P-ISSN: 2305-6622; E-ISSN: 2306-3599

International Journal of

Agriculture and Biosciences

www.ijagbio.com; editor@ijagbio.com

Research Article

Application of GIS and Remote Sensing for Forest Fire Risk Mapping, Northwester of Algeria

Amina Abdelbaki*[1], Mohamed Bensahraoui[2] and Djamal SAIDI[3]

[1]Laboratory of Conservatory Management of Water, Soil and Forests. Department of Forest Resources, University of Tlemcen, Algeria; [2]Faculty of natural and life sciences, earth and universe sciences, Abou bakr Bel Kaid University, Pole 2 of the ring road, Mansoura, BP 13000. Tlemcen, Algeria; [3]Department of Agronomy, Hassiba Benbouali University, PB 78C Ouled Fares, 02180 Chlef, Algeria

***Corresponding author:** mnabdelbaki@gmail.com

Article History: 12309 Received: 02-Feb-21 Revised: 12-Jun-21 Accepted: 14-Jun-21

ABSTRACT

The coastal region of Chlef (northwester of Algeria) suffers from both forest fires and the lack of scientific research in the subject, so in an effort to remedy that, the choice came to Dahra's municipality for a GIS and Remote sensing-based study for mapping forest fire risk. The model used combines six wildfire-causing factors for demarcating the forest fire risk zone map. Use a multitude of software and rely on multiple sources for data collection, the following variables were derived for the study area: vegetation moisture, slope, aspect, elevation, distance from roads, and the vicinity of settlements in the form of weighted layers. The result of the established modelling is the map of the fire risk index, where 50.5 % of the study area represents a high to very high risk.

Key words: Forest Fire Risk, GIS, Remote sensing, map, northwester-Algeria.

INTRODUCTION

Forests are the main natural resources which have vital importance and a decisive role in maintaining ecosystems (Suryabhagavan *et al.*, 2016). The health of this latters, in any given area, is a true indicator of the ecological conditions, habitat composition and species richness prevailing in that area (Datiko and Bekele 2014). The Mediterranean is acknowledged as one of the most important ecosystems globally considering its outstanding plant diversity (Siachalou *et al*., 2009). Changes in forest cover affect the delivery of important ecosystem services, including biodiversity richness, climate regulation, carbon storage, and water supplies (Foley *et al*., 2005).

As one of the major natural disasters, wildfires often lead to ecosystem imbalance and local structural damages (Liu *et al.*, 2020). The forest fire feeds on all possible fuels and thus spreads until they are exhausted. They are triggered in areas of tree, shrub and herbaceous vegetation which spread over at least one hectare to be considered as such (Trabaud 1992). Forest fires not only destroy forest areas, but also cause damage to ecosystems, habitats and especially human lives (Sari 2021). The causes vary from country to country and are very difficult to identify with certainty. They also vary over time, anthropogenic influence remains the main cause of fires in the world, since, 90% of forest fires are linked to human activities whether by accident, agriculture, deforestation and arsonists (Alexandrian and Gouiran 1990).

However, the serious forest fires that have broken out in different parts of the world have had very negative consequences for the environment and have attracted international attention. The average annual number of wildfires in undeveloped areas throughout the Mediterranean basin has increased significantly in the past 50 years (Adaktylou *et al*., 2020). In Algeria, from 1985 to 2020, the total area burned was 1238772.62 ha (72461 fires), the average area per fire is 17.10 ha. According to Addadi (2020), the analysis of the forest fire report in the city of Chlef (Algeria) during the period (2009-2019) reveals a financial loss of 980772714 Algerian Dinars, caused by 1110 fires sweeping 6484 ha. The severity of those wildfire warrants a more reliable system of prediction so measures of prevention can be taken before it's too late.

