbeam	7
Hilly beech forests with Hornbeam	2	Pedunculate oak forests with Poa angustifolia-*Carex praecox*	7
Neutrophile hilly beech forests	2	Pedunculate oak forests with *Rubus caesius*	7

Ecosystem type	IC	Ecosystem type	IC
Beech forests with Turkish hazel	2	Pedunculate oak forests with silver lime	7
Pedunculate/Mixed beech-pedunculate oak-silver lime forests	2	Pedunculate oak forests sandy soils	7
Beech forests with small-leaved lime	2	Hygrophile pedunculate oak forests	7
Beech forests with *Vaccinium myrtillus*	2	Mixed pedunculate oak and grey oak forests with Tartarian maple	7
Timberline beech forests	2	Downy oak forests with *Carex humilis*	7
Acidophilous mountain beech forests	2	Downy oak forests with eastern hornbeam and manna ash	7
Balkan neutrophile mountain beech forests	2	Downy oak forests with common smoke-tree	7
Dacian neutrophile mountain beech forests	2	Grey oak forests on sandy soils	7
Beech forests on limestone	2	Saint lucie cherry, Black locust and Small leaved elm	2
Acidophilous mixed Norway spruce-silver fir forests	2	Mixed poplars and willows species riparian forests	2
Mixed beech-silver fir forests on limestone	2	Popular species riparian forests *with Rubus caesius*	2
Low acidophilous mixed Norway spruce-silver fir forests	2	Willow species riparian forests	2

Finally, the digital map of the distribution of the combustibility index was created, which was later converted from vector format to raster format with a resolution of 30X30 m (Figure 4.4). The raster format is the format compatible with software applications used to model fire behavior.

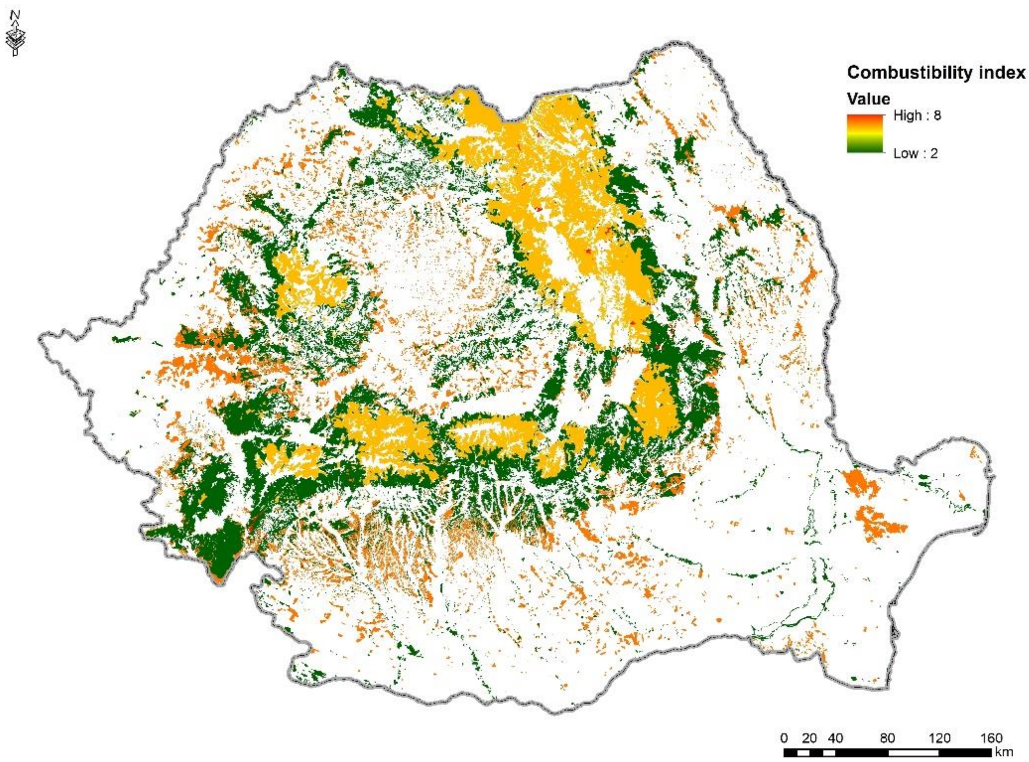


Figure 4.4. Map of combustibility indices for forest ecosystems in Romania

4.2 Hazard zoning and identification of driving factors for the occurrence of forest fires

4.2.1 Building the geo-spatial database and GIS map of fire events produced during the years 2006-2023

As a result of geo-locating fires based on geo-referenced forest management maps, a database in the Stereographic 1970 coordinate system and GIS (Geographic Information System) format was created concerning historical forest fires. Based on the location of the fires and their coordinates, a map of forest fires recorded during the period 2006-2023 was produced. (Figure 4.5).

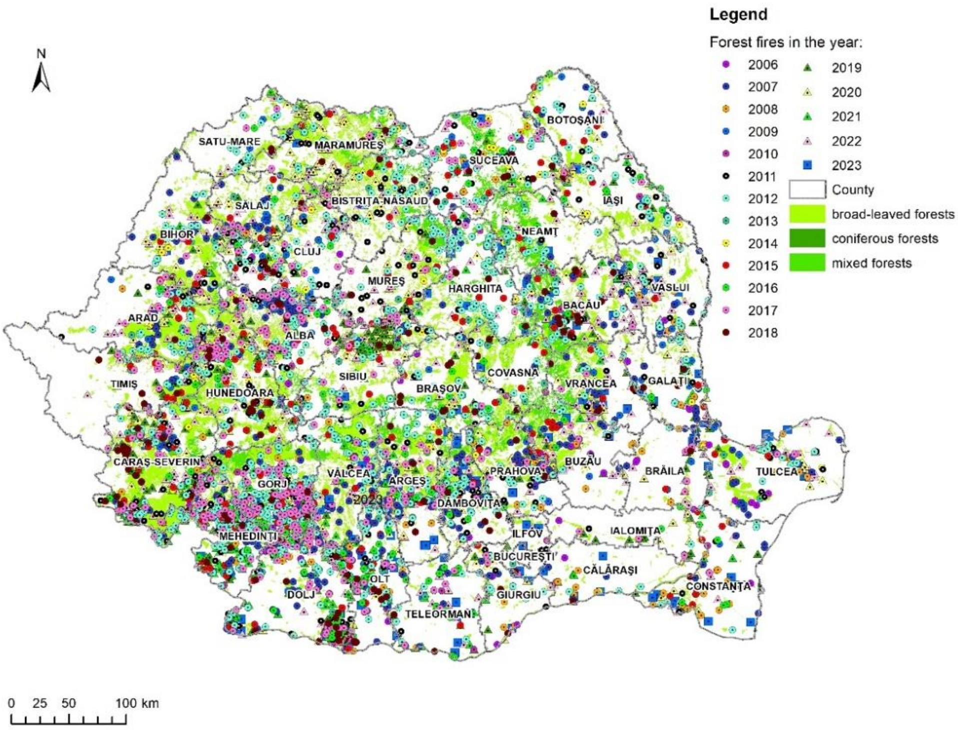


Figure 4. 5. Map of forest fires recorded during the years 2006-2023

The graph of the annual evolution of forest fires, in terms of number and affected area in the period 2006-2023 is shown in figure 4.6 and the monthly distribution of forest fires in Table 4.3.

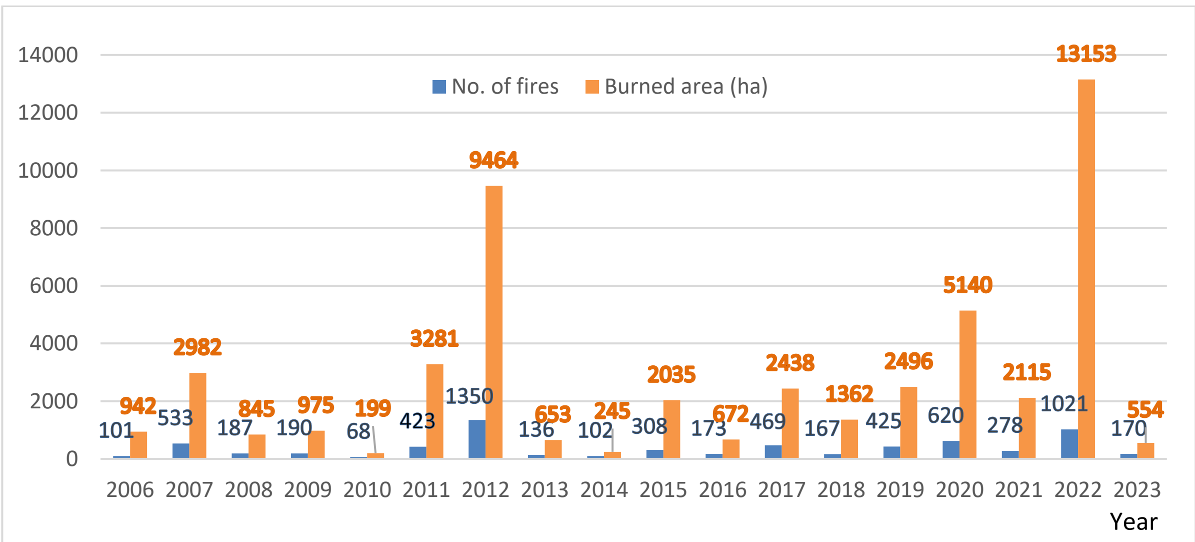


Figure 4.6. Annual distribution of the number of forest fires (orange) and affected areas (blue) during the years 2006-2023

Table 4.3. Monthly distribution of forest fires in the period 2006-2018

Month	Frequency		Surface	
	No.	(%)	(Ha)	(%)
January	90	2.2	255.0	1.0
February	60	1.5	191.2	0.8
March	1329	32.8	8913.0	35.8
April	714	17.6	3777.5	15.2
May	102	2.5	352.4	1.4
June	58	1.4	179.3	0.7
July	453	11.2	2212.8	8,9
August	537	13.2	2327.5	9.4
September	331	8.2	2257.3	9.1
October	110	2.7	738.7	3.0
November	198	4.9	2890.9	11.6
December	71	1.8	786.7	3.2
Total	**4053**	**100.0**	**24882.6**	**100.0**

The vector data set containing the fire points was converted into a continuous surface of the ignition density, using in this sense the *kernel modeling* of the probability density (Lorenț et al. 2018). The working method with a *fixed kernel* was thus adopted*,* with the aim of keeping the band width (i.e. the smoothing parameter) constant over the entire study area, and to define the size of the band width it was considered to be twice the average distance between the ignition points of fires. Figure 4.7 shows the obtained *kernel probability density.*

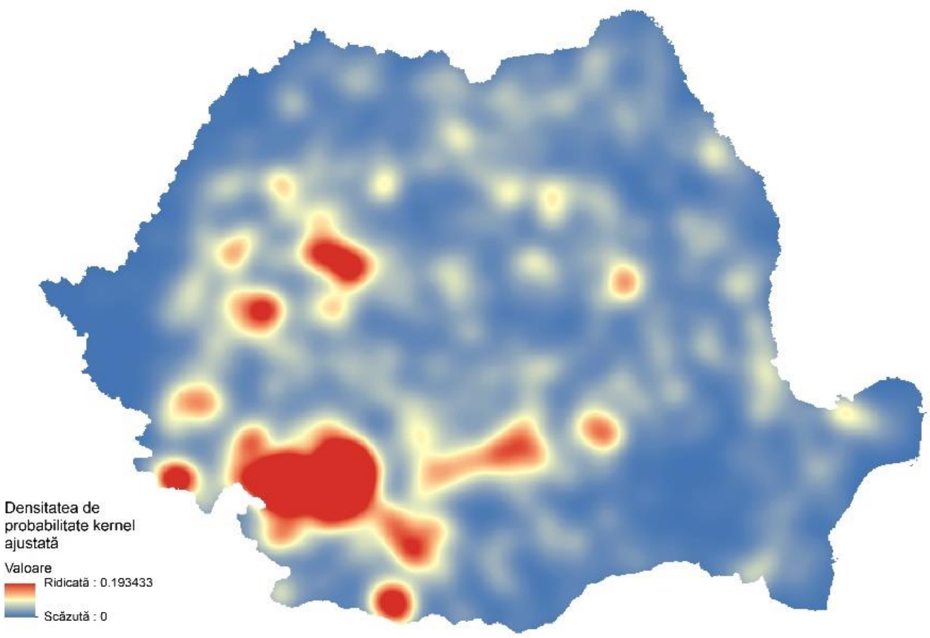


Figure 4.7. Probability density intensity obtained by the kernel model based on nationally located forest fire points

Finally, the 4220 fire points were intersected with the raster representing the fire density, thus being incorporated as a distinct attribute associated with the points, the *kernel density,* constituting the dependent variable used in the Random Forest predictive model.

4.2.2 Obtaining independent variables for forest fire hazard assessment and identification of contributing factors

The established model that describes the necessary elements for initiating a fire is the so-called fire triangle, consisting of an oxygen source, a heat source, and combustible material. These factors work together to trigger a fire. Therefore, to identify the determining factors of fires, these elements are firstly represented as geospatial data sets.

