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Towards an establishment of a wildfire risk system in a Mediterranean country

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ABSTRACT

Wildfire is one of many natural hazards affecting the Mediterranean basin; its consequences could be fatal for individuals and beyond repair for the environment. While factors worldwide included in a fire ignition are unstandardized, in this paper, we built a model from literature-cited factors – fourteen elements were included – to highlight the probability of wildfires' occurrence in the Lebanese forest. It was named Three-Type Model (TTM), where forests were classified into three types: pine, oak and mixed. Validations have been conducted by using thirty percent of datasets versus the other seventy percent; then, by comparing its accuracy to another model that study the forest as one unit only. Accuracy assessment of the model reached above 83%, and it could be portable to other Mediterranean-climate forests.

In addition, we produced a wildfire risk map by combining fire ignition-related factors with vulnerability-related variables. Results show that 15.9% of the Lebanese regions and 43.46% of the total amount of wildfires are human-induced wildfires. The majority of human-induced wildfires exists in a medium to high wildfire-ignition probabilities classes and in oak forests, representing approximately 93 and 83% of these wildfires, respectively. We concluded as well that only 1.6% of the Lebanese forest is at high risk of wildfire ignition. The implementation of our methodology in different Mediterranean countries is easy and straightforward, mainly because of the reduction of the ignition parameters as well as the usage of remote sensing datasets. It shall help decision-makers and official authorities in preventing, pre-suppressing and battling this phenomenon.

1. Introduction

Wildfires may be a natural phenomenon; however, it often occurs coupled with many negative impacts on human safety, health, regional economies and global climate change. The environmental effects of wildfires, including erosion, landslides, introduction of invasive species, and changes in water quality, are often more disastrous than the fire itself (USGS, 2006).

Mediterranean countries, including Lebanon, are always at high risk of fire. Pausas et al. (2008), for instance, has discussed the possible effects of this phenomenon in the region. Several authors have discussed the short-term effect of wildfires (Arcenegui et al., 2008; Hernández et al., 1997; Naveh, 1974; Piñol et al., 2005). Others have evaluated the physical changes such as soil erosion (Andreu et al., 2001; Inbar et al., 1997; Pardini et al., 2004; Shakesby, 2011) and hydrological response (Doerr et al., 2006; Lavabre, 1993; Mayor et al., 2007; Shakesby et al., 1993) in post wildfires. And numerous studies have modeled the propagation of wildfires (Moreira and Russo, 2007; Morvan and Dupuy, 2004; Pennington, 2007; Soto et al., 2013; Wilson et al., 2010).

In the literature, there is some ambiguity between "hazard", "vulnerability" and "risk" terms (Bentz et al., 1993; Hardy, 2005; Mhawej et al., 2015). By risk, political ecologists mean the compound function of biophysical hazard exposure and peoples' vulnerability, i.e., their ability to anticipate, respond to, and recover from a hazard event (Collins, 2008; Wisner et al., 2004). Vulnerability is then the consequences of a natural phenomenon, of given intensity, on a subject (Brugnot, 2013; Lollino et al., 2014). Then, the same phenomenon could have different vulnerabilities based on the studied subject. As a relational term, vulnerability refers to the combination of factors that influence the degree to which someone's life, livelihood, property, or assets are put at risk by the occurrence of a hazard event (Wisner et al., 2004). On the other hand, hazard is the probability of occurrence of a potentially damaging phenomenon, in one place, and at a certain time (ADPC, 2008; Griffiths, 2001; Marinos, 1997). It could be divided as well into two subcategories: number of occurrence and intensity.

Several studies have been conducted to detect or minimize the wildfire hazard, both on the scale of the Mediterranean basin (Chuvieco and Congalton, 1989; Kalabokidis et al., 2013; Moreira et al., 2009; Piñol

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et al., 1998) and locally (Faour et al., 2006a, b; Karouni et al., 2014a, b; Sakr et al., 2011). An assessment of the wildfire risk has been conducted as well (Baeza et al., 2002; Kaloudis et al., 2008; Millington et al., 2008; Mitri et al., 2015). The usage of remote sensing techniques has become a vital tool in those assessments. These techniques provide full coverage of the studied area, both temporally and spatially, with reduction of personal and costs. In this context, numerous wildfire risk studies were based on the Geographic Information System (Arroyo et al., 2008; Chuvieco, 2012; Chuvieco and Congalton, 1989; Díaz-Delgado et al., 2002; Koutsias and Karteris, 2003; Malak and Pausas, 2006; Ruiz-Gallardo et al., 2004). However, previous studies are missing the comprehensive list of factors affecting the forest fire ignition. In each research, factors used are questionable because they were selected based purely on the authors' knowledge and experiences. Furthermore, several authors (e.g. Faour et al., 2006a, b; Masri, 2005; Stone et al., 2010) noticed the lack of standard driving forces used in wildfire risk studies.