Forest fires are a periodically recurring problem all around the world and due to this importance, spatial analysis of forest fires and detecting susceptibility zones is a necessity revealed to improve prevention and prediction

Cite This Article as: Abdelbaki A, Bensahraoui M and Saidi D, 2021. Application of GIS and remote sensing for forest fire risk mapping, northwester of Algeria. Int J Agri Biosci, 10(3): 164-169. www.ijagbio.com

procedures (Tian *et al.*, 2013). Effective planning is essential to the success of fire management programs in order to achieve the goals of fuel hazard reduction and fire regime restoration and maintenance (Keifer *et al*., 1999). The terms hazard and risk have been formally associated with fire management in the United States since the inception of modern fire science in the 1920s (Hardy 2005).

Generally, forest fire management contains four steps of analysis and assessment of effective response to fires, namely, mapping both potential fire hazard and risk, detecting hot spots, monitoring active fires and assessing postfire degradation (Roy 2003). Several environmental factors, including fuel load (vegetation cover), climate condition and physiography (elevation and slope), have major impacts over the creation, propagation and intensity of forest fires (Mohammadi *et al*., 2014). Many fire risk models have been developed based on environmental factors that influence wildfire, quoting (Dgorne *et al*., 1994; Alonso-Betanzos *et al*., 2002; Caetano *et al*., 2004; Erten *et al*., 2004; Adab *et al.,* 2011; Arfa 2019; Adaktylou *et al*., 2020).

This study knocks on a specific type of prediction based on geographical data assessment and remote sensing to establish an index mapping zones more prone to fires, with the aim of assisting decision makers in Dahra's municipality get the best result with infrastructure and manpower placement. This region was chosen as it is part of the costal line of Chlef (Algeria) which is gravely impacted by forest fires. The choice of the area was mainly taken for the lack of other scientific inquires in the region, especially when it comes to those forest fires even though they are an interesting part of the overall dynamic.

MATERIALS AND METHODS

Study Area

With a coastal line of 129.5 km, the coast of the city of Chlef totals 06 municipalities (Beni Houa, Oued Goussine, Ténès, Sidi Abderahmane, El Marsa and Dahra) out of the 35 in this city. Dahra's municipality, with an area of 240 km², is located at 90 km northwest of the city of Chlef, 298 km west of Algiers (Fig. 1). It is situated in the semi-arid bioclimatic floor with a warm winter (the average minimum temperature is 9.08 ° C), climate type is "W.A.Sp.S" (winter. autumn. spring. summer). The average annual rainfall is 481 mm, with temperatures often exceeding 31°C during the summer.

For the land use of Dahra, we note the dominance of agricultural land (56%), forests cover 18% of the total area, which open onto the Mediterranean Sea to the north. While the dense and clear maquis occupy only 15 and 04 % respectively. With an elevation range of 00 m to 780 m, the anaglyph of the region is usually smooth.

Methodology

This study mainly focuses on mapping forest fire risk areas, giving authorities something to base their infrastructure placement on, by highlighting zones corresponding to certain risk degrees. This mapping was done with previously established models that combine various criteria to get as accurate as possible. GIS modes were implemented, which required specific data to be inputted, data that had to be constructed and updated based on several supports then edited to allow the final overlay. In this study, GIS analysis were performed by using QGIS. The key steps of the procedure are illustrated in Fig. 2.

The model adopted is the Hybrid Fire Index "HFI" (Adab *et al.*, 2011), it deals to combine geospatial data by GIS technology to construct the fire risk index, it is based on six parameters. This model has the advantage of not requiring a lot of data, in particular for those relating to forest fires. Based on the literature in this field, this model is widely used and has a high level of consistency with reality, it is described by following equation:

$$HFI = (100 \times \boldsymbol{v} + 50 \times \boldsymbol{s} + 25 \times \boldsymbol{a} + 10 \times (\boldsymbol{r} + \boldsymbol{c}) + 5 \times \boldsymbol{e})/10$$

