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A COMPARATIVE ANALYSIS OF DIFFERENT WILDFIRE RISK ASSESSMENT MODELS (A CASE STUDY FOR SMOLYAN DISTRICT, BULGARIA)

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Abstract

GIS and remote sensing technologies have become valuable tools for wildfire management. During the last three decades a lot of fire risk estimation indices, based on geo-spatial technologies, have been introduced. Wildfire in each part of the Earth has its own characteristics, so weights and variables in existing risk modeling indices could not be one and the same for different region (Adab, et al, 2011). Three models for risk zone identification are chosen and applied for the territory of Smolyan district, Bulgaria, and the results for each one are compared to historical fire events. The aim is the identification of an accurate risk assessment model for the particular territory, where wildfires are a frequent hazard, causing serious damages each year.

***Keywords**: Fire risk models, GIS, Remote sensing, Smolyan district*

1. INTRODUCTION

Recent natural disasters like earthquakes, floods and forest fires have shown the need for natural risk management not only in Europe but also world-wide, as they endanger directly public health and cause severe damages on the national economy (Honikel et al., 2000). Wildfires are one of the major environmental issues, creating economical and ecological damage while endangering human lives. It is one of the most important parts of land degradation that is caused by deforestation and desertification (Hernandez-Leal et al., 2006).

Due to the impact of climate change, fires frequency and intensity is constantly growing. Latest events confirm this world-wide trend, such as the wildfires in Greece and Italy in the year 2007, Portugal 2003 and 2005 etc. Fires have become a serious threat for Bulgaria as well. In the years 2000 and 2007 they reached the record number of 1 710 and 1479 (data from EFFIS – European Forest Fire Information System).

Geographic information systems (GIS) and remote sensing technologies have become valuable tools for prevention, detection and fire estimation. Managing a process as complex and dynamic as wildfire, requires a great variety of factors to be taken into account. The use of GIS and remote sensing techniques is quite obvious in this case, since these tools are ideal for managing spatial information and for providing adequate spatial processing and visualization of results.

According to Chuvieco et al., 2010, fire risk evaluation is a critical part of fire prevention, since pre-fire planning resources require objective tools to monitor when and where a fire is more prone to occur, or when it will have more negative effects. During the last 3 decades, a lot of studies on fire risk estimation have been introduced, based on geo-spatial technologies. Forest fire in each part of the Earth, has its own characteristics, so weights and variables in existing indices for fire risk modeling could not be one and the same for different regions. Indices should be modified over areas with different environmental conditions (Adab, et al, 2011). This paper analyzes 3 different approaches for a long-term wildfire risk assessment. Each one of them is applied for the territory of a mountainous district in Bulgaria and the results are compared with 481 past fire events, that have taken place in the same area for a 15 years period. The present paper doesn't aim to criticize existing fire assessment models, but to identify an accurate risk estimation approach for a particular territory.

2. DATA AND METHODOLOGY

2.1. Study area

Smolyan is one of the 28 administrative districts in Bulgaria. It is situated in the southern part of the country and is bounded by the regions of Plovdiv, Pazardzhik, Kardzhali and Blagoevgrad, and to the south it borders on Greece (Figure 1). Fires have always been a major problem in that part of the Bulgaria. A lot of measures have already been taken by the authorities on this matter, which includes the establishment of an early warning system in the framework of project "Through prevention to preserve the natural beauty of the Rhodope Mountains". For the needs of the project, data in a shape file format (ESRI Shape file) containing localities of 481 historical fires was created, which is used as a base for the analyzes in the present paper.

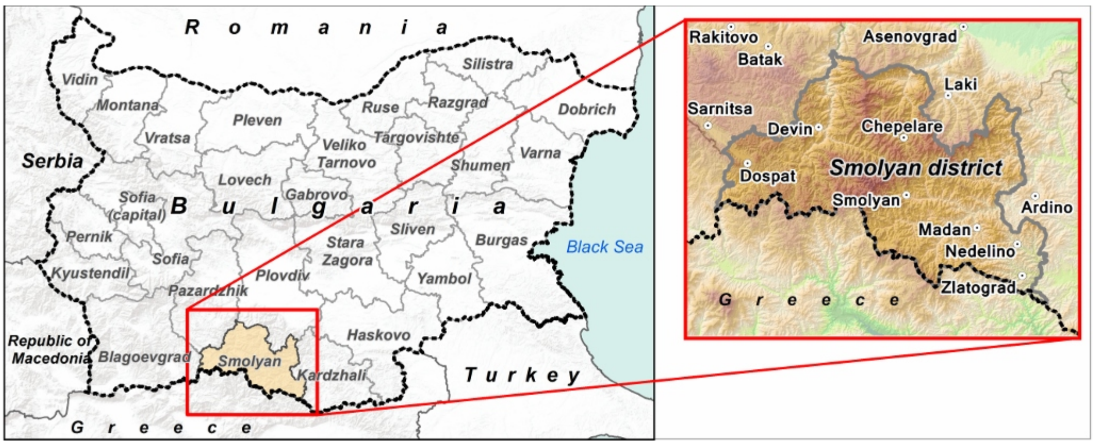

Figure 1. Study area

The relief of the region is mountainous as it covers the eastern part of the Rhodopi Mountains with venerable coniferous forests and pastures. The highest peak in the study area is Golyam Perelik, with an altitude of 2191m. The lowest elevation point is 373m. The study area is about 3200 square kilometers, more of 70% of which is covered by forests. The forestry sector is amongst the most important industries in Smolyan region. A typical forestry landscape from the district is shown in Figure 2.