In this paper, we focused on two objectives: the first was to build a wildfire hazard model, by using a literature-based, comprehensive list of ignition-related factors; this model shall assist future creation of wildfire hazard maps, within the Mediterranean-climate forests, even when historical wildfires datasets were missing. In addition, using a reduced set of parameters results in an efficient and reduced-cost prediction system, especially for developing countries; the second was the creation of the wildfire risk map for the Lebanese forests, with a spatial resolution of 1 km, to visualize and assess the actual condition of the wildfire's risk. It has been produced by the combination of hazard and vulnerability maps. Actually, datasets of factors used in these maps, dating from 1980 to 2014, were collected from satellite imageries and ground measurements. Ultimately, the wildfire risk map allows fire managers to implement fire prevention initiatives and plan for potential fires, thus contributing to the development of sustainable forest management plans.

2. Study area

Lebanon is localized on the eastern shore of the Middle East Basin. With an area of 10,452 km2, almost 20% of its total area is covered by forest (Fig. 1). Nearly 13% (i.e. 282 km2) of it is a habitat to pine trees. Over its half contains oak trees (i.e. 1077 km2). The rest is occupied by different type of trees and covering 778 km2 or 36% of the total forest area. In fact, the Lebanese forest is characterized by high vegetation biodiversity (i.e. 2500 species, including 92 endemic plants) (Faour et al., 2006a). It is considered a national heritage, a fascinating landscape, and a recreation zone.

In Lebanon, most forest fires occur between June and October with a maximum frequency in August and September, 25% and 27 of fires percent, respectively (Faour et al., 2006b). The burned areas can be subject to intense rainfall, which may increase the problem of water erosion

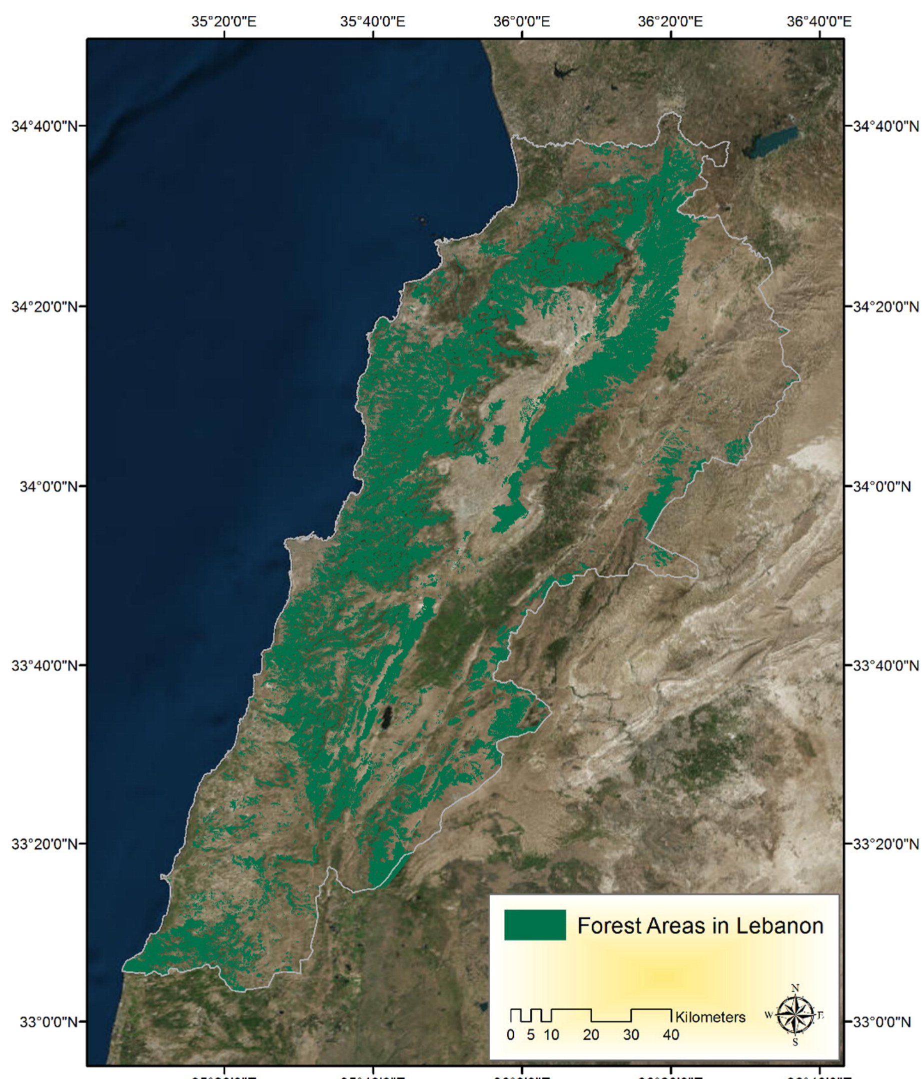

Fig. 1. Location of the Lebanese Forests.

(Bou Kheir et al., 2001). Annual timber losses could reach 20,000 USD/ha in the pine forests (Masri, 2005). Even with this alarming situation, there is a lack of an updated national wildfire risk map, which is essential for effective prevention of wildfires and pre-suppression actions (Faour et al., 2006b).

3. Materials and methods

3.1. Ignition-related factors

Based on a literature review, we have selected twenty eight factors that are potentially relevant for fire ignition; they were classified into five different categories (i.e. climatic, topographic, in-situ, historical and anthropogenic factors) and were presented in Mhawej et al. (2015). Only fourteen factors could be used in Lebanon due to the lack of appropriate data (Table 1). Most factors are based on remote sensing imageries.