Where, ***v***: vegetation moisture, topographic factors (***s***: slope, a: aspect and ***e***: indicate elevation), anthropogenic factors (***r***: distance from road and ***c***: distance from settlement). Those parameters were weighted based on their impact on the fire risk:

Vegetation moisture (A): Dryness is one of the most critical parameters in fire risk because it increases the flammability of the land. In order to assess the moisture of the vegetation the Normalized Difference Moisture Index (NDMI) is commonly used (Wilson and Sader 2002; Hemmleb *et al*., 2006; Sader *et al*., 2003; Jin and Sader 2005; Siachalou *et al*., 2009). By combining the strong absorption of SWIR radiation by thin layers of canopy and soil water with the high reflectance of NIR radiation by healthy green vegetation, the NDMI index highlights regions of healthy green vegetation with high moisture content. The following equation accurately describes it:

$$NDMI = \frac{(NIR - SWIR)}{(NIR + SWIR)}$$

The Landsat satellite images were downloaded from "Earth explorer" web site, for the study area from summer 2020 and then used in conjunction with the raster calculator tool on QGIS software to create the NDMI as control layer for the vegetation component of the index (Table 1). The risk classification is indicated in Fig. 3A.

Topographic factors: Topographic parameters are one of the most causative and decisive factors both before and during forest fires (Sari, 2021), which are related to wind behavior and hence, affects the fire proneness of the area (Jaiswal *et al*., 2002).

For the study area, to cover the entire surface of Dahra's municipality, four topographic maps at a scale of 1/25 000 were used, the contour lines were digitized, with 10 m intervals, to create a Digital Elevation Model (DEM).

Slope (B): According to several studies, slope is a significant factor in fire propagation (Weise, 1993; Jaiswal *et al*., 2002; Erten *et al*., 2004; Viegas 2005; Butler *et al*., 2007; Siachalou *et al*., 2009; Karabulut *et al*., 2013), it has a decisive role in forest fires, in terms of both the direction of fire spread and fire rate due to preheating and ignition. Considering the spread of fires, it seems to move faster through uphill (Rothermel 1983; Kushla and Ripple 1997; Sari 2021). At this point, the DEM was then used to construct the slope map, it was reclassified into five categories (Table 2): gentle (<5 %), low (5-15 %), medium (15-25 %), high (25-35 %), and steep (>35 %). The intensity at which a fire spreads increases as the ground slope rises, resulting in a high fire risk.

Fig. 1: Geographical location of the Dahra's municipality.

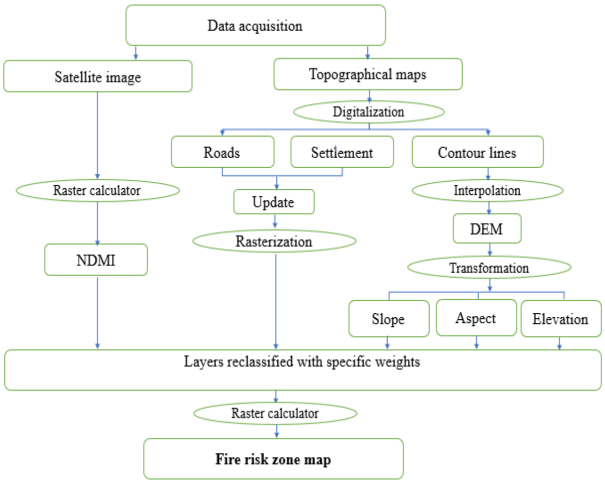

Fig. 2: Organizational chart of the key steps.