During the research, a number of 42 independent variables were generated in the form of rasters with a spatial resolution of 1 km ^{2} representing topographical, anthropic, bioclimatic elements and vegetation characteristics. These were chosen taking into account the research in the field, carried out both internationally and nationally, in which the factors that influence forest fires initiation and propagation were debated (Burlui 2013, Petrila et al. 2016).

In the research, **19 bioclimatic variables** derived from monthly temperature and precipitation values were investigated, capturing annual trends, seasonality, and extreme values for specific periods. These climate variables were downloaded from the WORLDCLIM geoportal, provided as 19 archived files in GeoTiff (.tif) format, each representing a distinct variable.

Additionally, raster data regarding **population distribution and density** across Romania for the year 2015 were obtained from the GHS-POP geoportal of the European Commission's Joint Research Centre (https://ghsl.jrc.ec.europa.eu/ghs_pop2019.php). The geospatial dataset was acquired at spatial resolutions of 250 m and 1 km, respectively.

For the generation **of topographical variables,** the digital model of the terrain was used using the satellite radar interferometry technique obtained by NASA through the *Shuttle Radar Topography mission Mission* (SRTM). An improved version of this product, version 3, based on radar C-band observations, has a spatial resolution of approximately 30 m and uses topographic data from other geospatial sources to supplement data missing from earlier versions of SRTM.

By applying specific tools for processing the SRTM digital elevation model, topographic variables (terrain exposure and slope) were obtained, as well as other topographic indices (topographic position index - TPI, topographic humidity index - TWI, topographic index for quantification of solar radiation - TRASP).

Terrain exposure is a circular variable that cannot be used in linear statistics. Thus, it was transformed into the topographic index for quantifying solar radiation, which takes values between 0 and 1, with high values of the index representing areas with sunny exposures, respectively low values of the index representing areas with shaded exposures. The index was calculated using the formula (4.1) and the index spatial distribution, on the territory of Romania, is presented in figure 4.8.

$$TRASP = \frac{I - \cos\left(\left(\frac{\Pi}{180}\right) * (\alpha - 30)\right)}{2}, \qquad (4.1)$$

Where α is the terrain exposure (hexadecimal degrees)

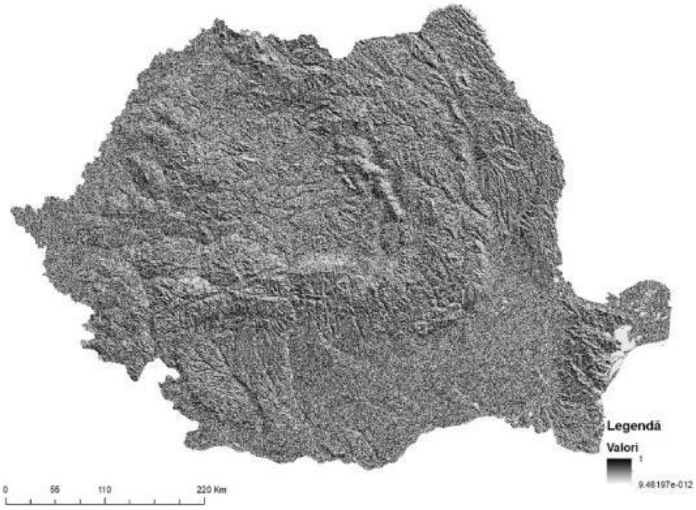


Figure 4.8. The distribution of the topographic index for the quantification of solar radiation – TRASP, for the territory of Romania.

At the same time, by applying specific tools for processing the SRTM model, the topographic position index - TPI, respectively the topographic humidity index - TWI were obtained.

The NDVI and EVI vegetation indices were downloaded as 1km [2] rasters from the EarthData platform (https://search.earthdata.nasa.gov), and vector data on the national road network (national roads, county and respectively other types of roads), the national railway network, the limits of localities, as well as vector data obtained based on the processing of the Corine Land Cover (CLC) 2018 maps (Figure 4.9).

This dataset is one of the most well-known and widely used products provided by the *Copernicus Land Monitoring Service.*

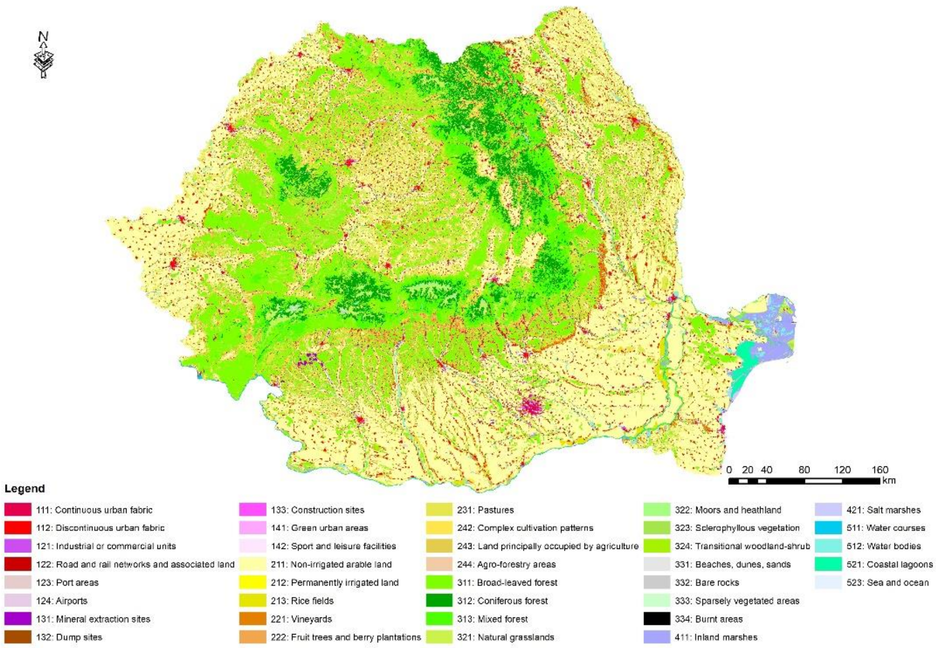


Figure 4.9. Distribution of land cover/use for Romania (Corine Land Cover 2018)

Spatial analysis using the Euclidean distance calculation in the ArcMap software was employed to create digital maps depicting these distances for vector layers containing the national road and railway networks, as well as for localities. The geospatial analyses were presented in raster file format with a resolution of 1 km.

Additionally, Euclidean distances were calculated from the boundaries of the following land cover/use classes based on the CLC 2018 classification*: secondary grasslands, predominantly agricultural lands mixed with natural vegetation, transition zones with shrubs, and forests*. The forest class analyzed includes boundaries highlighted in both the CLC2018 classification and the Map of Forests based on Ecosystem Types from the INCDS (Doniță et al., 2008).

For each land cover/use class—*secondary grasslands, predominantly agricultural lands mixed with natural vegetation, transition zones with shrubs, and forests*—their respective percentage coverage per unit area (1 km^2) was calculated. The results were presented in both raster file format and tabular form for all 42 independent variables generated at a spatial resolution of 1 km^2 (Table 4.4).

Table 4.4. Summary or centralization of the predictive variables used in the statistical analyses

No. crt	The name of the variable	The unit of measure/meaning of the variable	Source of vector layers/initial data
1	Euclidean distance for the vector layer national roads, county roads, highways	km	ESRI Romania
2	Euclidean distance for vector layer *other roads*	km	ESRI Romania
3	Euclidean distance for the *railway vector layer*	km	ESRI Romania
4	Euclidean distance for the *localities vector layer*	km	ESRI Romania
5	Euclidean distance for class CLC2018- *secondary grasslands (CLC231)*	km	Corine Land Cover 2018
6	Euclidean distance for class CLC2018- *predominantly agricultural land mixed with natural vegetation (CLC 243)*	km	Corine Land Cover 2018
7	Euclidean distance for class CLC2018- *transition zones with shrubs (CLC 324)*	km	Corine Land Cover 2018
8	Euclidean distance for *forests (CLC 31)*	km	Corine Land Cover 2018 and Forest Map by Ecosystem Units
9	Percentages per unit area of class CLC2018- *predominantly agricultural land mixed with natural vegetation (CLC 243)*	Percent * km^{-2}	Corine Land Cover 2018
10	Percentages per unit area of class CLC2018- *transition areas with shrubs (CLC 324)*	Percent * km^{-2}	Corine Land Cover 2018
11	Percentages per unit area of class CLC2018- *secondary pastures (CLC231)*	Percent * km^{-2}	Corine Land Cover 2018
12	Percentages per unit area of class CLC2018- *forests (CLC 31)*	Percent * km^{-2}	Corine Land Cover 2018 and Map of forests by ecosystem units
13	Percentage of vegetation cover	Percentage * 0.5km^{-2}	MODIS(MOD44B)
14	Normalized difference vegetation index	dimensionless	MODIS(MOD13A3)

No. crt	The name of the variable	The unit of measure/meaning of the variable	Source of vector layers/initial data
15	Fuel type	The litter layer of beech (FT1) / softwood (FT2) / xerophytic oak (FT3) / mesophytic oak (FT4) / other deciduous forests (FT5)	Corine Land Cover 2018 and Map of forests by ecosystem units
16	Herds of goats	number*locality $^{-1}$	National Veterinary Sanitary and Food Safety Authority
17	Average population density	Number* km $^{-2}$	https://ghsl.jrc.ec.europa.eu/ghs_pop2019.php
18	Slope	degrees	SRTM digital terrain model
19	Altitude	m	SRTM digital terrain model
20	Topographic index for quantifying solar radiation (TRASP)	$\frac{I-\cos(\left(\frac{\Pi}{180}\right)*(\alpha-30))}{2}$ α- the exhibition in degrees	SRTM digital terrain model
21	Topographic Position Index (TPI)	m	SRTM digital terrain model
23	Topographic Wetness Index (TWI)	dimensionless	SRTM digital terrain model
24	Bioclimatic data	19 bioclimatic variables: average annual temperature; Average diurnal interval; Isothermality; seasonal temperature; maximum temperature of the warmest month; minimum temperature in the coldest month; annual temperature range; average temperature of the rainiest quarter; average temperature of the driest quarter; average temperature of the warmest quarter; average temperature of the coldest quarter; annual precipitation; precipitation of the wettest month; precipitation of the driest month; seasonal rainfall; precipitation of the rainiest quarter; precipitation of the driest quarter; the precipitation of the warmest quarter and the precipitation of the coldest quarter.	WorldClim database (www.worldclimat.org)

4.2.3 Identification of factors favoring forest fires and hazard zoning by running explanatory models

4.2.3.1 Generating the hazard map and identifying the contributing factors to forest fires using the Random Forest model

The number of trees required to be generated by the model was set to 500, as errors tend to stabilize before this number of classification trees is reached (Lawrence et al., 2006). The *mtry* parameter, i.e.

the number of variables considered at each node division, was chosen as the square root of the number of input variables in the algorithm (Gislason et al., 2006).

The model was run using the *R programming language*. The dependent variable considered was the Kernel density of fires derived from processing geospatial data records from the period 2006-2018. For hazard calculation, independent variables from Table 4.5 were taken into account, and their influence on the hazard was tested, focusing on those identified by the model as having a significant impact (Figure 4.10). Thus, certain variables included bioclimatic factors, terrain characteristics, land configuration, aspect, distances of forests to roads and settlements, vegetation data, specific layers from Corine Land Cover, and statistical data on animal populations and human demographics.

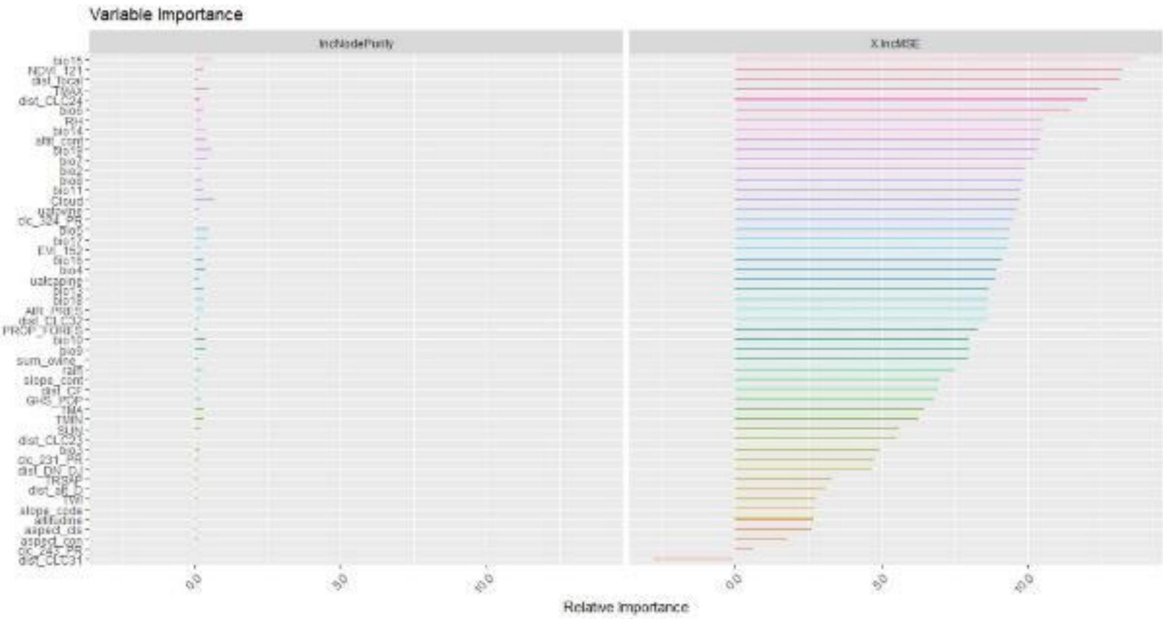


Figure 4. 10. Ranking of predictor variables by importance in the Random Forest model

After several iterations, a number of 9 variables were finally selected, as having a significant impact, while the resulting map is then adjusted for the area covered by forests. The variables influencing the fire hazard are presented as follows:

1. Seasonal precipitation (coefficient of variation)
2. NDVI - Normalized Differential Vegetation Index
3. Distance from localities
4. Maximum temperature of the warmest month
5. CLC 243 - proportion of agricultural land (from Corine Land Cover)
6. Altitude
7. Precipitation in the driest month
8. CLC 324 – Forest-shrubland transition (from Corine Land Cover)
9. Sheep population

The predictive capacity of the model, respectively the variance explained by it, was estimated at 63.46% (Figure 4.11), thus resulting in the map describing the hazard level for the area with forests (Figure 4.12).