Though lightning activity is essential for ignition, the presence of precipitation and humid air near the surface will augment the fuel moisture content (Hall, 2007), thus reducing the effect of lightning on wildfires' occurrence. In general, lightning-caused ignitions were associated with fuels and climatic and topographic factors (Díaz-Avalos et al., 2001; Narayanaraj and Wimberly, 2012), which are already included in the ignition-related factors (Table 1).

3.1.1. Climatic data

Precipitation data (i.e. TRMM2B31), from 1998 to 2009, were downloaded online at http://www.geog.ucsb.edu/~bodo/TRMM/TRMM. "TRMM" is the abbreviation of the Tropical Rainfall Measuring Mission, "2B31" is the degree of processing. In fact, the product was initially with a spatial resolution of 25 km; further processing was done by the Department of Geography at the University of California, Santa Barbara, California, in order to achieve a spatial resolution of 2.5 km. For this purpose, rainfall datasets from radar were combined by the TRMM microwave raw datasets. Erdas Imagine 2013 was used to calculate the precipitation average between June and October. As a result, average precipitation map were generated.

Land surface temperature (LST) was retrieved from MOD11A2, which is produced by the instrument Terra from MODIS satellite. "MOD" is the abbreviation of MODIS, "11" is the type of data such as land surface temperature, and "A2" is the level of processing. Actually, MOD11A2 provides information on the land surface temperature with a spatial resolution of 1 km. Thus, LST between 2000 – where MODIS/Terra was launched – and 2014 were calculated by using numerous specialized software such as MODIS Reprojection Tools from NASA, Erdas Imagine 2013 and ArcGIS 10.3. Average land surface temperature map for the months June–October was produced.

Evapotranspiration datasets were obtained from MOD16A2 with a spatial resolution of 1 km between 2000 and 2012. It is a product of the instrument TERRA from MODIS satellite containing Potential Evapotranspiration, Evapotranspiration, Latent Heat Flux and Potential Latent Heat Flux datasets. These data were processed with the same softwares used to produce the LST datasets (i.e. MODIS Reprojection Tools, Erdas Imagine 2013 and ArcGIS 10.3). Average evapotranspiration map for the months June–October was produced.

Drought datasets were deduced from the Aridity Index. This index is the ratio between precipitations and the potential evapotranspiration. Precipitations were obtained from TRMM2B31 product. The potential evapotranspiration was produced from MOD16A2. Both products have a spatial resolution of 1 km and are between 2000 and 2012. Classifications were acquired from the United Nations Environment Programme (UNEP 1992). Reclassifying of the outputs into those classes was made mainly by the "raster calculator" tools included in ArcGIS 10.3. As a result, average drought map for the months June–October was produced.

3.1.2. Topographic data

Altitude, slope and aspect were all estimated from the topographic map of Lebanon with a spatial resolution of 10 m. A further processing of this map on ArcGIS 10.3 by using different commands, such as "create tin" and "slope", allows the generation of these factors (i.e. Altitude, Slope and Aspect).

3.1.3. In-situ data

Soil texture is often related to soil water retention. In this context, the Lebanese soil map, with a numerical scale of 1:50 000 was used. It was prepared at the CNRS (National Council for Scientific Research) in 2006. In fact, over one hundred (i.e. 104) different soil's type exist in the Lebanese forests. For the sake of simplicity, each soil's type was placed in the triangle provided by the University of New South Wales (UNSW, 2007), Australia, in 2007, linking soil type with its water retention capacity. Then, these types were classified into seven categories, from the lowest water retention capacity to the highest. Finally, the soil water retention map in the Lebanese forests was produced.

In order to calculate the hardwood proportion, several Landsat platforms (i.e. Landsat 4, 5, 7 and 8) were used. The spatial resolution is 30 m, and they covered a time frame between 1982 and 2014. NDVI values were calculated for each of the images, in each instrument alone, as it was produced by Faour et al. (2015). NDVI (or Normalized Difference Vegetation Index) is the ratio between the difference of red and near-Infrared (NIR) divided by the sum of red and near-Infrared

Table 1
Ignition-related factors and their source(s).

Factors Type	Factors	Source(s)	Unit Used
A. Climatic	Precipitation[a]	TRMM2B31, 1998–2009, 2.5 km	Millimeters (mm)
	Land Surface Temperature[a]	MOD11A2, 2000–2014, 1 km	Celsius (°C)
	Evapotranspiration[a]	MOD16A2, 2000–2012, 1 km	Millimeters (mm)
	Climatic Drought[a]	Aridity Index, 2000–2009, 1 km	Classified according to UNEP (1992)
B. Topographic	Altitude[a]	Lebanon's Topographic Map, 10 m	Meters (m)
	Slope[a]	Lebanon's Topographic Map, 10 m	Degree (°)
	Aspect[a]	Lebanon's Topographic Map, 10 m	Degree (°)
C. In-situ	Soil water retention[a]	Lebanon's Soil Map, 1/50,000	Classified according to UNSW (2007)
	Hardwood proportion[a]	NDVI from LandSat 8, 2014, 30 m	No unit; values range between −1 and 1
D. Historical	Number of wildfires[a]	Archive data from the CNRS, Ministry of Environment, Ministry of Agriculture, Civil Defense, and several Lebanese journals, 1980–2014.	Unit of one
E. Anthropogenic	Proximity to agricultural land[b]	Land Cover/Land Use, 2005, 1:20,000	Meters (m)
	Proximity to roads[b]	Land Cover/Land Use, 2005, 1:20,000	Meters (m)
	Proximity to urban[b] areas	Land Cover/Land Use, 2005, 1:20,000	Meters (m)
	Proximity to recreation areas, breeding grounds, exploitation zones, etc.[b]	Land Cover/Land Use, 2005, 1:20,000	Meters (m)