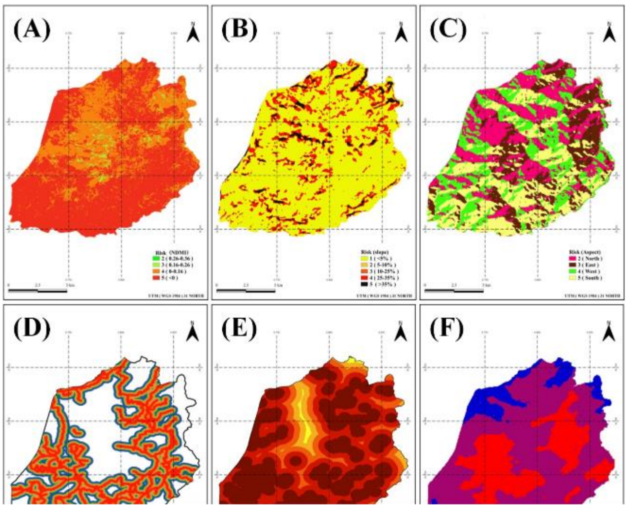

Fig. 3: The map parameters classification: A) Risk rating of the NDMI; B) Risk rating of the slope; C) Risk rating of the aspect; D) Risk rating of the proximity to roads; E) Risk rating of the vicinity to settlements; F) Risk rating of the elevation.

Aspect (C): Another important component is the aspect, south facing slopes have greater sun exposure in the north hemisphere, resulting in drier soil that is more receptive to ignition (Noon 2003). This factor is related to the sunlight and consequently to the temperature and humidity.

Table 1: Weight of vegetation moisture in determining the fire risk.

Parameter	Classes	Ratings of hazard	Weight	Fire sensitivity
NDMI	> 0,36	1	100	Very Low
	0,26 - 0,36	2		Low
	0,16 - 0,26	3		Medium
	0 - 0,16	4		High
	< 0	5		Very High

Table 2: Topographic factors and their weight in determining the fire risk.

Parameters	Classes	Ratings of hazard	Weight	Fire sensitivity
Slope	< 5%	1	50	Very Low
	10 - 5%	2		Low
	25 - 10%	3		Medium
	35 - 25%	4		High
	> 35%	5		Very High
Aspect	North	2	25	Low
	East	3		Medium
	West	4		High
	South	5		Very High
Elevation	> 2000	1	5	Very Low
	1000 - 2000	2		Low
	500 - 1000	3		Medium
	200 - 500	4		High
	< 200	5		Very High

Northern faces of the forests receive less sunlight than southern faces. Similarly, eastern faces of the forests receive sunlight earlier than western faces. Thus, southern faces are more susceptible to forest fires due to the longest exposure time to sunlight and as a result, vegetation and soil on southern faces tend to dry earlier than on other faces (Jose 2012; Sari 2021). For this parameter, DEM that was trained for the study area was used, it was reclassified into four categories, for 4 geographic directions (at 90° intervals) such as: north (315°- 45°), east (45°- 135°), south (135°-225°) and west (225° - 315°) (Table 2).

Elevation (F): Elevation is related to wind behavior, climatic conditions such as low humidity, high temperature, and availability of dry organic matter which increases the ignition risk and fire proneness (Rothermel 1983; Suryabhagavan *et al.*, 2016; Sari 2021). Since temperature has a constant lapse rate and oxygen levels are reduced with height, elevation and the fire occurrence are inversely related (Adaktylou *et al.*, 2020).

For the study area, the DEM was used for elevation values and was reclassified in five classes (Table 2). Forest fires are less common at higher elevations due to climatic conditions, so weightage is allocated accordingly, for elevations less than 200 m, a maximum weight of 5 is given. The risk rating of topographic factors is illustrated in figures "3B, 3C and 3F".

Anthropogenic factors: Fire incidence is highest in places where a large number of individuals and cars travel on a regular basis (Rogan and Miller 2006), Previous studies indicated that the fire risk increases as the roads and settlements get closer to the forest areas due to human factors (Jaiswal *et al.*, 2002; Sivrikaya *et al.*, 2014; Akay and Şahin 2019).