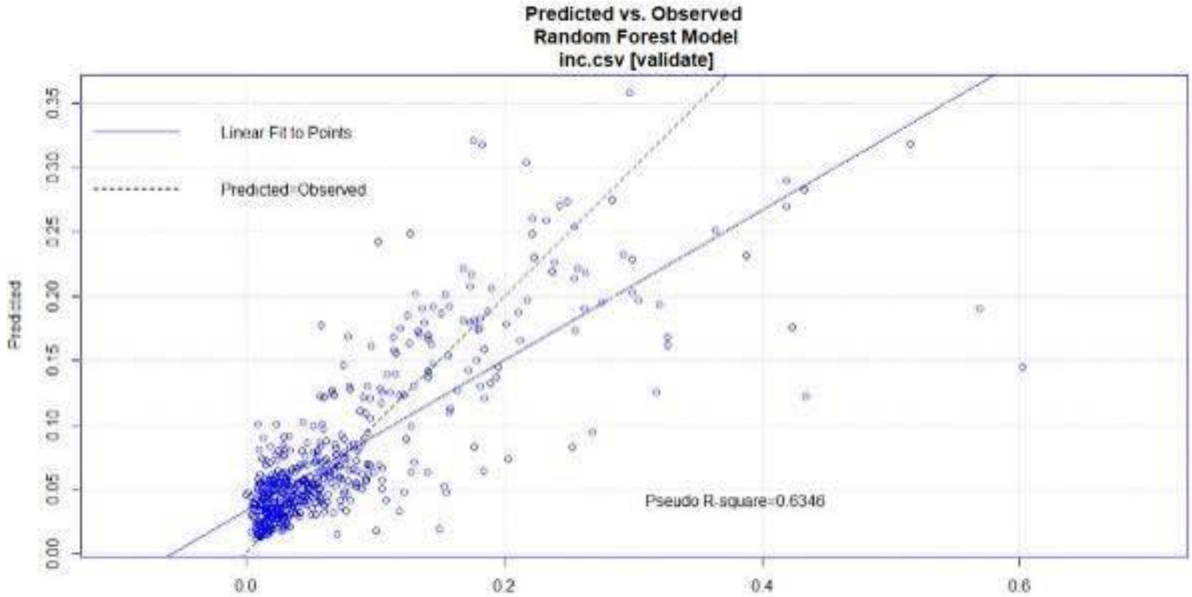


Figure 4.11. Diagram of predicted variables vs. observed variables in the Random Forest model

Validation of the model

To verify the accuracy of the map, fires detected by the VIIRS sensor aboard NASA's Suomi National Polar-orbiting Partnership meteorological satellites were utilized. The VIIRS sensor detects active fires in near real-time (similar to the MODIS sensor) and provides a spatial resolution of 375 meters. The vegetation fire database was downloaded in shapefile format for the period 2006-2018 from the NASA FIRMS platform. This dataset was intersected with the fire hazard zoning derived from Random Forest analysis, resulting in the intersection proportion of VIIRS fire detections with hazard zones (Figure 4.13).

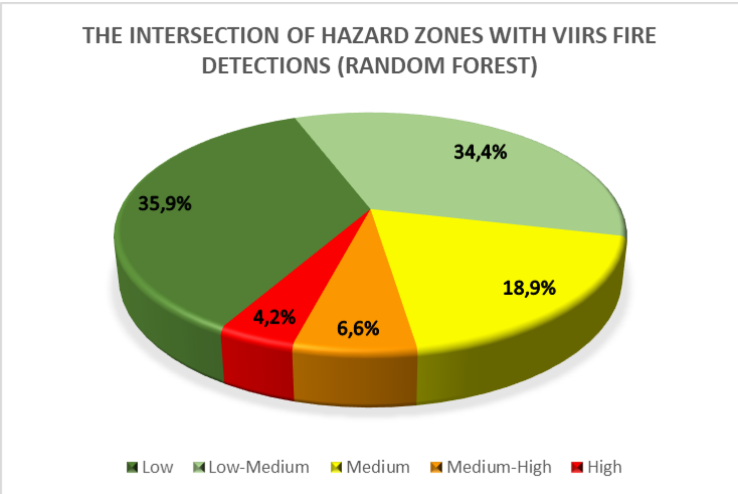


Figure 4.12. The share of fires detected by the VIIRS sensor on the hazard classes defined by the Random Forest model

It is noted that the weight of VIIRS fires by hazard classes is proportional to the area occupied by each class, which indicates a good predictive performance of the *Random Forest model.*

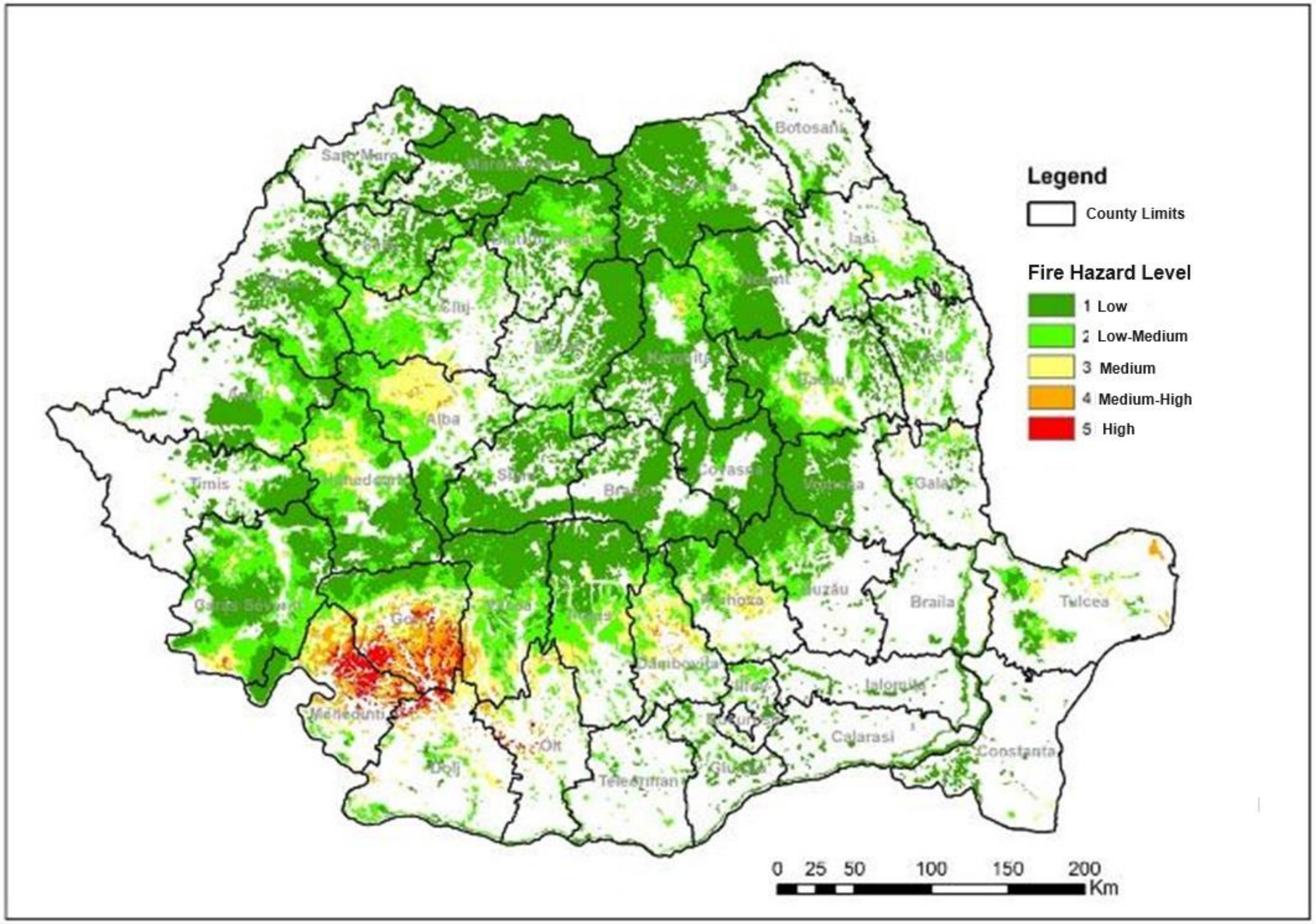


Figura 4.13. The forest fire hazard map obtained based on the Random Forest model

4.2.3.2 Generating the hazard map and identifying factors favoring forest fires using logistic regression

In the case of logistic regression, the dependent variable was considered on the one hand, the database with the 4220 fire points from the period 2006-2018 (dichotomous value 1), and on the other hand an equal number of non-ignition points (value dichotomous 0). These non-ignition points were generated as follows: a buffer zone of 3 km was created *around* the real fire points and with its help the area covered with forest at the national level (from *Corine Land Cover*) was cut and then a number of 4220 random points were generated in the forest area thus left. These points rather represent pseudo- nonignition points , since these surfaces are also susceptible to fires, but we assume that the probability of starting a fire is significantly lower in an area that was protected from this phenomenon during the analyzed period (2006- 2018). The 8440 points were intersected with all the rasters representing the independent variables and the data were entered into the SPSS statistical program to run the model. The collinearity of the variables was checked and the variables with collinearity problems were eliminated using the *Spearman test,* respectively those with a correlation higher than 0.8, after which the remaining variables were entered into the logistic model. 14 variables were thus eliminated from those 42 predictive variables.

Forward -Wald method was applied to build the multiple logistic regression model which starts with the model without any variable (only the constant) and then, by applying an iterative process, new variables are selected and introduced into the model based on the statistical significance score, eliminating variables by means of the *Wald probability test,* until reaching an optimal level where no omitted variable could contribute significantly to the model's performance. The overall significance was evaluated considering the Hosmer and Lemeshow test, for values of p>0.05 the model can be considered. Thus, a number of 32 models were generated from which the model with the highest determination coefficient R ^{2} (0.372 in our case) and p>0.05 (Hosmer's *test) was chosen* and *Lemeshow)*. Table 4.5 shows the variables considered in the logistic regression model.