Figure 2. A typical landscape from Smolyan district

2.2 GIS

A geographic information system is a system, that consists of hardware and software, database and users, designed to capture, store, manipulate, analyze, manage, and present geographical data with the aim of handling different tasks in a variety of fields (Popov, 2012). GIS has come to be used extensively in environmental applications such as forest fire management; its capacity to incorporate both qualitative and quantitative information for cartographic modeling makes it quite practical (Carter, 2010). These technologies allow a forest fire manager or researcher an access to the information and utilities necessary in developing a fire susceptibility map in order to determine and classify high risk areas (Carter, 2010).

The integration and manipulation of the data for the fire risk zones identification is done with ArcGIS 10 software, a product of the ESRI company. As source data are used, layers from the project „The Study on Integrated Water Management in the Republic of Bulgaria" and data from Corine land cover 2006 - both freely available. Data for the past fire events is provided from the project "Through prevention to preserve the natural beauty of the Rhodope Mountains".

2.3. Remote sensing

Remote sensing generally refers to the use of aerial sensor technologies for the acquisition of information about an object or phenomenon without making physical contact with it. Satellite remote sensing data are a regular and cheap source for environmental monitoring, as they cover a large area with a single pass and save time and money for work intensive field studies (Honikel, et al., 2000). Remote sensing is especially suitable for forest fire research.

The wide area coverage and repetitivity provided by satellite sensors, as well as their information on non visible spectral regions, makes it a powerful instrument in the fire management process. A satellite image of the study area is used for vegetation indexes calculations. A Landsat image of the territory from the year 2006 is downloaded from the Earth Science Data Interface web page.

2.4. Indices for fire risk assessment

Three groups of indexes are proposed by the European Union's (EU) Joint Research Center (JRC, 2002) based on their temporal scale as follows; (Adab, et al., 2011)

- Structural or long-term indices. They do not change in short time such as topography, vegetation type, land-cover, land-use, slope, aspect, distance to roads and vicinity to urban areas, population density, climate, and soils;
- Dynamic or short-term indices, which change moderately continuously over time, such as vegetation or weather condition. This index intend to detect the flammability of forest fuels during the fire season and hence it uses variables that changing in a short period of time.(Chuvieco., et al 2005). An example for a short-term index is the Canadian Fire Weather Index
- Integrated or Advanced indices that contain both structural and dynamic factors as mentioned above. But the most critical issue in this approach is how to combine effectively the relevant variables to get a coherent criterion (Adab, et al., 2011).

Long-term (structural) factors are the main focus of the present paper. The majority of the existing long-term models are taking into consideration the following factors: vegetation, proximity to roads, proximity to settlements, slope, aspect and elevation. The main differences of the existing indexes for a risk zone identification is the data used for the fuel risk estimation and in the weighting of the factors. Three models are chosen to be applied for the study area:

- Cáceres, C.,2011, „Using GIS in Hotspots Analysis and for Forest Fire Risk Zones Mapping in the Yeguare Region, Southeastern Honduras"
- Ozelkan, E., Ormeci, C., 2009 "Risk assessment of forest fires by using satellite data with remote sensing techniques"
- Adab, H., Kanniah, K. ,Solaimani, K., 2011 "GIS-based Probability Assessment of Fire Risk in Grassland and Forested Landscapes of Golestan Province, Iran"

Each model is named after the first author and the year for short. The variables and the classes of each model are presented in Table 1.

Table 1. Variables and classes of the three risk models

Risk model	Variables	Classes	Ratings of hazard*
Cáceres, 2011	**Land cover**	Rangeland(Scrub/ Shrubs), Forest Land ,Agricultural Land, Urban or Built-up Land , Barren Land and Water	0,1, 2, 3, 4
	Elevation	> 1501, 1001 – 1500, 501 – 1000, < 500	0,1,2,3
	Slope	> 35 % , 35 – 25 %, 25 – 10 % , 10 – 5 % , < 5 %	0, 1, 2, 3, 4
	Aspect	South, Southwest, Southeast, East , North , Northeast , Northwest	0, 0, 1, 1, 2, 2, 2
	Roads	<50, 50 – 100m, 100 – 200m, 200 – 300m , 300 – 400m, > 400m	0, 1, 2, 3,4, 5
	Settlements	<500m, 500 – 1000m, 1000 – 2000m , 2000 – 3000m, > 3000m	0, 1, 2, 3, 4
Ozelkan, 2009	**NDVI**	Few or no vegetation, Very dry, Dry, Moist, Fresh-like, Fresh	1, 10, 8, 6, 4, 2
	Slope	64-89, 45-64, 36-45, 29-36, 23-29, 17-23, 11-17, 3-11, 0-3	10, 9, 8, 7, 6, 5, 4, 3, 2
	Aspect	South, Southwest, Southeast, Flat, West, East, Northwest, Northeast, North	10, 9, 8, 7,6, 5, 4, 3, 2
	Roads	0 – 308, 308 – 616, 616 – 925, 925 – 1233, 1233 – 1541, 1541 – 1850	10, 8, 6, 4, 2, 1
	Elevation	1790 – 2300, 1425 – 1790, 1069 – 1425, 730 – 1069, 425 – 730, 24 – 425	10, 8, 6, 4, 2, 1
Adab,, 2011	**NDMI**	>0.36,0.26-0.36,0.16-0.26,0-0.16,<0	1,2,3,4,5
	Elevation	>2000,1000-2000, ,500-1000 , 200-500, <200	1,2,3,4,5
	Slope	<5%, 10-5%, 25-10%, 35-25%, >35%	1,2,3,4,5
	Aspect	North, East, West, South	2,3,4,5
	Roads	>400 , 300-400, 200-300, 100-200, <100 m	1,2,3,4,5
	Settlements	>2000 , 1500-2000, 1000-1500, 500-1000, <500m	1,2,3,4,5

* Ratings of hazard are different for each of the modes: Cáceres, 2011 -highest risk value 0, lowest risk value 4; Adab,2011 - highest risk value 5, lowest risk value 1; Ormeci, 2009 - highest risk value 10, lowest risk value 1

The choice of these particular models is motivated by the fact that they are similar and could be compared. Basically, the same factors are used but they are weighted and classified in a different way. The main difference of the three models is the data, used for calculation of the vegetation risk.