[a] Factors related to flammability.
[b] In relation with the source of ignition.

reflectances. NDVI is one of several vegetation indexes, and the most widely used. It varies between 1 and −1. A greater value of NDVI reflects denser and/or greener vegetation. We used NDVI values as a surrogate for the proportion of hardwood for a specific type of forest. As a result, average NDVI map in the Lebanese forest was generated between the months of June and October.

3.1.4. Historical data

Data were collected from several sources in order to produce a wildfire database in Lebanon. These sources were mainly the CNRS (National Council for Scientific Research), the Ministry of Environment, the civil defense. Finally, we could build a database that dates from the early 1980's. Because of some limitations in defining the exact location of wildfires in certain datasets, a natural neighbor interpolation, with a pixel size of 500 m, has been conducted. A map showing the number of forest fires in the Lebanese forests was generated.

3.1.5. Anthropogenic-related data

The Land Cover/Land Use of the year 2005 in Lebanon was used to produce these distances. Generally, these different types of land are recognizable, even directly or indirectly, within classes found in the LC/LU (Land Cover/Land Use) map. As a result, maps of each factor needed (i.e. Proximity to Agricultural Land, Proximity to Roads, Proximity to Urban Areas, Proximity to Recreation Areas, Breeding Grounds, Exploitation Zones, etc.) were produced.

3.2. Data preparation

In order to pinpoint areas at the greatest risk from forest fires, the Lebanese forests were divided into circular areas, each with a radius of 500 m, representing a pixel size of 1 km. The objective was to isolate each region, where the minimum resemblance is present (Fig. 2). Only fully circular shapes were used to minimize the boundary effect as well as eliminating any misleading results (Fig. 3). Thus, 566 circles were identified. Datasets from those fourteen factors were collected above these areas, with the average value was considered when the pixel size was smaller than 1 km. Then, the Lebanese forests were classified into three types of trees: 1) *pine*, which corresponds to pine trees only such as *Pinus pinea and Pinus brutia*; 2) *oak*, which corresponds to oak trees only such as *Quercus cerris*, *quercus inferctoria*; and 3) *mixed*, which corresponds to other species such as cedars, cypress, hophornbeam, and plane trees included in a fully circular shape. This

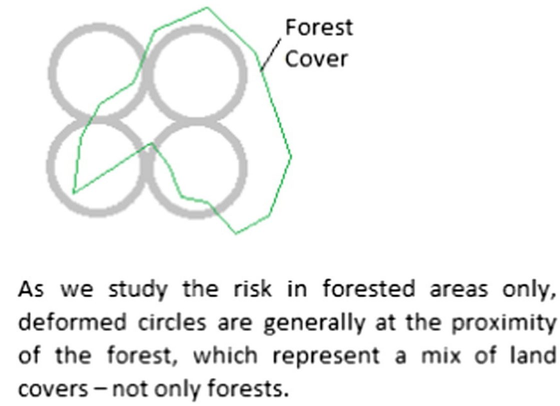

Fig. 3. The purpose of using fully circular shapes.

classification is based on the fact that the pine (i.e. *Pinus pinea and Pinus brutia*) forest has the worst economic losses (Masri et al., 2002) as well as it is the most inflammable species. It is followed by the oak (i.e. *Quercus cerris*, *quercus inferctoria, and quercus calliprinos*) forest; the others were labeled as "mixed" (e.g. *Cedrus libani*, *Juniperus excelsa*, *Juniperus drupacea*, *ostrya carpinifolia*, *Platanus orientalis*).

3.3. Generating of the wildfire hazard map

From the historical number of wildfires – which is one of the factors studied – the probability of occurrence of a wildfire could be calculated. Nevertheless, the problem lies in the transformation of the number of occurrence into probabilities, and then in their classifications. One of the methods used is, to summarize the number of wildfires over a large area. The probability is then the number of wildfires occurred in a predefined region over the total number of wildfires in that large area. However, chosen regions might be biased. Therefore, plotting each of the thirteen factors and the number of wildfires were produced in each type of forests (Appendix I). Actually, natural breaks appear at the same numbers in each forests' type and dividing the number of wildfires into four different categories: low, low to medium, medium to high, and high probability of occurrence of a wildfire (Table 2). As a result, the plotting approach has solved both the transformation of the number of occurrence into probabilities and their classifications issues.