Table 4.5. Variables considered in the logistic regression model

Variable	B.	it	Wald	df	Sig .	Ex (B)	95% CIfor EXP(B)	
							Lower	Upper
altitude	.001	.000	11,018	1	001.	1,001	1,000	1,001
precipitation of the driest month	-.012	.001	108,157	1	.000	.988	.985	.990
precipitation of the driest quarter	.002	.001	9,275	1	.002	1,002	1,001	1,003
precipitation of the coldest quarter	.002	.001	11,359	1	.001	1,002	1,001	1,003
average temperature of the warmest quarter	1,092	.131	69,933	1	.000	2,981	2,308	3,851
proportion of secondary pastures	.007	.002	13,295	1	.000	1,007	1,003	1,011

Variable	B.	it	Wald	df	Sig .	Ex (B)	95% CIfor EXP(B)	
							Lower	Upper
proportion of agricultural land	.007	.003	3,923	1	.048	1,007	1,000	1,014
proportion of shrub areas	.032	.004	75,320	1	.000	1,032	1,025	1,040
railway distance	.000	.000	14,347	1	.000	1,000	1,000	1,000
the distance from the forests	.000	.000	13,294	1	.000	1,000	1,000	1,000
distance DN/DJ	.000	.000	12,659	1	.000	1,000	1,000	1,000
the distance between towns	.000	.000	69,754	1	.000	1,000	1,000	1,000
the population density	.002	.000	31,840	1	.000	1,002	1,001	1,003
NDVI	-.001	.000	244,285	1	.000	.999	.999	.999
slope	.015	.003	18,956	1	.000	1,015	1,008	1,022
flocks of sheep and goats	.000	.000	36,984	1	.000	1,000	1,000	1,000
TRSAP	.279	.075	13,949	1	.000	1,322	1,142	1,530
constant	2,911	.540	29,063	1	.000	18,384		

The fire hazard distribution map was generated by taking the regression coefficients resulting from **SPSS modeling** and generating the raster in the **ArcGIS program** using the *Raster Calculator function* (Figure 4.14). The classes were generated by the *Natural Breaks method.*

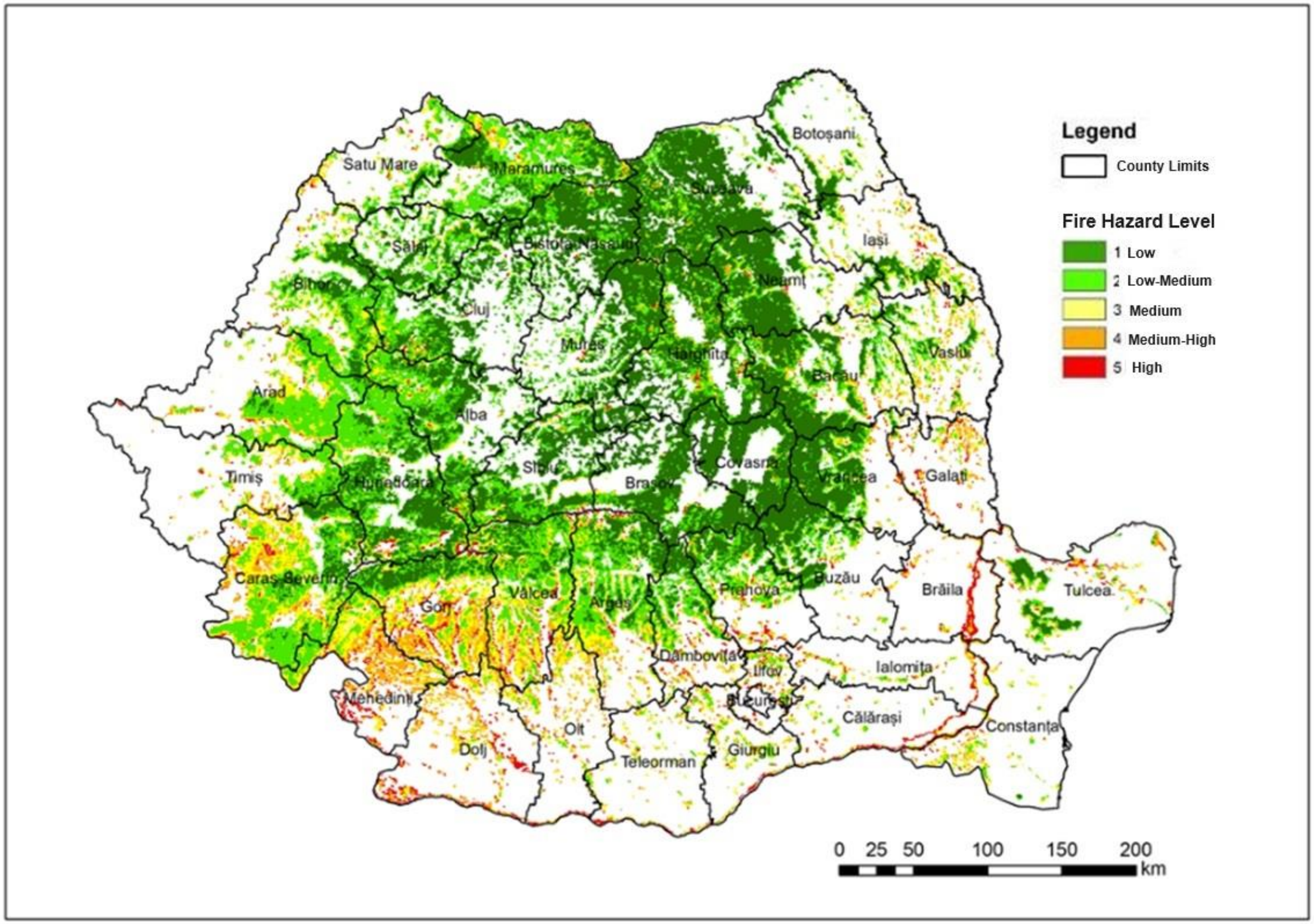


Figure 4.14. Forest fire hazard map according to the logistic regression method

Validation of the model

Validation of the model was also achieved by intersecting hazard zones with satellite fires detected by the VIIRS sensor (Figure 4.15).

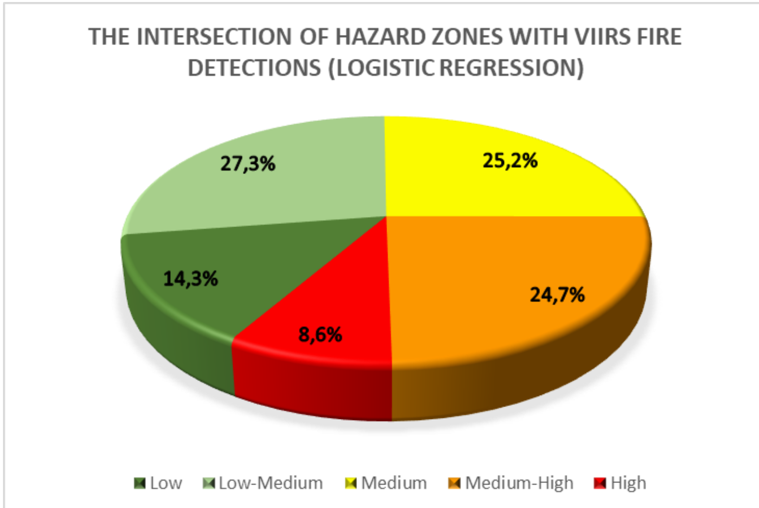


Figure 4.15. The share of fires detected by the VIIRS sensor on the hazard classes defined by the logistic regression method

Analysis of hazard zoning and favoring factors obtained through the two explanatory models

In the case of the ***Random Forest model,*** a set of influencing factors with an impact on forest fire hazard are represented by forest vegetation (presence/absence) alongside the state of vegetation (NDVI), so by those related to the presence of fuels. The small areas covered by forests in lowland areas and their relative isolation/fragmentation imply a higher level of hazard, compared to mountain areas where forests occupy extensive and compact areas.

It is also evident that climatic data, particularly maximum temperature and seasonal precipitation during the driest month, have a more significant impact, directly influencing the conditions for ignition and spread of vegetation fires, specifically fuel moisture. This means that, from a statistical point of view, the forests located in the mountain area, with a more humid climate, present a lower level of fire hazard. Altitude has a combined influence, determined by temperatures/precipitation but also by human presence.

It is obvious that the presence and action of man are decisive, having the greatest weight as a triggering factor, through the distance from the localities, the proportion of agricultural land and the transition zone between forests and scrubs and the presence of sheep herds. This aspect is particularly visible in the subcarpathian area, where forests, agricultural lands and settlements are most interspersed. Practically, this constitutes the area with the highest risk of fires under normal conditions, all the criteria necessary for the initiation and propagation of fires being fulfilled, respectively drought, extensive areas of mosaic forests with localities and agricultural lands. At the same time, the hypothesis that the main causes of forest fires are predominantly anthropogenic is supported by numerous studies.

The hazard map obtained is also confirmed by previous studies carried out in Romania, based on the application of the *kernel* estimation method of the probability density, where research has highlighted the existence of areas with a high level of hazard for forest fires in the counties of Gorj, Mehedinți, Alba, Caraș-Severin, Dolj and Vâlcea (Lorenț et al., 2018).

Regarding the spatial distribution of the hazard zones obtained through **logistic regression,** we can state that the adopted model captured the real situation with a high degree of confidence, since the medium-high and high hazard zones are in the areas of forest fragmentation, hilly or plain, where it is strongly fragmented by agricultural land or pastures, where practices of burning plant residues are frequent, the population density is high and the climate is drier. In the mountain forest massifs, the danger of fire is particularly low, an aspect confirmed by the fact that fires occur here less often, more during the summer, when they occur as a result of the negligence of tourists or forest workers. The forest in the Danube corridor was placed in the maximum danger class, which is rather debatable, given the fact that this area does not have frequent forest fires, the explanation being that the model gave the highest importance to climatic factors indicating dryness and proximity localities.

Regarding the factors that influence the occurrence of forest fires, the model selected topographical variables (altitude, slope, TRASP - topographical index for quantifying solar radiation), climatic variables (precipitation of the driest month, average temperature of the warmest quarter, precipitation of the coldest quarter, precipitation of the driest quarter), anthropogenic variables (number of sheep, goats, population density, distance to national and county roads, railway distance, proportion of agricultural land, proportion of secondary pastures) or calculated according to the type of vegetation cover forest or scrubland (NDVI, distance from forests, proportion of shrub areas).

Terrain aspect (quantified by the TRASP index) influences fire hazard in several ways: a sunny exposure causes greater dryness, lower humidity, higher microclimate temperatures, longer daylight hours, etc.; a shaded exposure causes higher humidity, lower microclimate temperatures, shorter daylight hours, etc.

The distance to forest, the anthropogenic areas and the road networks, directly influences the risk of fire, through the causes that determine its outbreak, which are in their vast majority started by the human factor (propagation of fire from agricultural lands as a result of burning to clear pastures and stubble, negligence, accidents).

Low precipitation during the winter period causes the dryness of fuels to be high in the spring, which leads to an increase in fire susceptibility. Combined with a period of drought and high temperatures, the vegetation ignites much more easily and the fire spreads quickly.

The slope of the land influences the air currents, implicitly the way the fire evolves. On the one hand, on high slopes, the fire spreads much faster and at the same time complicates the intervention process (impossibility of access for special vehicles, sending water uphill requires a surplus of means (motor pumps, intermediate basins) and great effort for their handling.

The presence of sheep and goats herds as a factor in influencing fires can be interpreted bivalently: on the one hand, grazing reduces the risk of fire by the fact that the animals reduce the amount of fuel (the grass and shrub layer) and on the other hand it indicates an anthropic presence, which through negligence it can trigger the occurrence of fires.

4.3 Determination of burned forest areas and the degree of severity of the fires

The analysis of the different indices found in the specialized literature (Llorens, R. et al. 2021, Mallinis G. et al. 2018) showed that the dNBR index was the most suitable for estimating the severity of fires, providing more accurate results, at least for our study area.

After performing the index calculation, the resulting images were taken into the ArcGIS application, which presents more efficient facilities for visualization, defining colors, overlaying raster and vector layers, etc.

Index images are monochrome, having a single layer, and the conventional representation for monochrome digital images is by *maximum value* = white, *minimum value* = black, and a number of shades of gray in between (proportional to the difference of the numerical values). Since the human eye has a harder time distinguishing shades of gray from one another, conventional coloring is done using a color palette. In the examples presented, a green-red color palette was chosen, the minimum values being represented by the color green and the maximum values by the color red.

Vegetation indices generally show maximum values for healthy vegetation and minimum values for vegetation affected by disturbing factors, in the present case of fires.

In order to better understand what the calculated indices highlight, a comparison with the original images was made. Thus, the result of the classic NDVI index, adapted to Sentinel 2 bands (MSI) and, respectively, of the NBR index were analyzed compared to the original images, for the image recorded on 01.08.2021 (before the fires started in the area) and on 11.08.2021 (Figure 4.16).