2.5. Variables and their relation to past fires in the study area

2.5.1. Vegetation

The type of vegetation plays a large role in determining the relative risk and likely behavior of forest fire (Carter, 2010). There is a variety of existing land-cover and vegetation type classifications on the one hand and a various methods for estimation of the biomass condition on the other (such as NDVI and NDMI) that could serve as data for fuel risk estimation. Each of the applied models uses a different data for the fuel risk estimation – land-cover, NDVI and NDMI, but in all three the vegetation risk has the highest weight.

Land – cover – Corine - In 1985 the Corine programme was initiated in the European Union. Corine means 'coordination of information on the environment' and it was a prototype project working on many different environmental issues. The Corine databases and several of its programmes have been taken over by the EEA (European Environmental Agency). One of these is an inventory of land cover in 44 classes of the 3-level Corine nomenclature , and presented as a cartographic product, at a scale of 1:100 000.

There are 17 Corine land-cover types in the study area, which are matched to the 6 categories, used by Cáceres, 2011 in the model for the risk classification (Table 2).

Table 2: Corine land-cover - fire risk classification

Land-cover Corine classification	% of the total district area	Reclassification according Cáceres, 2011 risk model	Fire rating
Discontinuous Urban Fabric	1,18	Urban or Built-up Land	Low
Industrial or Commercial Units	0,15	Urban or Built-up Land	Low
Road and Rail networks	0,01	Urban or Built-up Land	Low
Mineral extraction sites	0,16	Urban or Built-up Land	Low
Sport and Leisure facilities	0,15	Urban or Built-up Land	Low
Non-irrigated arable land	0,46	Agricultural Land	Medium
Pastures	0,64	Rangeland (Scrub/ Shrubs)	Very high
Complex cultivation patterns	2,55	Agricultural Land	Medium
Land principally occupied by	9,89	Agricultural Land	Medium
Broad Leaved forest	14,09	Forest Land	High
Coniferous forest	35,60	Forest Land	High
Mixed forest	19,99	Forest Land	High
Natural grassland	4,44	Rangeland (Scrub/ Shrubs)	Very high
Transitional woodland scrub	9,94	Rangeland (Scrub/ Shrubs)	Very high
Bare rocks	0,05	Barren Land and Water	Very low
Sparsely vegetated areas	0,37	Barren Land and Water	Very low
Water bodies	0,35	Barren Land and Water	Very low

Complex cultivation patterns cover only 2,55 of the total area, but 11,6 % of the fires have taken place there. Land cover type- land principally occupied by agriculture with areas of nature is 10% of the total area and but 23% of the total fire events have happened there. (Figure 3)

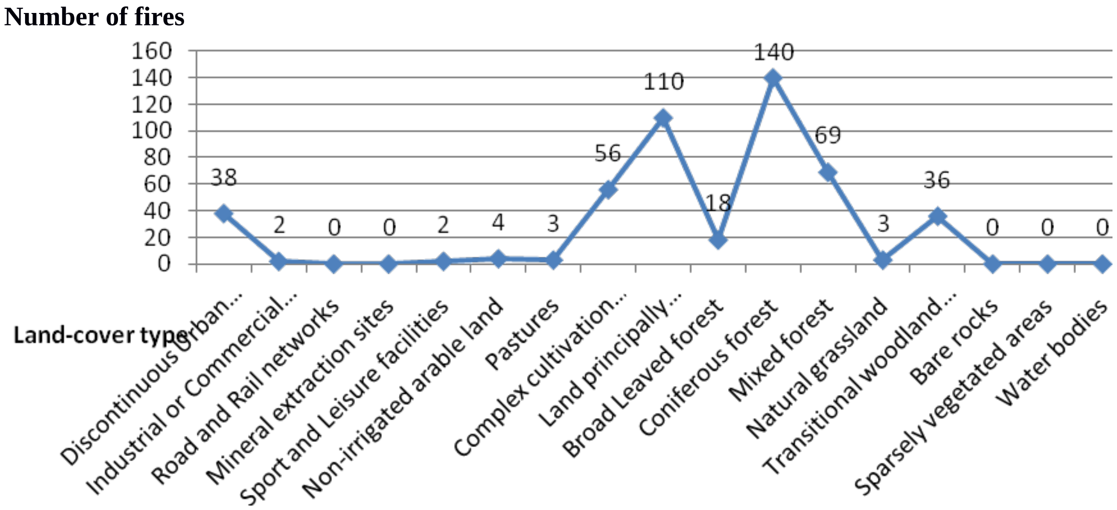

Figure 3. Relation between land-cover type and past fire events in the study area

NDVI - A Normalized Difference Vegetation Index is an equation that takes into account the amount of infrared reflected by plants. Live green plants absorb solar radiation, which they use as a source of energy in the process of photosynthesis. The reason NDVI is related to vegetation is that healthy vegetation reflects very well in the near-infrared part of the electromagnetic spectrum. The NDVI ratio is calculated by dividing the difference in the near-infrared (NIR) and red color bands by the sum of the NIR and red colors bands for each pixel in the image as follows:

$$NDVI = (NIR – R) / (NIR + R)$$

NDVI varies between -1.0 and +1.0. Negative values of NDVI (values approaching -1) correspond to deep water. Values close to zero (-0.1 to 0.1) generally correspond to barren areas of rock, sand, or snow. Low, positive values represent shrub and grassland (approximately 0.2 to 0.4), while high values indicate temperate and tropical rainforests (values approaching 1). The typical range is between about -0.1 (for a not very green area) to 0.6 (for a very green area) (Source: Villanova University). The majority of fires in the study area have occurred in territories with values of the index between 0,3-0,4, which means in grassland and shrub vegetation type (Figure 4)