Distance from roads (D) and Vicinity of settlements (E): Based on the topographic maps, data layers reflecting the road network and settlements were created. An update of the two vector layers was essential via “SAS.Planet” web site, by downloading a coverage of Dahra’s municipality at 0.96 m of resolution. The use of this coverage under GIS and the digitalization of the two layers in the current state allowed us to have more complete data for these two parameters. In order to assign forest fire risk limits for the forest areas depending on their proximity to roads and settlements, the “Buffer” utility in QGIS was used to establish buffer zones around these elements. The highest weightage was assigned to the areas closest to settlements and roads during the process of assigning weights to the distance class (buffer).

Based on relevant literature, for roads, the buffer zones are 100 m, 200 m, 300 m, and 400 m, using the raster converter tool of QGIS too. To investigate the impact of settlement factor on forest fire vulnerability, buffer zones were established at 500 m intervals from the study area's settlements (Table 3). The Fig. 3D and 3E demonstrates the risk rating of anthropogenic factors.

RESULTS AND DISCUSSION

According to DEM's slope map, it was observed that 22 % of the study area was on steep slope, while 64 % was on high slope class. For the aspect map of Dahra’s municipality, results indicated that 31.3% of the study area was located on north aspect, followed by west aspect (18.8%) and east aspect trailing closely behind (13.7 %). The proportion of south-facing aspects was 36.2%, which has higher fire risk due to high temperature and low humidity. For elevation, 15.8% of the study area is located between 0 and 200 m, 56.3% (200-500 m) and 27.9% between 500 et 780 m, respectively.

According to the findings, 33.4 % of the research area was within 100 m of road networks, while 39.3 % was more than 400 m distant.

In terms of proximity to settlements, the majority of the forest area (41.7%) was located more than 500 and 1000 m away from the settlements, only 07.9 % and 03.4 % of the forest area was within 1500 m and 2000 m distance from the settlements, respectively.

Previous studies indicated that the fire risk increases as the roads and settlements get closer to the forest areas due to human factors (Jaiswal *et al.*, 2002; Sivrikaya *et al.*, 2014; Akay and Şahin 2019).

The models range of output goes from 22.5 (very low risk) to 100 (very high risk) when all the parameters in the equation are inputted with the extreme values (1 or 5), as it is shown in Table 4. Based on the model formula and the values of each pixel in the area of interest on the different input layers, the resulting index has values ranging from 40 to 100, indicating three rating of fire risk (40-60) with medium risk, (60-80) with high risk and (80-100) with very high risk. The fire risk is more focused in the south relative to the north, in the north of the Dahra’s municipality, the coastal line is more prone to fires. The center displays the most of the very low risk area (Fig. 4). The very low risk zone occupies 43 % of the total area (corresponding with 103 km²), result of the absence of both the road network and any near settlements, a low elevation and a flatness of the terrain accompanied by high values of NDMI. The medium risk spreading over 6.5% of the study area

Table 3: Anthropogenic factors and their weight in determining the fire risk.

Parameters	Classes	Ratings of hazard	Weight	Fire sensitivity
Distance from roads	> 400	1	10	Very Low
	300 - 400	2		Low
	200 - 300	3		Medium
	100 - 200	4		High
	< 100 m	5		Very High
Distance from settlements	> 2000	1		Very Low
	1500 - 2000	2		Low
	1000 - 1500	3		Medium
	500 - 1000	4		High
	< 500 m	5		Very High

Table 4: The definition of risk level

v	*s*	*a*	*r*	*c*	*e*	Risk index	Rating of hazard
1	1	2	1	1	1	22.5	Very low
2	2	2	2	2	2	40	Low
3	3	3	3	3	3	60	Medium
4	4	4	4	4	4	80	High
5	5	5	5	5	5	100	Very high