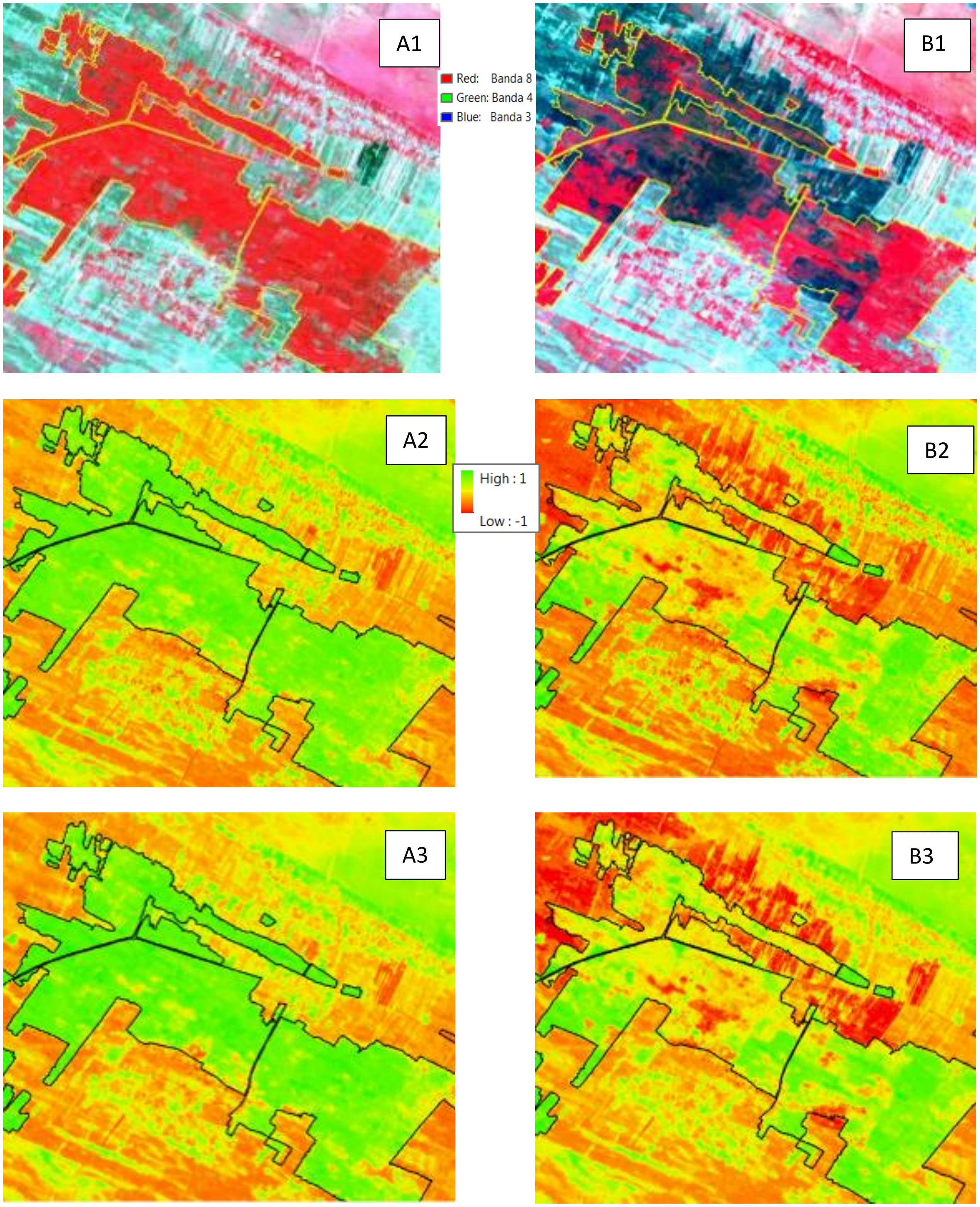


Figure 4.16. Comparison between the original Sentinel 2 images for the Jiana forest body in Mehedinti county (A1 - 01.08.2021; B1 - 11.08.2021), Color infrared (RGB 8-4-3), NDVI (density slices), (A - 01.08 .2021; B2 – 11.08.2021) and NBR) (A3 - 01.08.2021; B3 – 11.08.2021). The limits of the forest fund are marked with yellow and black lines respectively.

Differential indices

In order to better highlight the effects produced by fires, differential indices are used, which represent a simple arithmetical difference between the index values calculated from the pre-event image and the post-event image. In the case of NBR we get the dNBR index (*Difference Normalized Burn Index),* the differences between them being highlighted for the image dated August 11, 2021 (Figure 4.17).

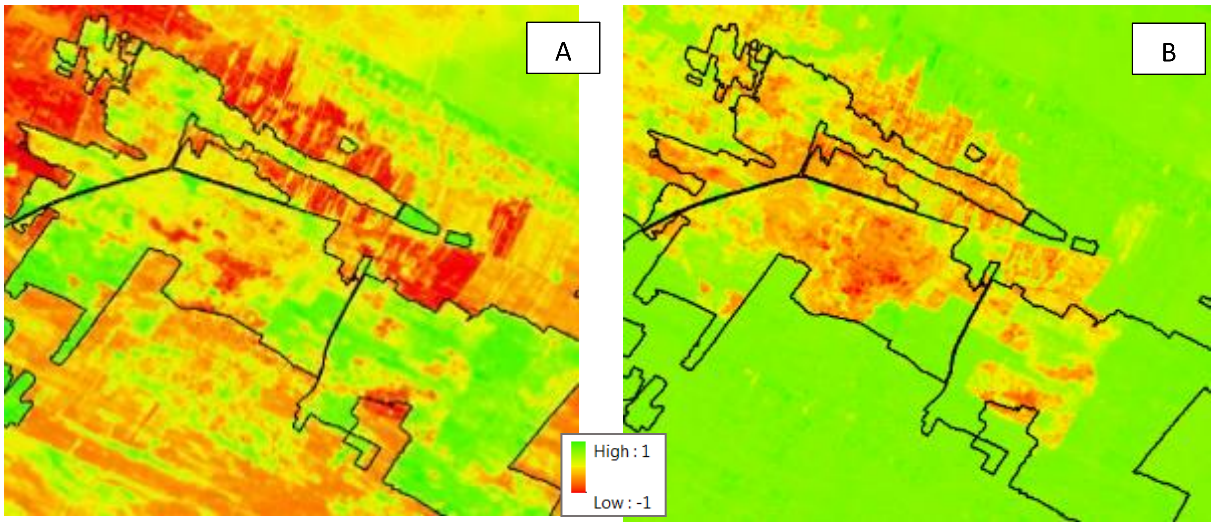


Figure 4.17. Comparison of NBR (A) and dNBR (B) indices (density slices) of the Sentinel 2 image from 11.08.2021 (see Figure 5 A2). Black lines mark the limits of the forest fund (Jiana forest body from Mehedinți county)

In Figure 4.17 it can be seen that on the image of the dNBR index only the areas affected by fires are highlighted (with shades of red), while on the image of the NBR index all the areas with reduced vegetation are highlighted, regardless of the cause (fires or land plowing on agricultural land areas). This effect is quasi-similar for all vegetation indices that are based on pixel values in the red, near-infrared, and mid-infrared bands.

In order to be able to estimate which indices proposed in the specialized literature are more suitable for estimating the effects produced by forest fires, a series of such indices were calculated in the test area for the image dated August 11, 2001 and were visually compared, using coloring with the same color palette and gradient (Figure 4.18).

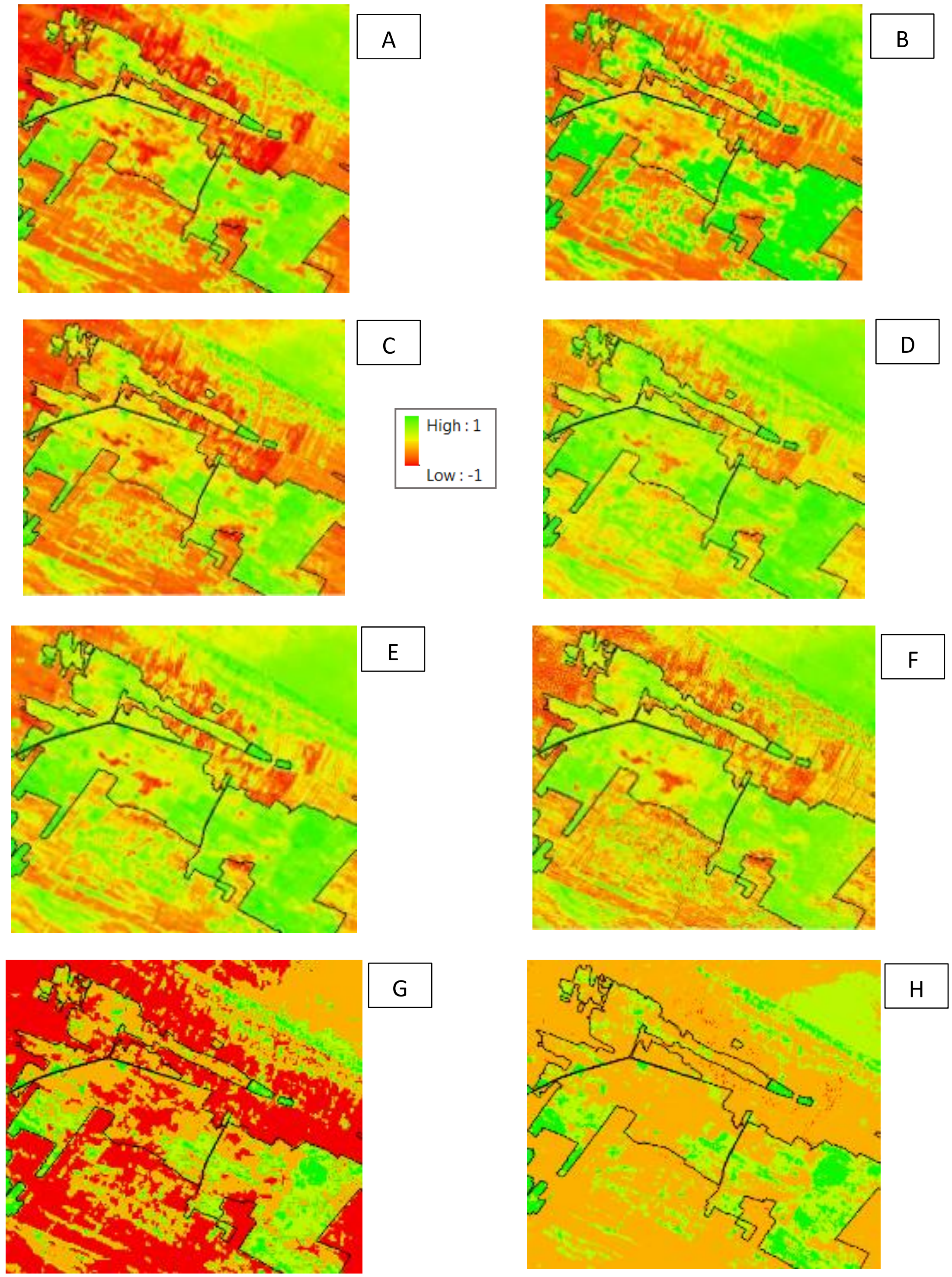


Figure 4. 18. Comparison between the images of indices A- NBRn, B- CIre, C-NDVI, D-GNDVI, E-NDVIre1, F-NDVIre1n, G-MSRre1, H-MSRre1n on 11.08.2021. The black lines delimit the forest background (Jiana forest body in Mehedinți county).

Visual interpretation of the results indicated that the differential index of normalized burn ratio (dNBR) led to the best results in estimating fire severity for the study area. The dNBR severity classes were initially classified according to the thresholds established by Key and Benson (2006), thus obtaining the burn severity classes derived from this index for one of the areas most affected by fires (Figure 4.19).

Figure 4. 19. dNBR index obtained from Sentinel 2 images on 2021-08-01 (pre-fire), 2021-08-11 (post-fire). The yellow line marks the limits of the forest (Jiana forest body in Mehedinți county).

dNBR index map shows a severity distribution apparently close to that estimated visually on the Sentinel 2 image recorded on August 11, 2021. A more detailed analysis showed that burn severity depends on canopy cover and tree heights, at least in black locust stands, which naturally have less crown coverage and, implicitly, a lower crown density than other deciduous species. This was initially observed on Sentinel 2 images before the fire (01 August 2021), on aerial images (30 May 2015) and confirmed in the field. The relationship between dNBR index and canopy cover confirms that low canopy cover indicates falsely high severity on the dNBR index map and vice versa, due to the fact that burned grass and understory are more visible from above and more abundant in stands with low density. Also, a low tree height induces a high severity on dNBR, with the flames and heat produced by the burned understory easily reaching the crowns. This observation was therefore used to adjust the severity map after the fire. The next stage consisted in verifying the hypothesis that the severity classes determined on the satellite images correspond to the actual degrees of damage in the field. In this sense, a field campaign was carried out to verify the correspondence of the burn severity classes with the real impact of the fires. It was found that the severity estimated on the satellite/aerial images does not exactly correspond to the severity observed on the ground. Thus, following the fires in the summer of 2021 in Mehedinți county, it was found that young black locust stands (defined as those with a height up to 10 meters, considering this approximate limit reflects the point beyond which the heat generated by surface fires affects the canopy) are most affected by surface fires (fueled by tall and dry grass, litter and sometimes underbrush). Trees with an average height greater than 10 m were least affected, as their thicker bark and canopy height make them less vulnerable. Image severity estimation tends to be overestimated for short stands and underestimated for tall stands compared to the field estimate.

dNBR index distribution was converted into a vector map representing the 5 severity classes. This was later intersected with the layer representing crown cover and tree height classes. Thus, the severity classes were adjusted according to the correction key in Table 4.8, obtaining the new fire severity map (Figure 4.20).

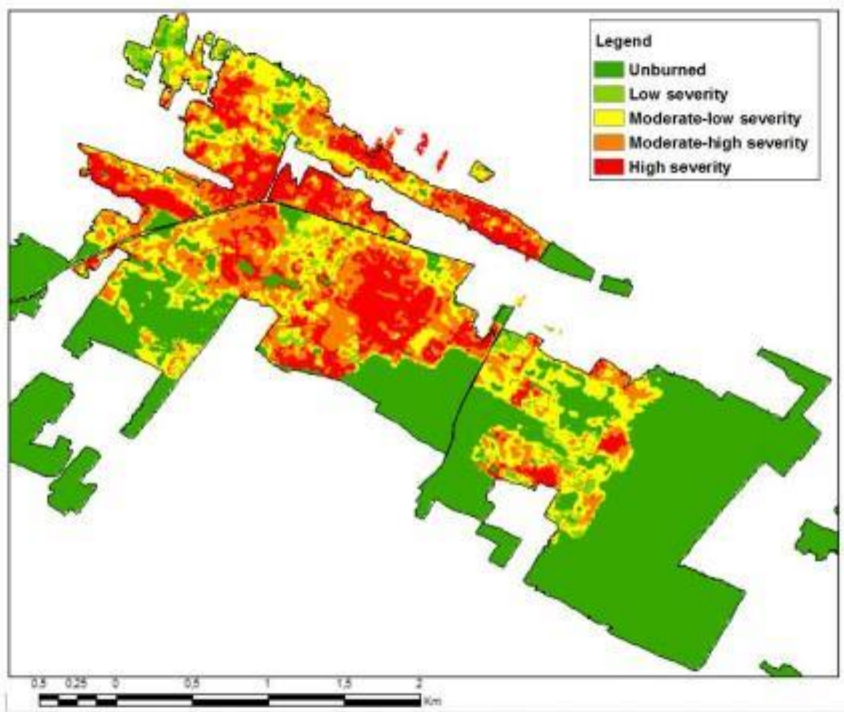


Figure 4. 20. New corrected severity map based on crown cover index and tree height. The black line marks the limits of the forest (Jiana forest body in Mehedinți county).