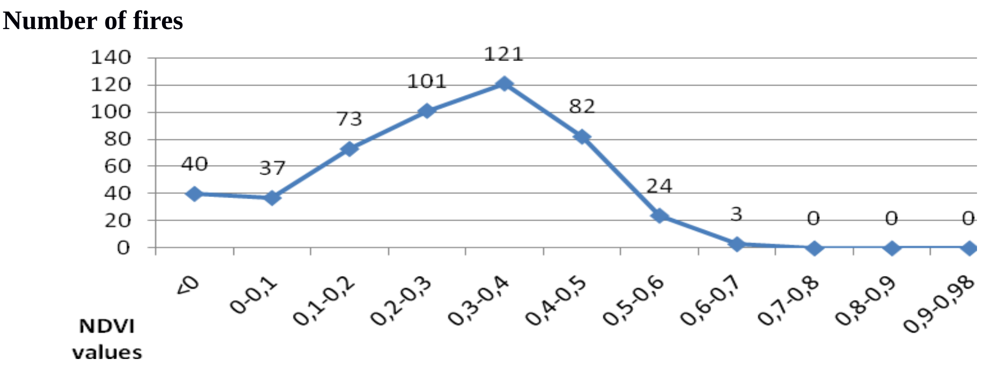

Figure 4. Relation between NDVI and past fire events in the study area

NDMI - The Normalized Difference Moisture Index is similar to NDVI and is commonly used to evaluate the moisture of the vegetation (Adab, et al., 2011). Dryness increases the flammability of the forest due to the fact that the moisture influences the spreading of the fire. (Hemmleb et al, 2006) The following equation defines it;

$$NDMI = (NIR - MIR) / (NIR + MIR)$$

Where; NIR is the near infrared spectral wavelength, and MIR is mid infrared spectral wavelength.

The statistics very clearly show how the number of fires in the study area is reducing with the increase of its values. (Figure 5)

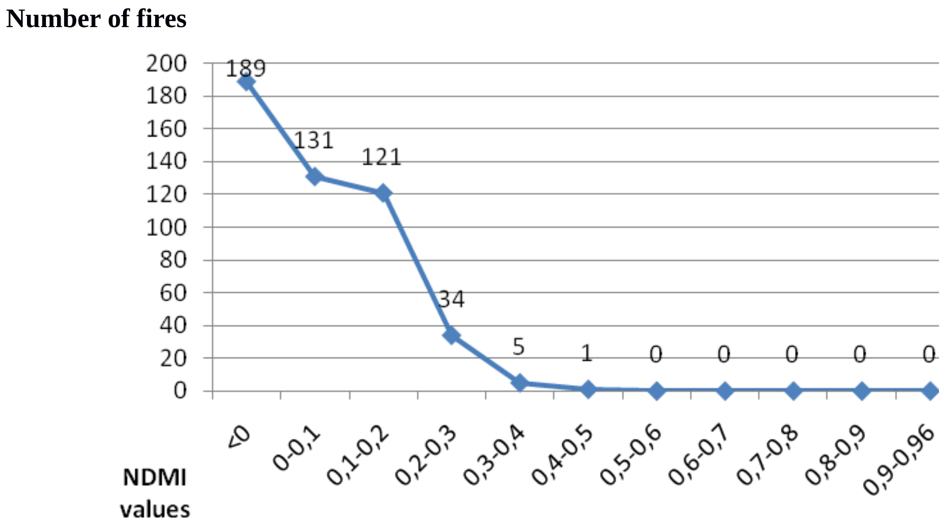

Figure 5. Relation between NDMI and past fire events in the study area

NDMI, used as data for estimating vegetation risk, has the best match with historical fires for the study area, compared to land cover and NDVI.

2.5.2. Elevation

There are contradictive classifications of fire risk, when elevation is concerned. Ozelkan, 2009 model suggests that higher altitudes are more prone to fire than lower altitudes. Cáceres, 2011 and Adab, 2011 models, on the contrary, estimate areas with lower altitudes as riskier. The statistics in the study area shows that 28% of the territory is below 1000m height but 50% of all fire events have occurred there. On the other hand 17% is above 1500m with only 1% of total fires (Figure 6).

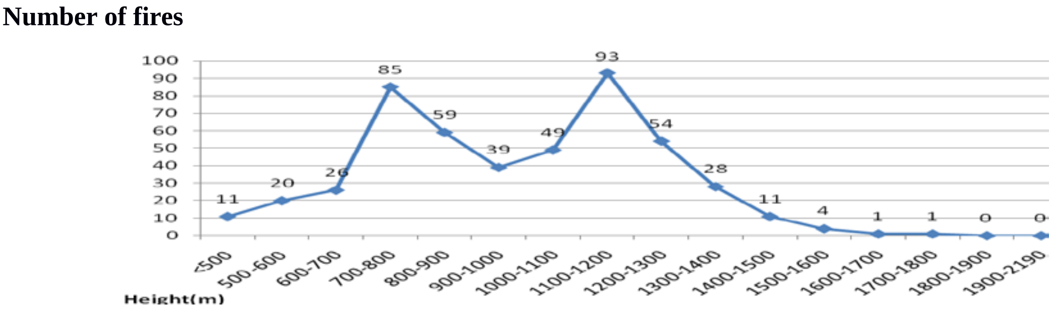

Figure 6. Relation between elevation and past fire events in the study area

Low altitudes mean more human activity, which is probably the main factor for more fires there. Elevation risk should be always estimated, according to the specifications of each particular territory. The risk classification of this variable in the Cáceres, 2011 and Adab, 2011 models are more related to historical fires, than the one suggested by Ozelkan,2009 model.