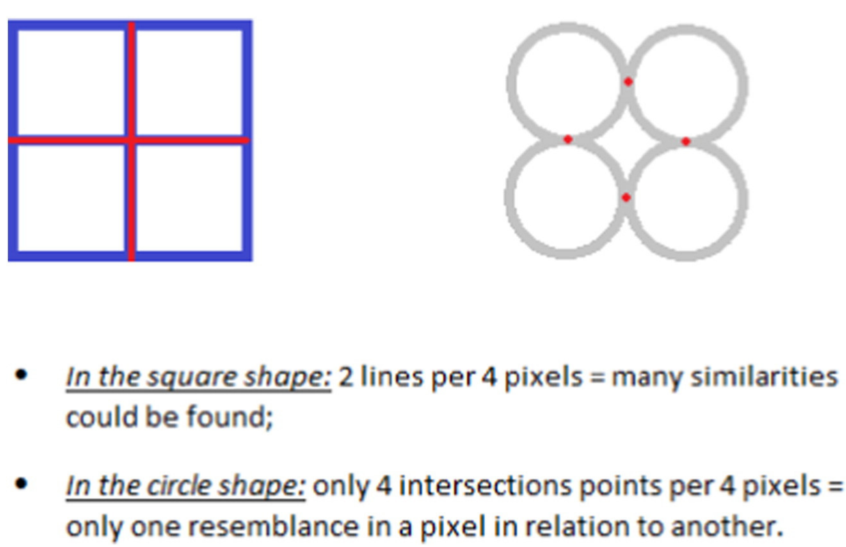

Fig. 2. The purpose of using circular shapes.

Table 2
Wildfire ignition probability classes according to forests' type and wildfires' number.

	Forest Type		
	Pine	Mixed	Oak
Low classes	0–5	0–5	0–10
Low to medium	5–10	5–15	10–20
Medium to high	10–15	15–25	20–30
High	>15	>25	>30

Three maps were created, representing pine, oak and mixed forests and each classified into four classes (i.e. low, low to medium, medium to high, and high probability of occurrence of a wildfire). Then, an overlapping between these maps has been made to generate the wildfire hazard map of Lebanon.

3.4. Modeling ignition factors

With the number of wildfires as an independent variable, the model describing the probability of ignition of forest fires could be created. All datasets were exported as one table and conducted several statistic tests: Adjusted R-Squared, Akaike's Information Criterion, Jarque-Bera p-value, Koenker (BP) Statistic p-value, Max Variance Inflation Factor, Global Moran's I p-value. Criteria used were as follows: 1) Min Adjusted R-Squared >0.50; 2) Max Coefficient p-value <0.05; 3) Max VIF Value <7.50; 4) Min Jarque-Bera p-value >0.10; 5) Min Spatial Autocorrelation p-value >0.10. The best model that surpasses the most criteria used in these tests were used in each type of forests. The model was

Table 3
Vulnerability values in correspondence to population density, proximity to civil defense centers and trees' regeneration capacity.

Tree flammability						
		Mixed	*Oak*	*Pin*		
Population density	*Low*	3/4	4/5	5/6	*Near/far*	Proximity to civil defense centers
	High	4/5	5/6	6/7	*Near/FAR*	

based on the Ordinary Least Squares method. It has a general equation as follows:

$$Y = \beta x + \beta' x' + \beta'' x'' + \text{etc.} + \varepsilon$$

3.4.1. Model validation

The validation of the model has been prepared through two different approaches. The first is by holding 70% of the locations/circles against 30% of them. The first (Fig. 4) set of data (i.e. 70%) was interpolated using the natural neighbor interpolation. Then, these locations were classified into four categories (i.e. low, low to medium, medium to high and high) by applying our model. The other set (i.e. 30%) was considered as reference data, where locations were classified into four categories (i.e. low, low to medium, medium to high and high) according to the plotting approach. They aimed to measure the accuracy of our model. The second method intends to model the Lebanese forest as one entity. With the probability of occurrence of a wildfire are now classified into four categories, already deduced from the plotting approach (Appendix I), accuracy assessment could be generated.