Stands with low canopy cover but tall trees may actually have a lower severity resulting from dNBR because, if only surface fuel is burned and the trees are not actually affected, the signal from the ground will be dominate and therefore, the dNBR index will have a high value. In dense and taller stands with the same severity of burned area, the signal will be dominated by the crowns, which are less affected. These stands could appear on the dNBR map as unaffected or mildly affected, even though the actual severity could be different (from "low" to "medium-low" or even higher) if the upper crowns were not affected. For other tree species in the area, such as Scots pine, the effect was more severe, with stands being burned to the top and the severity shown by dNBR being closer to reality. Gibson et al. (2020) also found, using Sentinel 2 imagery to assess wildfire severity in eastern Australia, that greater canopy cover and topographic complexity were associated with a greater rate of underestimation due to limitations visualization of the burnt subtree in the low severity classes.

Regarding the forest area affected by fires in the two forest bodies during the analyzed period, the area obtained from the MODIS data totals 859,47 ha, of which 493,30 ha in the Jiana forest body and 366,17 ha in the Pătulele forest body. From the data reported by the forestry administration, the total burnt area for the Jiana body was 308.65 ha (7 fires), and for the Pătutele body it was 303,3 ha (4 fires) with a total on the two bodies of 611,85 ha. There is an additional difference of 247,62 ha (40,47%) of the total burned area determined from MODIS images compared to field data. We note that the burned areas downloaded from the EFFIS platform are determined based on daily MODIS images with a spatial resolution of 250 m, and the fire perimeters are refined from 2018 by also using Sentinel 2 images with a resolution of 20 m. As a result of the low spatial resolution, the MODIS sensor tends to miss fires over small areas, with its fire detection performance increasing as fire size increases (Coskuner 2022, Katagin and Gitas 2022)**.**

4.4 Detecting and locating forest fires and tracking their evolution based on high temporal resolution satellite images

An example of forest fire detection and localization in quasi-real time based on high temporal resolution satellite images is the one that presents the fire situation in the case of the Pătulele forest body, where a fire on an agricultural land, started on August 9, 2021 was later extended to the forested area. Thus, the Sentinel 2 image recorded on August 6 of the same year shows the situation before the fires started (Figure 4.21).

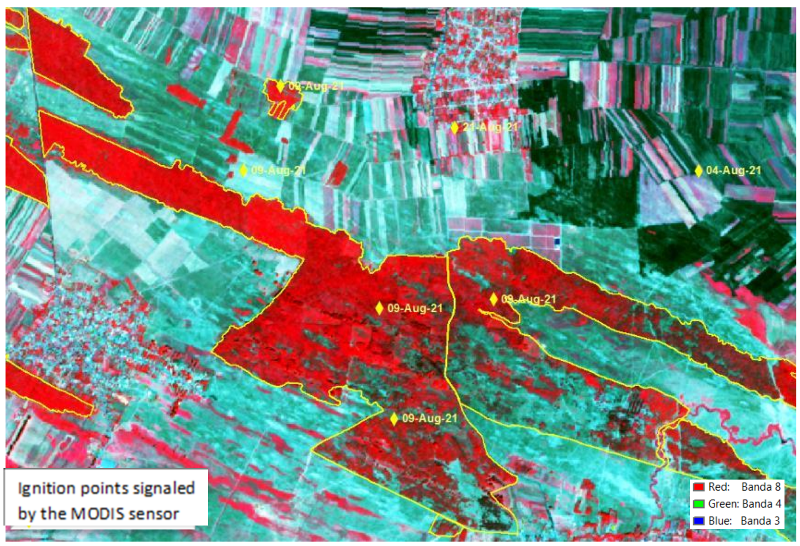


Figure 4.21. Sentinel 2 image, Pătulele forest body, Mehedinți county. The situation on August 6, 2021 showing the ignition points signaled by the MODIS sensor.

On August 9, 2021, a fire occurs on the agricultural land in the north-west of the forest body. The image captures the extension of the fire at 9:30 GMT (12:30 local time, daylight saving time), the moment when the fire outbreak is reported in the forest as well (Figure 4.22). Smoke plumes and even open fires are also observed on agricultural land. It should be noted that at that time the wind was blowing at about 5 km/h from the northeast direction (the weather data was downloaded from [https://www.visualcrossing.com/weather/weather-data-services)](https://www.visualcrossing.com/weather/weather-data-services). Thus, the points signaled by the MODIS product, that indicate the outbreak and spread of the fire on August 9, 2021, are noted.

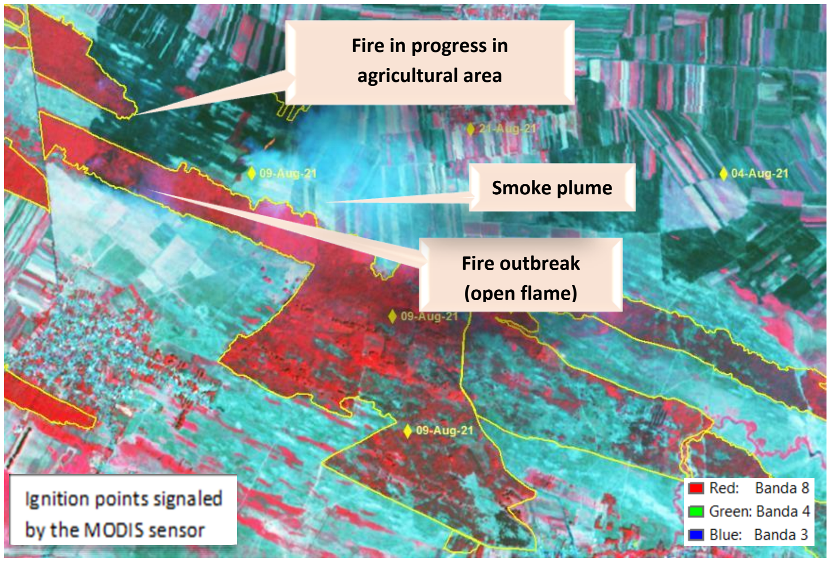


Figure 4.22. Sentinel 2 image, Pătulele forest, Mehedinți county. The situation as of August 9, 2021, showing the points indicated by the MODIS sensor.

The next available Sentinel 2 image was recorded on 11 August 2021 (Figure 4.32). This image shows the final extension of the fire both on the agricultural land and in the forest. The fire spread rapidly from the agricultural land to the forest floor on the same day, as indicated by the MODIS sensor signals. The affected area extracted from the MODIS image coincides very well with that visible on the Sentinel 2 image, especially in the eastern part of the Pătulele forest body.

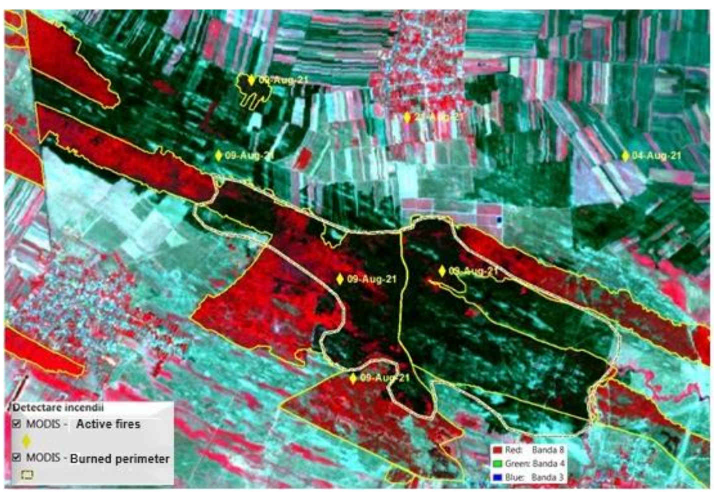


Figure 4.23. Sentinel 2 image, Pătulele forest, Mehedinți county. The situation on August 11, 2021 showing the points signaled by the MODIS sensor.

Regarding the situation of the fire outbreak, it was analyzed on a PlanetScope Dove satellite image, recorded on August 9, 2021, at 8:30 GMT.

A series of images of a detail from the surface of the Pătulele forest body, where the fire started, are presented to highlight the stages of its evolution (Figure 4.24). On the Sentinel 2 image dated 08/06/2021 (Figure 4.24A) it can be noted that the place where the fire occurs in the forest floor is represented by a small gap in the forest. This suggests that the fire spread through litter, a fact also confirmed by field observations. On the PlanetScope satellite image Dove, recorded on 08/09/2021 at 8:30 GMT (11:30 local time, summer time), one hour before the Sentinel 2 satellite passes, the burnt agricultural area is observed, the fire is ongoing and has spread and in the forest area in the south, where it is at the beginning (Figure 4.24B). On the Sentinel 2 image from 2021-08-09 at 9:30 GMT (12:30 local time, daylight saving time), so one hour after the PlanetScope image Dove, it can be seen that the fire spread both on the agricultural surface and in the forest, and open fire was also reported on the agricultural surface (Figure 4.24C). From the comparative analysis of Figure 4.24B and 4.24C, it can be seen that the fire spread in one hour over a distance of approximately 500 m (measured on the image, in the GIS environment), also favored by the wind from the northeast, which was blowing at that time.

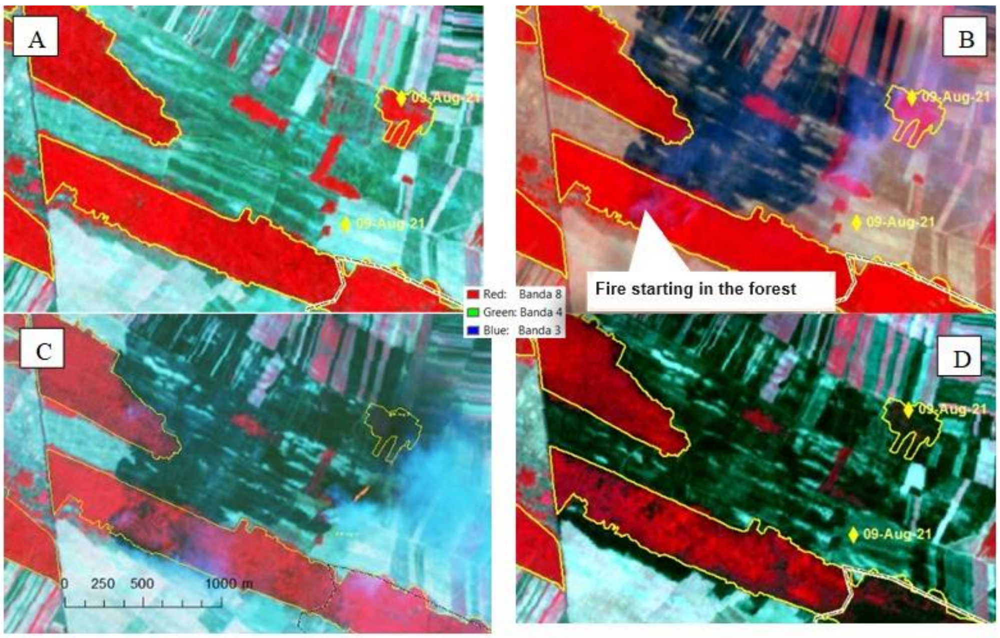


Figure 4.24. The forest body Pătulele - detail. A) Image Sentinel 2, 06.08.2021: no fire outbreak appeared; B) PlanetScope image Dove, 09/08/2021 8:30 GMT: agricultural area burned, ongoing fire has also spread to forest area to the south; C) Image Sentinel 2 (09.08.2021 9:30 GMT): fire in progress, both on the agricultural surface and in the forest; open fire is also observed; D) Image Sentinel 2, 11.08.2021: the effect of the fire.

Thus, from the combination of different sources of remote sensing data, it was possible to reconstruct the evolution of the fires in August 2021 within the Pătulele and Jiana forest bodies. MODIS and VIIRS data correctly signaled the active fire outbreaks in the area, a fact confirmed both by the fire reports of the forestry administration structures (forest boundaries) and by the Sentinel 2 and PlanetScope satellite images Dove.