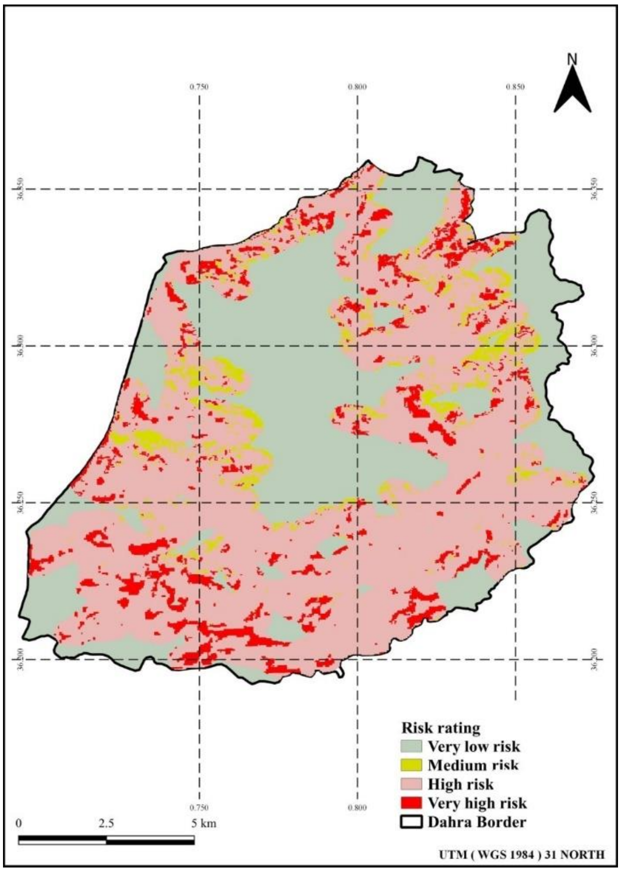

Fig. 4: The fire risk zone map.

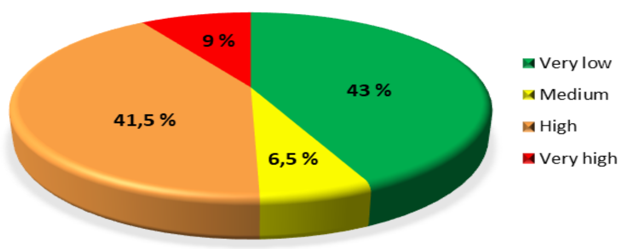

Fig. 5: The risk rating percentage.

(translating to 15.77 km²), where 50.5 % of the study area represents a high to very high risk (121.24 km^2) (Fig. 5). Based on the findings of the research, a series of management decisions can be taken concerning infrastructure installation and manpower distribution favoring zones with higher risk:

- Water points can be established to facilitate the provisioning in water during the fires;
- Surveillance towers can be located according to higher risk rating making the process all the more efficient;
- Trails and tracks providing accessibility to areas most endangered by the fire;
- Reinforcing active efforts such as patrols.

The human factor is a major one in forest fire, both starting it and helping it propagation, to limit the involuntary fires caused by ignorance local authorities can focus on more public awareness campaigns insisting on the notion of risk and showing interactive maps and charts.

Conclusion

In the Dahra's municipality, the fire risk reflects both the probability of ignition and the risk of spreading. In the current model, the slope, aspect, and elevation variables, which affect the probability of spreading, increase the fire risk. The model illustrates the crucial fact that even if a forest form has a low risk weighting, the likelihood of a forest fire occurring is still high.

The study area represents a high proneness to forest fires (50.5 %) due to its slopy terrain and vegetation moisture levels as well as the high elevations, the south facing aspects and the proximity to roads and urban areas making it so that the risk index highlighted most of the municipality's territory as potential hot spots with significant risk ratings, concentrated around the road network as well as urban agglomerations.

From a management point of view, the fire fighting and prevention infrastructures should focus on the locations with higher risk, providing accessibility for first responders, water points for quick refills and surveillance towers for earlier detection of forest fires.

REFERENCES

Adab H, DK Kanniah and K Solaimani, 2011. GIS-based probability assessment of fire risk in grassland and forested landscapes of Golestan Province, Iran. In: International conference on environmental and computer science, IPCBEE V 19, IACSIT Press Singapore, pp: 170-175.