2.5.3. Slope

Slope is one of the factors, that does not influence that much the possibility of fire ignition, but the fire behavior and speed of spreading. Fire moves more quickly up slope and less quickly down slope (Adab et al. 2011). Also, in steeper slopes, rate of fire spread might rise, since flames are angled closer to the surface of ground and wind effects can supply the process of heat convection for the fire produced. All three models suggest similar slope risk classifications.

2.5.4. Aspect

South aspects receive more sun light and exposure in the North hemisphere. Because of that, drier soil is more capable to ignition. South aspect slopes have higher temperatures, robust winds, minor humidity and lower fuel moistures because Southern aspects receive more direct heat from the sun.(Adab et al. 2011) The statistics of historical fires confirms, that the number of fires on slopes with south, southwest and southeast aspect is higher than on other sites (Figure 7). All three models classify aspect risk in a similar way.

Number of fires

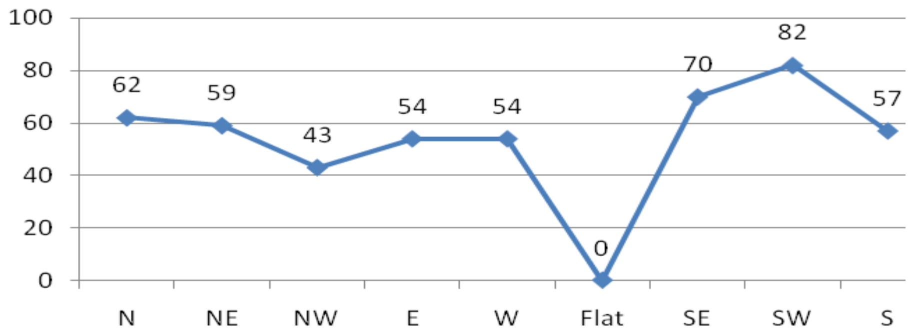

Figure 7. Relation between aspect and past fire events in the study area

2.5.5. Proximity to roads and settlements

The total length of the roads in the study area is 1400 km (according to data used from the project “The Study on Integrated Water Management in the Republic of Bulgaria”) and there are 243 settlements with a combined population of a little more than 120 thousand people (according to census 2011, published by the National Statistical Institute of Bulgaria). Human activities on roads provide opportunities for accidental / man-made fires. Forests in closer proximity to roads are therefore more prone to fire. People are known to carelessly throw burning matches and lit cigarette butts from their cars; such careless activities represent a substantial cause of man-made forest fires. Similarly forests within the urban-wildland interface are substantially more prone to incidences of fire. (Carter, 2010) The above stated facts are proven by the statistics, as there is a very strong relation between proximity to roads and settlements and fires in the study area (Figure 8 and Figure 9)

Number of fires

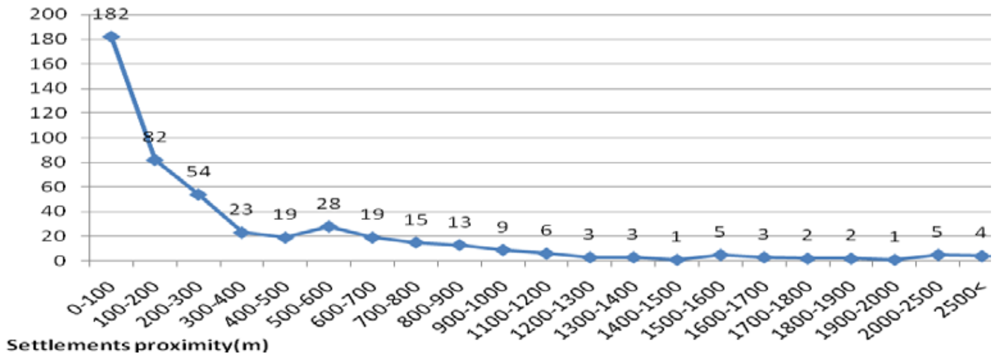

Figure 8. Relation between distance from settlements and past fire events in the study area

Number of fires

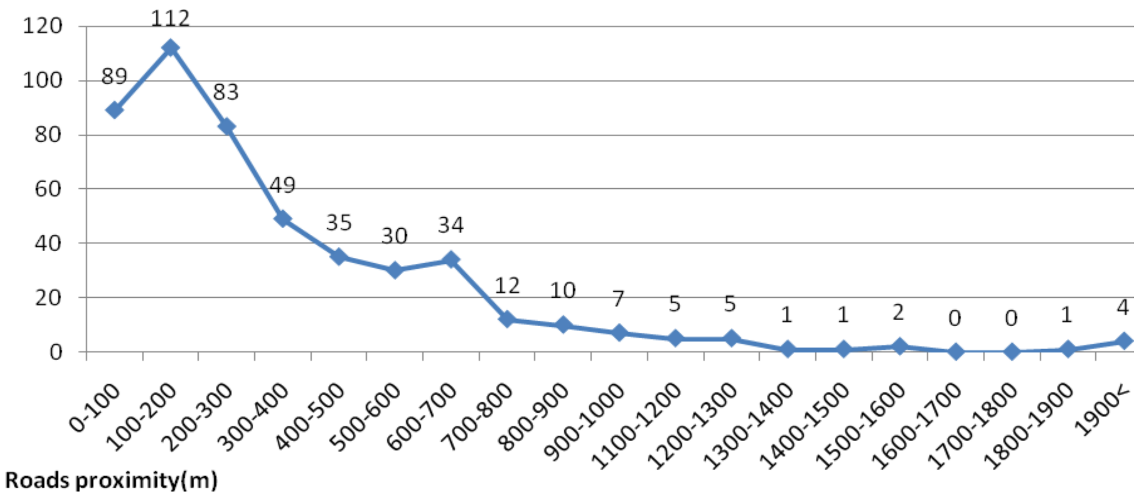

Figure 9. Relation between distance from roads and past fire events in the study area