5. CONCLUSIONS

Based on the research conducted, information processing, and analysis of the results obtained in the doctoral thesis, pertinent conclusions can be formulated, grounded in scientific principles and contribute to the advancement of knowledge regarding the use of geomatics techniques and procedures in assessing wildfire hazards, monitoring active fires, and analyzing their impact, as follows:

- **Regarding the mapping of fuel types on the territory of Romania**

  The combination of vector geospatial data sets with satellite remote sensing data made it possible to obtain, through the indirect mapping method, the distribution map of the types of vegetable fuels (on a large (national) scale, starting from the information describing the distribution of vegetation and equating them with fuel types. It was also possible to obtain the forest vegetation density map (degree of tree crown coverage) based on MODIS satellite data (MOD44B product) and by combining forest ecosystem types at the national level with the information provided by the thematic map regarding the land cover (Corine Land Cover 2018) from which the classes of non-forest vegetation were extracted. Twenty classes of vegetative fuels have been identified, covering forested areas, agricultural lands, as well as transition zones from agricultural to forested areas, from which frequently initiate fires that subsequently spread into forested areas. Each type of fuel represents at the same time a fuel model as it represents "an identifiable association of combustibility elements belonging to distinctive species: shape, size, continuity, which presents a characteristic fire behavior under defined burning conditions". These types of fuels can be identified and highlighted in the future in detail at a small (local) scale, in an activity that involves intensive measurements in the field to calibrate and refine the results.

  Furthermore, based on the combustibility indices for the main tree and shrub species in Romania's forests, determined in relation to wood density, burning speed, and calorific power (Adam, 2006), and using the ecosystem types map (Doniță et al., 2008), it was possible to equate these combustibility indices at the ecosystem type level and ultimately create a map of combustibility indices for Romania's forest ecosystems in digital format. In order to be compatible with the software applications used to model the fire behavior of the combustible, it was later converted from vector format to raster format with the resolution of 30X30 m. Due to the resin content and the lower density of the wood, it was highlighted that the areas occupied by softwoods have a higher combustibility than those specific to hardwoods. Therefore, to understand the propagation of forest fires, it is necessary not only to understand the distribution of fuels represented by forest vegetation, but also those belonging to other vegetation groups and plant associations, due to their mosaic (interspersed) distribution and the current trend towards an integrated risk management, at the level of the ecosystem complex. At the same time, European fuel type classification systems focus, in particular, on Mediterranean ecosystem complexes, which historically are the most affected by fires, rather than on biomes in the boreal or temperate zones. Neither the American nor Canadian systems can be directly adopted for the case of Romania, so it is necessary to find an optimal way to combine and adapt them to the national specifics. Thus, on the occasion of the conducted research, a classification of fuel types adapted to the specifics of forest and non-forest vegetation at the level of Romania was developed.

- **Regarding the creation of the geo-spatial database of historical fire events produced during the years 2006-2023**

The centralization of existing information on forest fires for the period 2006-2023 for the territory of Romania revealed a great annual and intra-annual variability of them. Thus, following an exceptional fire season such as the one produced in 2012, there followed a period of several years of relative calm in terms of the manifestation of forest fires, after which was recorded another year (2022) with an exceptional manifestation of this phenomenon. This can be explained on the one hand by the fact that years of prolonged drought manifest themselves with some cyclicality and on the other hand, following an intense season of forest fires, the fuels from the surface of the soil are consumed (litter, dry branches, etc.) and it takes a period of several years before they accumulate again in significant quantities. The intra-annual variability of forest fires can be explained by their seasonal manifestation, with a maximum recorded in the spring period (March-April) and another, but less intense, in the months of July-August. The spatial representation of forest fires also highlighted the fact that they have a great spatial variability at the level of the country, namely there is a "hot zone" in the southwest of Romania made up of Mehedinți and Gorj counties. The sub-Carpathian area is also more prone to fires, while in the high mountain area forest fires are relatively rare.

The method of collecting and recording fire events could be improved by implementing a geoportal type information system that would allow standardized and unified data entry as well as the precise location of fire ignition points. It is also necessary to correlate the forest fire records coming from the forestry administration with those made by the military firefighters.

- **Regarding the testing and validation of some geo-spatial methods for identifying and analyzing the determining factors for forest fire occurrence:**

Following the comparison of hazard zoning through the two analyzed models (i.e. *Random Forest* and *logistic regression)*, there is consensus between them regarding the identification of the most vulnerable areas in our country, namely Mehedinți and Gorj counties. Using logistic regression, it results that the area of high risk is more extensive, including significant areas in the counties of Vâlcea, Argeș, Olt but also the counties of Galați and Brăila, the latter not being recognized until now as having special problems with this type of disaster. Thus, the *Random Forest* model led to the identification of a narrower area than the *regression* and *logistic model* with the highest degree of danger of forest fire occurrence, especially concentrated in the points of maximum density of historical fires, while the medium-high risk and high risk areas are more extensive in the case of logistic regression, a situation that could also be explained by the fact that this model takes into account several climatic parameters. This difference in the weight of the classes was also highlighted following the validation of the models based on the archive of fires detected by the VIIRS satellite sensor.
The fire hazard maps, both the one obtained by the *logistic regression model* and the one obtained by the *Random Forest model,* highlighted the fact that the most prone to forest fires are the sub-carpathian areas where agricultural lands are interspersed with forests and human settlements. Corroborating at the same time the areas with high fire frequencies with the monthly occurrence statistics, the emerging hypothesis is that forest fires occur according to the vegetation management works practiced by the locals. Specifically in the spring, for cleaning plant debris, pastures and orchards are set on fire, the most affected area being the hill area, while in the plain area and in Dobrogea a maximum is recorded during the summer as a result of the practices of burning stubble and agricultural residues. At the same time during the summer, the incidence of fires also increases in the mountain area, when there is a peak in human activity and presence, driven by intensified tourist activities.

From the point of view of *the determining factors* selected as influencing the occurrence of forest fires, it can be stated that both models highlighted the fact that forest fires are determined by a combination of climatic factors (extreme temperatures and low precipitation), topographical factors (altitude, slope, exposure), anthropogenic (population density, road density, proximity of arable land and pasture) as well as specific vegetation (shrub cover, NDVI index).

Based on what has been presented, it can be stated that both methods tested for hazard zoning, *logistic regression* and the *Random Forest* model, present an important limitation that must be emphasized, namely the fact that the accuracy of the results is dependent on both the quality and the variety of the geospatial explanatory variables used in running these models. This shortcoming can be reduced by constantly updating this information as well as generating it to greater degrees of precision and detail. This, however, can result in hazard zoning that differ significantly one from another, which would obstruct a judicious temporal comparison of wildfire-prone areas. This could be avoided by using for hazard zoning only the map obtained based on the *kernel probability density* since it is generated exclusively based on the fire points and therefore, the results can be compared with each other if a new edition of the map is generated as a result of the addition of new annual series of fire points. However, these two predictive analysis models (*logistic regression* and *Random Forest*) can provide valuable information about the factors involved in the forest fire regime and the relationships between them, with potential consequences on how to manage this type of hazard.

- **Regarding near-real-time detection of wildfires and tracking the evolution of fire propagation from Sentinel 2 and PlanetScope Dove satellite data:**

By combining medium and high spatial resolution satellite data (i.e. Sentinel 2 and PlanetScope Dove) with the points of fire outbreaks from the EFFIS (European *Forest Fire Information System)* platform, it was possible to reconstruct with satisfactorily fidelity the evolution of the spread of fires from the moment of their initiation until they are extinguished. Thus, it was also possible to highlight the fact that the fires in the study area initially ignited in agricultural lands and then spread to the neighboring forest areas. However, the exclusive use of Sentinel 2 satellite images for this purpose is insufficient, but the disadvantage of PlanetScope Dove images is that they are acquired at a cost. However, Landsat 9 satellite images could be additionally used to improve the time interval between two successive images for the same area. It should be noted that the method is applicable only under the condition that the sky is not covered by clouds over the burned area.

Fire ignition points derived from high temporal resolution satellite sensor data (MODIS and VIIRS) and provided by EFFIS correctly captured the forest fire initiation points/outbreaks analyzed in the research area of Jiana and Pătulele communes in Mehedinți county. It is therefore recommended to use these systems based on remote sensing for alerting fires to emergency teams in unpopulated areas, where fires not signaled in time can spread in an alarming way. It should be noted that satellites carrying MODIS sensors pass over the same area once every 1-2 days, while VIIRS sensors do so 4 times a day. Therefore, the information provided by these sensors cannot replace early warning systems, which can be achieved through the improvement of ground-based monitoring systems.

- **Regarding the mapping of forest areas affected by fires and the estimation of the severity of forest fires based on Sentinel 2 satellite images:**

The results obtained from assessing the impact of fires after their occurrence allow for the assertion that both the areas affected by fire and the estimation of the severity of the fire's effects can be derived with sufficient accuracy from Sentinel 2 images. In this way, it supports more accurate reports of the impact of fires, especially when they occur over large areas, in support of forestry personnel and other institutions that report areas affected by fires.

Through the comparative analysis of the most popular spectral indices used in the science of wildfires, it was confirmed that the Normalized Differential Burning Ratio, calculated as the ratio between the values in the near-infrared and mid-infrared bands, offers the best results for mapping burnt surfaces and estimating the severity of fires in the case of black locust forests in the lowland area. It is necessary that the degrees of severity of the fires, established as threshold values of the Normalized Differential Burning Ratio, to be calibrated locally as the index values are influenced by the composition and the vertical and horizontal structure of the forest stands as well as the topography of the land. Thus, it was highlighted that, for a more accurate estimate of fire severity levels based on satellite images, it is necessary to take into account the influence of canopy density and tree height on severity. According to research, the severity of fires in black locust forests in the two forest areas studied is associated with the degree of crown coverage and tree height. The correlation between the dNBR index and tree density is negative, which means that a low crown density may indicate a higher damage in satellite images, because herbaceous vegetation and the understory of trees are more visible and prominent in these images. In addition, trees with low height (below 10 m) are more susceptible to fires due to the heat generated by burning herbaceous vegetation and leaf litter, which propagates more easily in tree crowns, leading to higher fire severity index values.

In the case of the analyzed research area, the total burned area mapped using Sentinel 2 images differed significantly from that obtained by aggregating the areas reported by forestry administration structures, being 24% larger. In order to analyze to what extent areas from the official reports differ from the surfaces estimated by remote sensing methods and what are the causes of the discrepancies between them, it is recommended to expand the research within a series of statistically representative fires, stratified by landforms, types of fires and the type of forest ecosystems. However, estimates of burned forest areas are achieved with satisfactory accuracy by MODIS satellites, especially in the case of fires that occur over large areas and in less dense stands, as the low spatial resolutions of the sensors have limitations in the case of mapping litter fire, developed under closed canopy and high density stands. This fact was highlighted by mapping the areas affected by fires in black locust forest stands, using Sentinel 2 satellite images, and comparing the results with the perimeters of EFFIS burned areas derived from MODIS images that present a significantly lower spatial resolution (i.e. 10 m versus 250 m).

*

*   *

The research undertaken in the framework of the doctoral thesis highlighted the special potential that satellite remote sensing data combined with geospatial vector data from different sources offers to the risk management of natural disasters caused by forest fires both in the prevention and preparation phase, detection - alerting phase, as well as in the post-event analysis phase. The scientific results obtained constitute some of the solutions, models and geo-spatial technologies that can provide stakeholders (authorities, intervention structures, administrators and owners of forests, civil society, etc.) with useful information to reduce the impact of this type of disaster on the ecosystem complexes in general and on forest ecosystems in particular.

6. ORIGINAL CONTRIBUTIONS

The results obtained and the conclusions drawn based on them, following the research carried out on the occasion of the preparation of the doctoral thesis, have highlighted achievements and personal contributions of originality, regarding the exceptional potential that satellite remote sensing data combined with vector geospatial data from various sources offer for managing the risk of natural disasters caused by forest fires, as follows:

- Updating the geospatial database on forest fire events in Romania by integrating the existing information in the period 2019-2023, thus making the transition from data recorded in tabular format to geospatialy referenced data that offers the possibility of representing and highlighting the spatial variability of forest fires forest in the country.

- Creation of an improved map of the types of vegetable fuels for the entire territory of Romania that includes not only forest fuels but also non-forest fuels (agricultural lands and those in transition from agricultural land to forest land), the forest vegetation being segmented according to its density (degree of coverage of tree crowns).

- The development, for the first time for our country, based on the combustibility indices established in relation to wood density, burning speed and caloric power of the main species of trees and shrubs and the distribution of ecosystem types in Romania, of the map of combustibility indices for forest ecosystems, in digital format.

- Justification for implementing a geoportal-based information system, based on the collection and recording of fire events, which allows for standardized and unified data entry and precise localization of fire points.

- Testing and comparing two methods for modeling forest fire hazard in Romania (*logistic regression* and *Random Forest*), among which one was applied for the first time in our country (*Random Forest*), leading to the identification of areas in Romania where the risk of this type of disaster is high.

- Elaboration of fire hazard maps by using logistic regression and Random Forest models and highlighting the fact that the most prone to forest fires are the sub-Carpathian areas characterized by a pronounced mosaic of land cover (agriculture, settlements, forests, other categories of vegetation etc.)
- Highlighting, through geospatial analysis methods, the contributing factors favoring forest fires in Romania and the relationships between them, validating and expanding on previous research results that indicate forest fire occurrence is caused by a combination of topographic, climatic, anthropogenic, and vegetation factors that interrelate with each other.