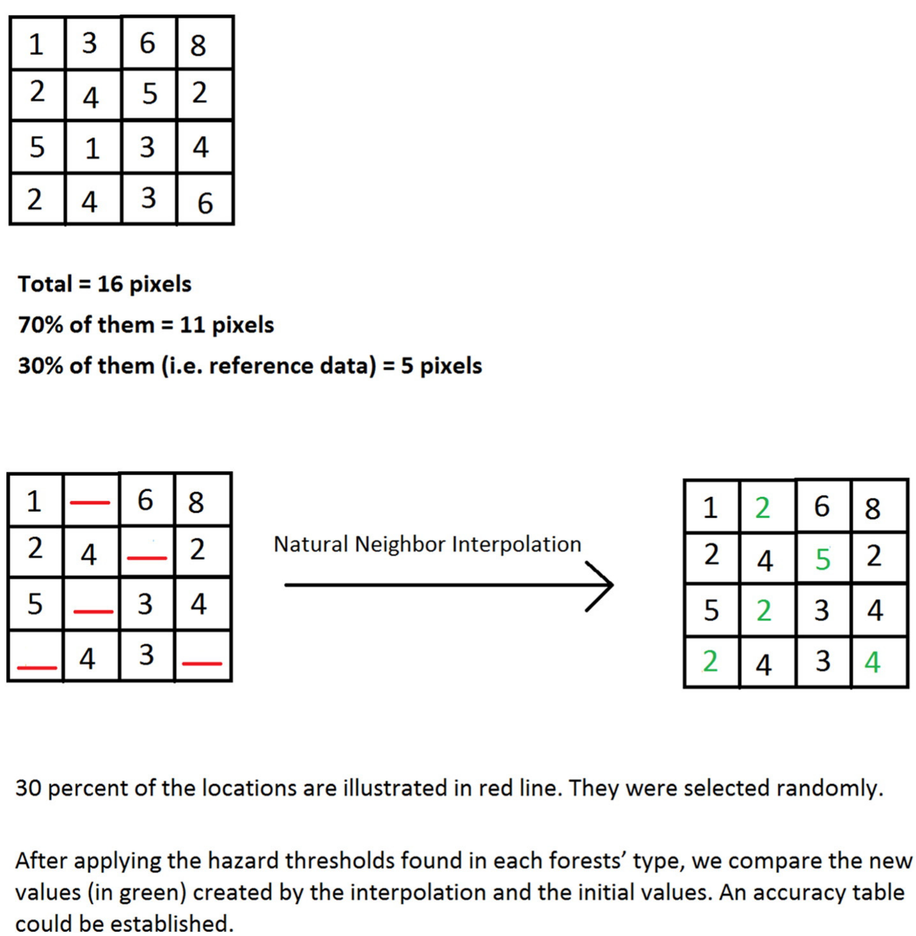

Fig. 4. An example of the model validation through 70 vs. 30% method.

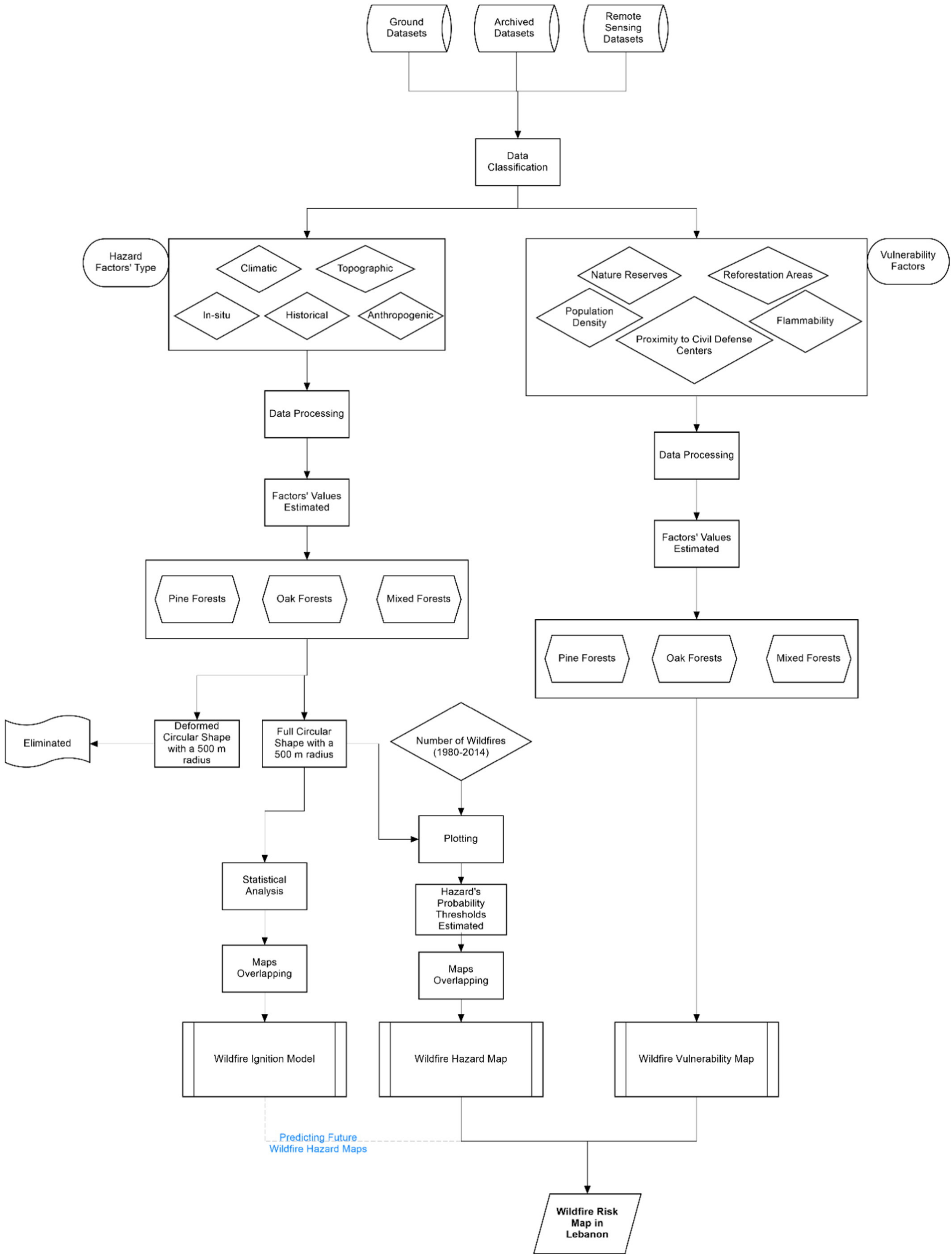

Fig. 5. Simplified Methodology Flowchart.