The three models classify both proximity to roads and to settlements in a similar way. (Ozelkan, 2009 model doesn't include proximity to settlement in the equation)

2.6. Application of the models

Equations of the models:

FR Cáceres, 2011 = 1 + 100land cover + 30slope + 10aspect + 5roads + 5settlements + 2elevation

FR Ozelkan, 2009 = NDVI * 0,9 + slope * 0,7 + aspect * 0,8 + roads * 0,6 + elevation * 0,5

FR Adab, 2011 = **(**100NDMI + 50slope + 25aspect + 10 * (roads + settlements) + 5elevation) / 10

Each of the factors is reclassified and weighted according to Table 1 values for the 3 models and the factors are calculated according to the equation for each of the models. The final results are 3 calculated fire risks divided into 5 risk categories - very low, low, medium, high and very high. The results are presented in Figure 10, Figure 11 and Figure 12.

An example of how the risk categorizing is done is given for Adab, 2011 model. The variables in the equation are replaced with their highest and their lowest possible values. In the case of Adab, 2011 model highest risk value is 5 and lowest is 1 - consequently: (100x5+50x5+25x5+10x(5+5)+5x5)/10, which makes 100. The lowest possible value of the same equation would be equal to: (100x1+50x1+25x1+10x(1+1)+5x1)/10, which makes 20. The values between 100 and 20 are divided in 5 categories by equal intervals: 20 - 36 - very low risk, 36-52 - low risk, 52-68 - medium risk, 68 - 84 - high risk, 84-100 - very high risk. The same statistical approach is used for the other two models, according to the specific rating of hazards of each model.