- Development, for the first time in Romania, of a method to accurately reconstruct the evolution of fire spread from ignition to extinguishment using optical satellite images from Sentinel 2 and PlanetScope Dove, combined with active fire points generated by the EFFIS (*European Forest Fire Information System*) platform.

- Verifying the accuracy of forestry administration reports regarding fire-affected areas by comparing them with areas affected and determined based on the Normalized Burn Ratio (NBR) obtained from Sentinel 2 optical satellite images, highlighting significant differences between these areas and the opportunity to use satellite remote sensing data and technologies to improve forest fire impact estimation.

- Testing and validating the detection, based on data provided by satellite sensors with high temporal resolution (MODIS and VIIRS) and provided by EFFIS, of fire initiation points or forest fire outbreaks analyzed in the research area of Mehedinți County, demonstrating the usefulness of these systems based on remote sensing techniques for signaling fires and alerting firefighting teams in unpopulated areas where fires not identified in time can spread alarmingly.

- Customizing the application of a method for estimating the fire severity on black locust stands, based on the use of the normalized differential burn index obtained from Sentinel 2 optical satellite images, highlighting the fact that the severity thresholds must be adjusted taking into account the stand density and height of the trees.

7. DISSEMINATION OF RESULTS

A. Papers from the field of the doctoral thesis, published in ISI-indexed journals

1. Capalb, F., Apostol, B., **Lorenţ, A.,** Petrila, M., Marcu, C., & Badea, N.O. (2024). Integration of Terrestrial Laser Scanning and field measurements data for tree stem volume estimation: exploring parametric and non-parametric modeling approaches. Annals of Forest Research, Res. 67(1) (corresponding author) https://www.afrjournal.org/index.php/afr/article/view/3664/1286

2. Mallinis, G., Petrila, M., Mitsopoulos, I., **Lorenţ, A.,** Neagu, Ş., Apostol, B., Gancz, V., Popa, I., Goldammer, J. G. (2019). Geospatial Patterns and Drivers of Forest Fire Occurrence in Romania. Applied Spatial Analysis and Policy, 12, 773-795, DOI : 10.1007/s12061-018-9269-3, WOS:000501905800002. https://doi.org/10.1007/s12061-018-9269-3

B. Papers from the field of the doctoral thesis, published in BDI-indexed journals

1. **Lorenţ, A.,** Petrila, M., Capalb, F., Apostol, B., Marcu, C., & Badea, N.O. (2024). Overview of the Forest Fires Defense System in Romania. Environmental Protection and Disaster Risks (EnviroRisks 2024) - Proceeding of the 3rd International Conference on Environmental protection and disaster risks and 11th Annual CMDR COE conference on Crisis management and disaster response. edited by: Nina Dobrinkova, Stefka Fidanova, Springer Nature Switzerland – in course of publication

2. **Lorenţ, A.,** Gancz, V., Petrila, M., Apostol, B., Capalb, F., Marcu, C., & Badea, N.O. (2023). Detectarea și localizarea incendiilor de pădure și urmărirea evoluției acestora pe baza imaginilor satelitare de înaltă rezoluție temporală. [*Detection and localization of forest fires and tracking their evolution based on high temporal resolution satellite images*]. Revista de Silvicultură și Cinegetică, nr 52, 2023, pp. 63-69, ISSN 1583 – 2112, ISSN 2284 – 7936 (on line). http://progresulsilvic.ro/wp-content/uploads/Revista-de-Silvicultura-si-Cinegetica-nr.-52_2023-.pdf

3. **Lorenţ, A.,** Petrila, M., Gancz, V., Capalb, F., Apostol, B., & Badea, N.O. (2022). Quick assessment of burn area and burn severity on black locust stands using Sentinel 2 imagery in South-West Romania. In D. X. Viegas & L. M. Ribeiro (Ed.), *Advances in Forest Fire Research*, pp. 1282–1291. University of Coimbra. https://doi.org/10.14195/978-989-26-2298-9_194

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C. Papers outside the field of the doctoral thesis, published in ISI-indexed journals

1. Chivulescu S., Hapa M., Pitar D., **Lorenţ A.**, Marmureanu L., Leca S., Radu R., Cazacu R., Dobre A.C., Pascu I.S., Marcu C., Verghelet M., Vezeanu C., Racoviceanu T. & Badea O. (2024). Integrating monetary and non-monetary valuation for ecosystem services in Piatra Craiului national park, Southern Carpathians: a comprehensive approach to sustainability and conservation. Front. For. Glob. Change 7:1280793. DOI: 10.3389/ffgc.2024.1280793, WOS:001184279300001. https://doi.org/10.3389/ffgc.2024.1280793
2. Ciuvăţ, A.L., Abrudan, I.V., Ciuvăţ, C.G., Marcu, C., **Lorenţ, A.,** Dincă, L. Szilard, B. (2022). Black Locust (Robinia pseudoacacia L.) in Romanian Forestry. Diversity, 14, 780, DOI: 10.3390/d14100780, WOS:000874343200001. https://doi.org/10.3390/d14100780
3. Apostol B., Petrila M., **Lorenţ A.,** Ciceu A., Gancz V. & Badea, O. (2020). Species discrimination and individual tree detection for predicting main dendrometric characteristics in mixed temperate forests by use of airborne laser scanning and ultra-high-resolution imagery Sci. Total Environ., 698 (2020), Article 134074, DOI : 10.1016/j.scitotenv.2019.134074, WOS:000500580700013. https://www.sciencedirect.com/science/article/abs/pii/S0048969719340513
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D. Papers outside the field of the doctoral thesis, published in BDI-indexed journals

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E. Participation in international conferences

1. **Lorenţ, A.,** Petrila, M., Capalb, F., Apostol, B., Marcu, C., & Badea, N.O., 2024. Overview of the Forest Fires Defense System in Romania. Environmental Protection and Disaster Risks (EnviroRisks 2024). The 3rd International Conference on Environmental protection and disaster risks and 11th Annual CMDR COE conference on Crisis management and disaster response, 04 June – 06 June 2024, Sofia, Bulgaria

2. Capalb, F., Petrila, M., **Lorenţ, A.,** Apostol, B., Marcu, C, Badea, O., 2023. Experimenting an improved tree point cloud segmentation method of TLS data in a spruce forest inventory network. Forest science for people and societal challenges - The 90th "Marin Drăcea" INCDS Anniversary, 2-5 October 2023, Bucharest, Romania

3. Capalb, F., Petrila, M., **Lorenţ, A.,** Apostol, B., Marcu, C., Badea, O., 2023. Predicting Tree Crown Width of Individual Trees In The Western Southern Carpathians Using Terrestrial Laser Scanning And Random Forest Algorithm. Forest science for people and societal challenges - The 90th "Marin Drăcea" INCDS Anniversary, 2-5 October 2023, Bucharest, Romania

4. **Lorenţ A.,** Petrila M., Apostol B., Capalb F., Marcu C., Badea O., 2023. Identification Of The Driving Factors For The Occurrence Of Forest Fires And The Zoning Of Forest Fire Hazard Through Logistic Regression And Random Forest In Romania, 42nd EARSeL Symposium, Bucharest, Romania, 3-6 of July 2023
5. Apostol B., **Lorenţ A.,** Chivulescu Ș., Ciceu A., Petrila M., Capalb F., Marcu C., Badea O., 2022. Integration of Terrestrial Laser Scanning (TLS) and Airborne Laser Scanning (ALS) Processed Data for the Assessment of Norway Spruce Dendrometric Characteristics – a Case Study, 41st EARSeL Symposium, Paphos, Cyprus, 13-16 September 2022
6. Apostol B., Petrila M., Duro J.G., **Lorenţ A.,** Capalb F., Marcu C., Farcaș S., 2022. Integration of Canopy Height Models Derived from Airborne LiDAR Data and UAV Aerial Imagery by DTM-DSM Matching in the Forest Free Areas, 41st EARSeL Symposium, Paphos, Cyprus, 13-16 September 2022
7. **Lorenţ A.,** Gancz V., Petrila M., Capalb F., Apostol B., Soare I., 2022. A web GIS mapping service for a better exploitation of the forest melliferous resources in South East Romania, 41st EARSeL Symposium, Paphos, Cyprus, 13-16 September 2022
8. Apostol B., Pascu I. S., Petrila M., Dobre A.C., **Lorenț A.,** Gancz V., Badea O., 2019. ”A comparative assessment of the area-based approach and individual tree detection for volume estimation in mixed temperate forests using Airborne Laser Scanning data”, SilviLaser Conference 2019, 16th edition, Foz do Iguazu, Brasil, 8-10th October 2019

F. <u>Participation in national conferences</u>

1. **Lorenț A.,** Petrila M., Neagu, Ș., Apostol B., Gancz V., 2019. ”Utilizarea datelor geospațiale silvice ca suport informațional pentru managementul incendiilor de pădure”, Conferința Națională de Medicină de Urgență și Salvări în Situații Speciale, SARTISS, Băile Felix, Romania, 6-9th November 2019

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SCURT REZUMAT

Pădurile și ecosistemele forestiere sunt de o importanță deosebită pentru viabilitatea și dezvoltarea socială, economică și de mediu. Acestea joacă roluri semnificative în comunitățile rurale și urbane, oferind bunuri și servicii și complexe și protejând biodiversitatea.

Schimbările sociale și economice majore în utilizarea terenurilor în țara noastră determinate de mișcările populației din zonele rurale spre cele urbane, abandonarea utilizării tradiționale a terenurilor în mediile rurale, reducerea utilizării pădurilor pentru producția de materii prime, creșterea utilizării recreative a zonelor împădurite, creșterea continuă a zonei de interferență între mediul natural și cel construit, informarea și conștientizarea publicului inadecvate, sunt câțiva dintre factorii principali care conduc la creșterea riscurilor de incendii forestiere.

Considerând acestea și luând în considerare tendința de intensificare a manifestării incendiilor de pădure în țara noastră remarcată în ultimele două decenii, este necesar și oportun studierea acestui fenomen atât natural cât și antropic astfel încât să fie generate informații care să conducă la creșterea gradului de pregătire și prevenire la incendii de pădure și la o înțelegere mai aprofundată a acestui tip de risc.

Cercetările întreprinse în cadrul acestei teze de doctorat constituie un demers în sprijinul acestui deziderat, urmărind să studieze fenomenul incendiilor de pădure utilizând tehnologii geospațiale moderne cum ar fi teledetecția și sistemele informatice geografice. În acest sens, prin combinarea unor seturi de date geospațiale reprezentând factorii topografici, antropici de vegetație și climatici, au fost testate două modele pentru cartarea hazardului la incendii de pădure pentru teritoriul României și totodată s-au identificat și analizat factorii determinanți a acestora. Cartarea tipurilor de combustibili de vegetație, forestieri și neforestieri, este de importanță în prognoza pericolului la incendiu dar și în modelarea comportamentului acestuia. Prin urmare unul dintre obiectivele tezei s-a concentrat în jurul acestui aspect.

Totodată, prin combinarea imagisticii satelitare de înaltă și medie rezoluție temporală și spațială (i.e. Sentinel 2, PlanetScope Dove, MODIS, VIIRS) și a produselor derivate din acestea, a fost elaborată o metodă pentru determinarea suprafeței afectate de incendiu și evaluarea severității incendiului pentru păduri de salcâm afectate de incendii și totodată a fost explorat potențialul acestor imagini în vederea detectării și localizării incendiilor de pădure și urmărirea evoluției acestora.

SHORT RESUMES

Forests and forest ecosystems are of exceptional importance for social, economic, and environmental viability and development. They play significant roles in rural and urban communities, providing complex goods and services and protecting biodiversity.

Major social and economic changes in land use in our country, driven by population movements from rural to urban areas, abandonment of traditional land use in rural areas, reduced use of forests for raw material production, increased recreational use of forested areas, continuous growth of the wildland-urban interface area, and inadequate public information and awareness are some of the main factors leading to increased forest fire risks.

Considering these factors and the observed trend of increasing forest fire incidents in our country over the past two decades, it is necessary and timely to study this natural and anthropogenic phenomenon to generate information that will lead to improved preparedness and prevention of forest fires and a deeper understanding of this type of risk.

The research undertaken in this doctoral thesis supports this goal, aiming to study the phenomenon of forest fires using modern geospatial technologies such as remote sensing and geographic information systems. In this regard, by combining geospatial data sets representing topographic, anthropogenic, vegetation, and climatic factors, two models were tested for forest fire hazard mapping in Romania. Additionally, the determining factors were identified and analyzed. Mapping types of vegetation fuels, both forest and non-forest, is essential for fire danger prediction and modeling its behavior. Therefore, one of the thesis objectives focused on this aspect.

Furthermore, by combining high and medium temporal and spatial resolution satellite imagery (i.e., Sentinel 2, PlanetScope Dove, MODIS, VIIRS) and their derived products, a method was developed for determining the area affected by fire and assessing fire severity for black locust forests affected by fires. The potential of these images for detecting and locating forest fires and monitoring their evolution was also explored.