Table 4
Factors included in the model as well as their coefficient in pine forests.

Pine forests	Coefficient
Land surface temperature	−0.882
Proximity to roads	−0.0035
Proximity to recreation areas, breeding grounds, exploitation zones, etc.	0.0017
Constant (ε)	29.505

Table 5
Factors included in the model as well as their coefficient in oak forests.

Oak forests	Coefficient
Land surface temperature	−0.329
Climatic drought	14.384
Altitude	−0.0031
Aspect	−0.013
Hardwood proportion	−39.967
Proximity to agricultural land	−0.0013
Proximity to recreation areas, breeding grounds, exploitation zones, etc.	0.0004
Constant (ε)	26.986

Table 6
Factors included in the model as well as their coefficient in mixed forests.

Mixed forests	Coefficient
Land surface temperature	−0.754
Altitude	−0.0081
Slope	−0.164
Aspect	−0.014
Proximity to agricultural land	−0.002
Proximity to roads	−0.0011
Proximity to recreation areas, breeding grounds, exploitation zones, etc.	0.0005
Constant (ε)	43.042

3.5. Generating of the wildfire vulnerability map

The vulnerability of forests to ignite a fire was evaluated from five datasets: location of nature reserves and reforestation areas, population density, proximity to civil defense centers and tree flammability. The goal, however, is to combine all these values into four classes of vulnerability.

The location of natural reserves was given the value of 1, representing the lowest vulnerability to a forest fire. In fact, these regions are the most conserved, with routine actions of preventions and rehabilitations. When a wildfire occurs, several personals, well-experienced and trained, are present near the natural reserve to assist in battling this phenomenon. Consequences will be minimal. These data were provided by the CNRS.

Reforestation areas take the value of 2; these are regions more or less managed by human to reduce vulnerability. Data were collected from various Lebanese reforestation initiatives and projects.

Table 8
Factors included in the One Entity Model as well as their coefficient.

Lebanese forests	Coefficient
Land surface temperature	−0.511
Climatic drought	15.372
Altitude	−0.0041
Aspect	−0.014
Hardwood proportion	−25.809
Proximity to agricultural land	−0.0014
Proximity to roads	−0.0015
Proximity to recreation areas, breeding grounds, exploitation zones, etc.	0.0005
Constant (ε)	31.864

The other vulnerability values (i.e. 3 to 7) were identified in a table of three inputs (Table 3). Data from the UNCHR (United Nations High Commissioner for Refugees), dating from January 30, 2014, are used to generate the population density in the Lebanese municipalities. These datasets included the distribution of Syrian refugees in Lebanon as well. Thus, population density of Lebanon in 2014 was produced and then classified into two classes: low and high. In fact, according to the World Bank in 2014 (available on http://data.worldbank.org/indicator/EN.POP.DNST), the population density in Lebanon was 441 person/km^2. Therefore, the first class (i.e. low) is smaller than the average population density in Lebanon (i.e. 441 persons/km^2), whereas, the second class (i.e. high) is greater than this average.

Civil Defense centers are obtained from the CNRS. Each Civil Defense center may cover an area with a maximum radius of 5 km according to the Lebanese Civil Defense; any proximity to Civil Defense centers below 5 km is considered as the first category (i.e. near), while above 5 km stands for the second category (i.e. far).

Pine trees have foliar characteristics that make them extremely flammable (Hough and Albini, 1978). Pine and Oak trees rank among the most flammable species ever measured (Behm et al., 2004; Ellair and Platt, 2013; Varner et al., 2015; Wear and Greis, 2002). Studies on pines and oaks have shown that pine litter is more flammable than oak litter (Rebertus et al., 1989; Williamson and Black, 1981) and that without fire, pines are replaced by oaks (Bond and Midgley, 1995; Williamson and Black, 1981). Thus, three classes were presented: the lowest (i.e. mixed forests), average (i.e. oak forests), and highest flammability trees (i.e. pine forests).

3.6. Generation of the wildfire risk map

Risk is the combination of hazard and vulnerability. While hazard map are already classified into four categories (i.e. low, low to medium, medium to high and high), vulnerability map needs to be classified into four classes as well instead of seven. Vulnerability classes 1 and 2, which refer to the natural reserves and reforestation sites in Lebanon, have remained the same; Classes 3, 4 and 5 were converted into Class 3: it represents a medium vulnerability. Then, classes 6 and 7 were changed into class 4 – high vulnerability.

Table 7
Contingency table crossing reference and model data from TTM.

		Data from model (TTM)				Total	Producer's accuracy (%)
		Low	Low to medium	Medium to high	High		
Reference data	Low	**121**	11	0	0	132	91.66
	Low to medium	12	**45**	0	0	57	78.94%
	Medium to high	1	2	**0**	0	3	-
	High	7	0	0	**2**	9	22.22%
Total	141	58	0	2	201		
User's accuracy (%)		85.81%	77.58%	-	100%		
Total accuracy = 83.58%							

Table 9
Contingency table crossing reference and model data from OEM.