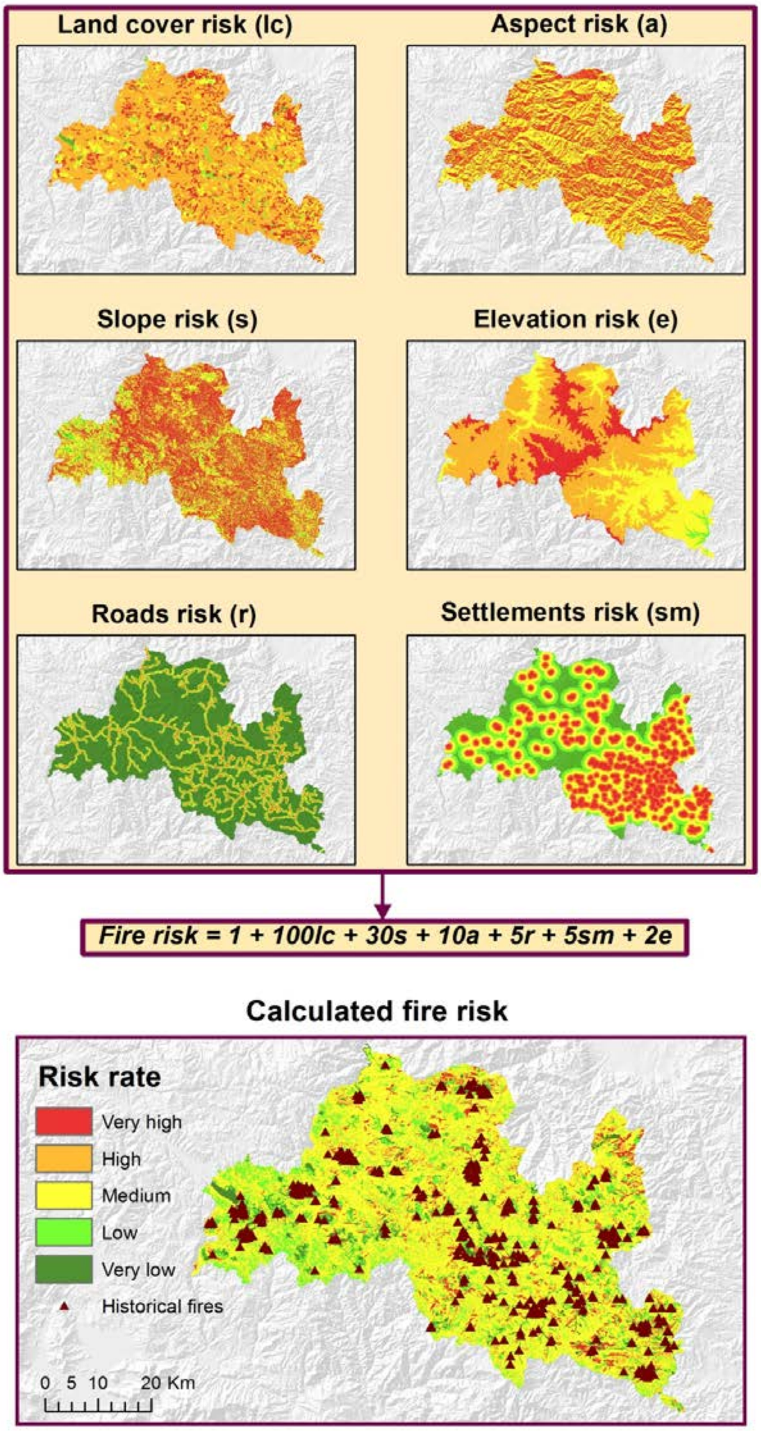

Figure 10. Cáceres,2011 fire risk model results

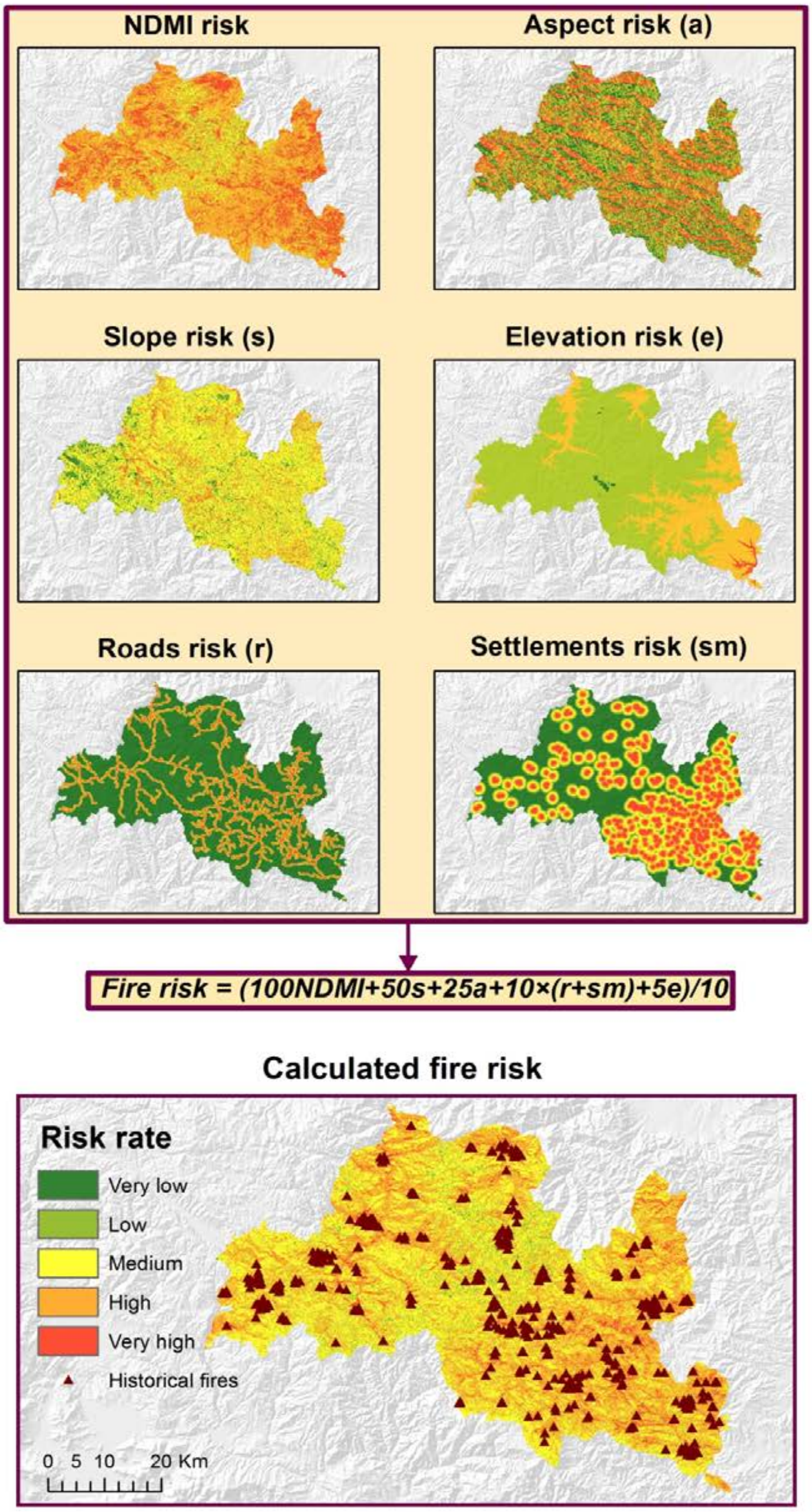

Figure 11. Ozelkan,2009 fire risk model results

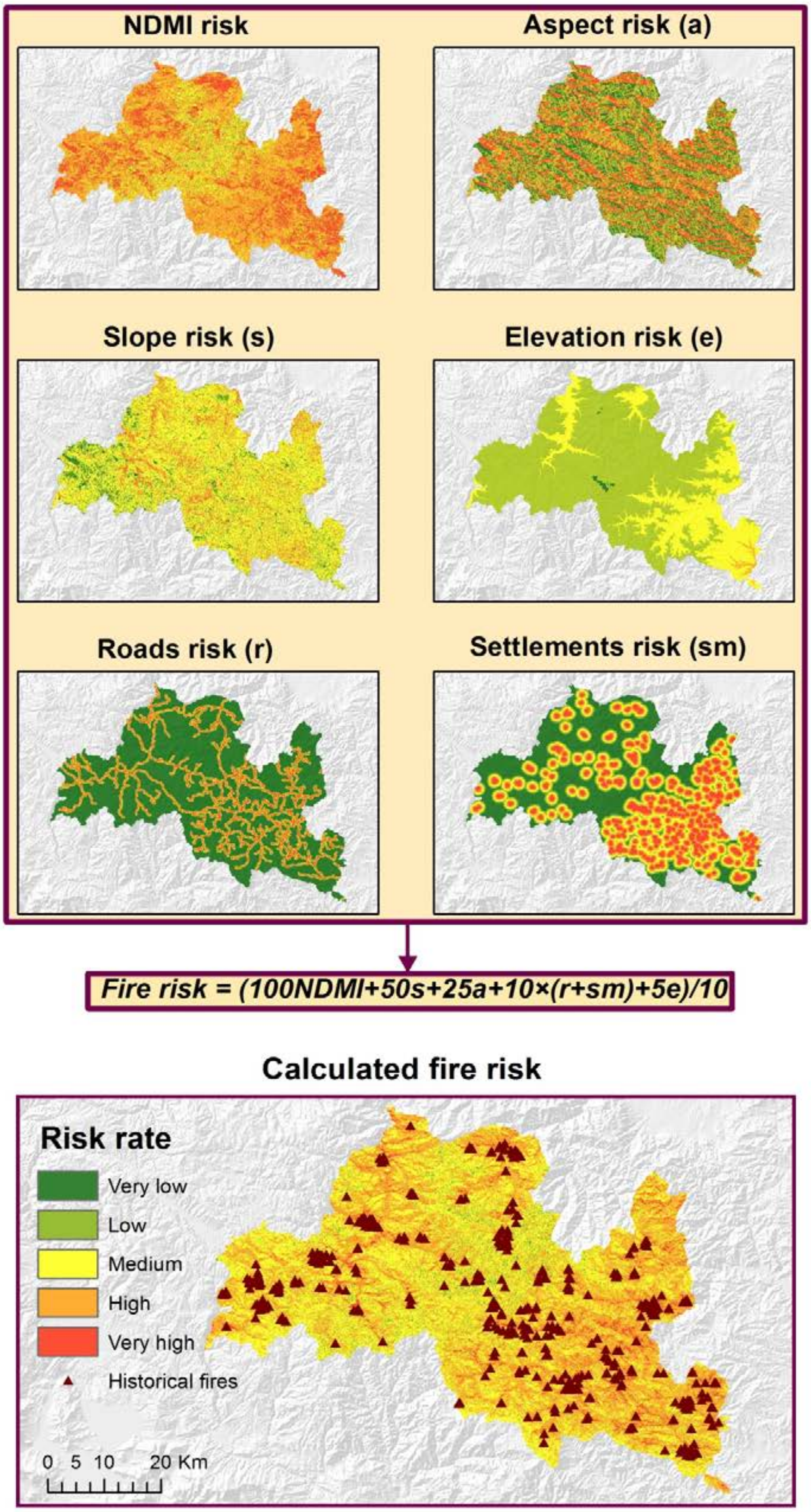

Figure 12. Adab,2011 fire risk model results

3. RESULTS AND CONCLUSIONS

The risk zones of the three models are compared with the historical fires data (Table 3)

Table 3. Risk zones and past fire events

Risk model	Risk zone	% of the total area	Number of fire events	% of total fire events
Cáceres, 2011	Very high	6,3	17	3,5
	High	20,9	16	3,3
	Medium	62,4	222	46,2
	Low	6,3	149	31
	Very low	4,1	77	16
Ozelkan, 2009	Very high	1,3	10	2,1
	High	25,3	182	37,9
	Medium	52,2	244	50,7
	Low	20,6	44	9,1
	Very low	0,6	1	0,2
Adab, 2011	Very high	5,3	66	13,7
	High	46,6	288	59,9
	Medium	43	118	24,5
	Low	4,9	8	1,7
	Very low	0,2	1	0,2

Cáceres, 2011 model estimates, that about 30% of the territory is in a high or a very high risk zone, but the number of past fire events in that zones is less than 7%. On the other hand only 10% of the territory is determined to be low or very low risk zone, but 47% of the fire events have occurred in that zones. The level of match between the model results and the fires in the particular area could be determined as poor. The reasons for the lack of relation between historical fires and high risk zones could be found in the following:

- The variable with the highest weight in the model (the land-cover) doesn't correspond to historical fires in the proposed classification. A higher risk for agricultural land should be embedded. These lands are often intentionally set on fire, which very often leads to an uncontrolled wildfire.
- The equation of the Cáceres, 2011 model gives a very low weight value to the distance to roads and settlements variables. The comparison between past fires and those two variables shows that they are strongly related.