Adaktylou N, D Stratoulias and R Landenberger, 2020. Wildfire Risk Assessment Based on Geospatial Open Data: Application on Chios, Greece. ISPRS. International Journal of Geo-Information, 9, 516, 19p.

Addadi M, 2020. « Analyse des incendies de forêts de la Wilaya de Chlef ». Master's degree memoir. Chlef Universty. Algeria. 64p.

Alexandrian D and M Gouiran, 1990. Les causes d'incendies: levons le voile. Revue forestière française numéro spécial (Espaces forestiers et incendies), 42: 33-41.

Akay AE and H Şahin, 2019. Forest Fire Risk Mapping by using GIS Techniques and AHP Method: A Case Study in Bodrum (Turkey). Eur J Forest Eng 2019, 5: 25-35.

Alonso-Betanzos A, O Fontenla-Romero, B Guijarro-Berdinas, E Hernandez-Pereira, J Canda, E Jimenez, JL Legido, S Muniz, C Paz-Andrade and MI Paz-Andrade, 2002. A neural network approach for forestal fire risk estimation. 15th European conference on artificial intelligence. ECAI, pp: 643-647.

Arfa AMT, 2019. Application du SIG et de la télédétection pour un outil cartographique d'aide à la gestion des feux de forêts dans la wilaya d'El Taref. Doctorat Thesis. Constantine Universty, Algeria. 230 p.

Butler BW, WR Anderson and EA Catchpole, 2007. Influence of slope on fire spread rate, Conference proceedings of the fire environment--innovations, management, and policy, U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, pp: 75-82.

Caetano MR, S Freire and H Carrão, 2004. Fire risk mapping by integration of dynamic and structural variables. Remote Sensing in Transition 1: 319-326.

Datiko D and A Bekele, 2014. Habitat association and distribution of rodents and insectivores in Chebera Churchura National Park, Ethiopia. Tropical Ecology, 55: 221-229.

Dgorne A, Y Duché, JM Castex and JY Ottavi, 1994. Protection des forêts contre l'incendie et système d'information géographique. Forêts méditerranéennes, 15: 422-425.

Erten E, V Kurgun and N Musaoglu, 2004. Forest fire risk zone mapping from satellite imagery and GIS: a case study. XXth Congress of the International Society for Photogrammetry and Remote Sensing, Istanbul, Turkey, pp: 222-230.

Foley JA, R DeFries, GP Asner, C Barford, G Bonan, SR Carpenter, FS Chapin, MT Coe, GC Daily, HK Gibbs, JH Helkowski, T Holloway, EA Howard, CJ Kucharik, C Monfreda, JA Patz, IC Prentice, N Ramankutty and PK Snyder, 2005. Global Consequences of Land Use. Science, 309 (5734): 570-574.

Hardy CC, 2005. Wild land fire hazard and risk: problems, definitions, and context. Forest ecology and management, 211(1-2): 73-82.

Hemmleb M, F Weritz, A Schiemenz, A Grote and C Maierhofer, 2006. Multi spectral data acquisition and processing techniques for damage detection on building surfaces, Image Engineering and Vision Metrology, ISPRS, Dresden, Germany.

Jaiswal RK, S Mukherjee, KD Raju and R Saxena, 2002. Forest fire risk zone mapping from satellite imagery and GIS. International Journal of Applied Earth Observation and Geoinformation 4: 1-10.

Jin S and SA Sader, 2005. Comparison of time series tasselled cap wetness and the normalized difference moisture index in detecting forest disturbances, Remote Sensing of Environment, vol. 94, issue 3, pp: 364-372.

Jose KS, 2012. Geospatial characterization and conservation potential for Agasthyamala Biosphere Reserve, Western ghats, India. Phd thesis in School of Environmental Sciences. Mahatma Gandhi University.