The results of Ozelkan, 2009 model shows a better match degree. 26,6% of the territory is a zone with high or very high risk, where 40% if the fire events have occurred. 21,2 % is estimated to be a low or very low risk zone and less than 10% of the fire events are located in that zones. As a weakness of the model for the specific area could be considered the fact, that the elevation classification in the model (higher elevation – higher risk) contradicts to the actual fires altitude distribution.

Adab, 2011 model shows the best relation between risk zones and fires in the study area. Almost 75% of all historical fires are placed in high risk or very high risk zones. Less than 2% of past events are in estimated as low or very low risky zones. The classification of each variable shows a good relation to historical fires in Adab,2011 model. It could be concluded, that the model could serve as a very reliable source of information for wildfire prone zones identification for the study area. The model weights and variables could be further modified and adapted to even better fit the conditions of the particular environment.

GIS and remote sensing technologies have emerged as a significant tool for the developing of fire risk models. Their application in forest risk zones identification helps for a better understanding of wildfire behavior, likeliness of spreading over large areas and causing serious damages, which makes them a very useful approach for precautionary measures. Using historical fire data and taking into consideration the specific characteristics of a territory could serve as a method for an improvement of a model's accuracy, so as it could better suit the conditions in different areas.

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http://eea.government.bg/corine-land-cover/mapviewer.jsf?width=1059&height=498

Data from project „The Study on Integrated Water Management in the Republic of Bulgaria":http://www.wabd.bg/bg/index.php?option=com_content&task=view&id=437&Itemid=56

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