Karabulut M, A Karakoç, M Gürbüz and Y Kızılelma, 2013. Determination of forest fire risk areas using geographical information systems in Başkonuş Mountaın (Kahramanmaraş). J Int Soc Res 6(24): 171–179.

Keifer M, A Caprio, P Lineback and K Folger, 1999. Incorporating a GIS model of ecological need into fire management planning. Joint Fire Sciences Conference and Workshop, Boise June 15-17, 1999; University of Idaho, Moscow.

Kushla JD and WJ Ripple, 1997. The role of terrain in a fire mosaic of a temperate coniferous forest. Forest Ecology and Management, 9.5: 97- 107.

Liu S, Y Zheng, M Dalponte and X Tong, 2020. A novel fire index-based burned area change detection approach using Landsat-8 OLI data. European Journal of Remote Sensing, 53: 104-112.

Mohammadi F, MP Bavaghar and N Shabanian, 2014. Forest fire risk zone modeling using logistic regression and GIS: an Iranian case study. Small-scale Forestry, 13: 117-125.

Noon EK, 2003. A Coupled Model Approach for Assessing Fire Hazard at Point Reyes National Seashore: FlamMap and GIS', Proceedings of 2nd International Wildland Fire Ecology and Fire Management Congress, Coronado Springs Resort, Orlando, Florida.

Rogan J and J Miller, 2006. Integrating GIS and remotely sensed data for mapping forest disturbance and change, in M. Wulder and S. Franklin (ed), Understanding Forest Disturbance and Spatial Pattern: Remote Sensing and GIS Approaches, CRC Press, Taylor & Francis, pp: 133-143.

Rothermel RC, 1983. How to predict the spread and intensity of forest and range fires. USDA Forest Service Intermountain Forest and Range Experiment Station General Technical Report INT-143.Ogden, UT.

Roy PS, 2003. Forest fire and degradation assessment using satellite remote sensing and geographic information system. Satellite Remote sensing and GIS applications in agricultural meteorology, pp: 361-400.

Sader SA, M Bertrand and EH Wilson, 2003. Satellite Change Detection of Forest Harvest Patterns on an Industrial Forest Landscape, Forest Science, vol. 49, no. 3, pp: 341-353.

Sari F, 2021. Forest fire susceptibility mapping via multi-criteria decision analysis techniques for Mugla, Turkey: A comparative analysis of VIKOR and TOPSIS. Forest Ecology and Management 480 (2021) 118644. 16p.

Siachalou S, G Doxani and M Tsakiri-Strati, 2009. Integrating remote sensing processing and GIS to fire risk zone mapping: a case study for the Seih-Sou forest of Thessaloniki. 11p. https://www.researchgate.net/publication/228399593

Sivrikaya F, B Sağlam, AE Akay and B Nuri, 2014. Evaluation of Forest Fire Risk with GIS. Pol. J. Environ. Stud. 23: 187-194

Suryabhagavan KV, M Alemu and M Balakrishnan, 2016. GIS-based multi-criteria decision analysis for forest fire susceptibility mapping: a case study in Harenna forest, southwestern Ethiopia. Trop Ecol, 57: 33–43.

Tian X, F Zhao, L Shu and M Wang, 2013. Distribution characteristics and the influence factors of forest fires in China. Forest Ecol Manag, 310: 460–467.

Trabaud L, 1992. Community dynamics after fire disturbance: short-term change and long-term stability. Ekistics 59: 287-292.

Viegas DX, 2005. A mathematical model for forest fires blowup, Combustion science and technology, vol. 177, no. 1, pp: 27-51.

Wilson EH and SA Sader, 2002. Detection of forest harvest type using multiple dates of Landsat TM imagery, Remote Sensing of Environment, vol. 80, no. 3, pp: 385-396.

Weise DR, 1993. Modelling wind and slope-induced wildland fire behavior, PhD thesis, University of California at Berkeley, Berkeley.