		Data from Model (OEM)				Total	Producer's accuracy (%)
		Low	Low to Medium	Medium to High	High		
Reference data	Low	**94**	19	0	0	113	83.18%
	Low to Medium	14	**46**	0	0	60	76.66%
	Medium to High	0	6	**3**	0	9	33.33%
	High	13	0	0	0	13	-
Total	121	71	3	0	195		
User's accuracy (%)		77.68%	64.78%	100%	0		
Total Accuracy = 73.33%							

Both hazard and vulnerability maps are now ready to be merged to produce the wildfire risk map of Lebanon in 2014. Fig. 5 represents a simplified flowchart of the methodology. Actually, the four classes used in the risk map could be defined as follows:

- Class I: Low Risk; it corresponds to a natural reserve with a low wildfire occurrence (*i.e. maximum* one wildfire every seven years for pine and mixed trees; maximum two wildfires every seven years for oak forests). Minimum mitigations and assessments are required;
- Class II: Low to Medium Risk; it corresponds to areas where wildfire occurrence ranges between low and medium to high (*i.e. maximum* four wildfires every nine years for pine trees; maximum one wildfire per year for oak forests; maximum four wildfires in three years for mixed forests). In addition, these areas are outside natural reserve boundaries. Further assessments should be prepared to identify the main cause, even related to site vulnerability or biophysical hazard;
- Class III: Medium to High Risk; it corresponds to areas with different wildfire occurrence and vulnerability. While these areas are outside natural reserve boundaries, they either located in a high vulnerability site versus low occurrence wildfires, or the opposite. Further assessments should be prepared to identify the main cause,

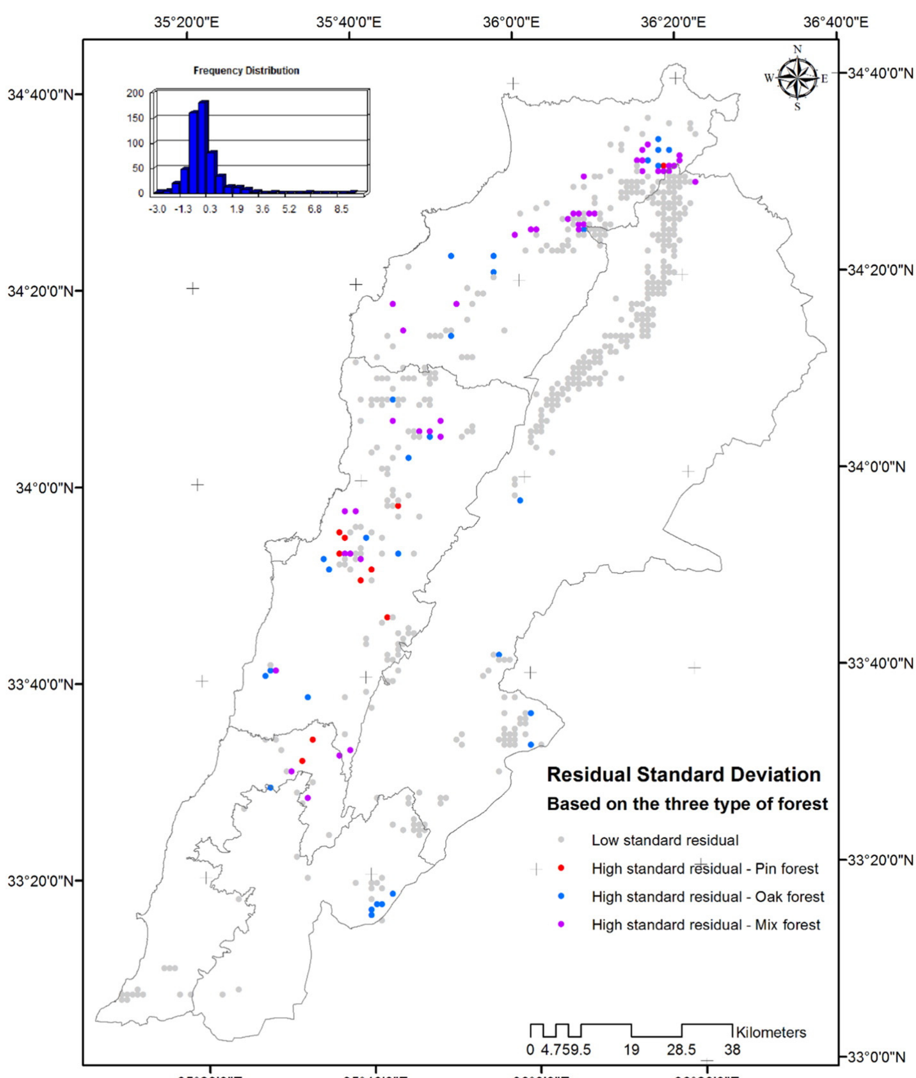

Fig. 6. Distribution of the standard deviation of residuals based on the three type of forest, as well as the frequency distribution in the upper-left; a normal distribution could be identified.

even related to site vulnerability or biophysical hazard and try to mitigate it;

- Class IV: High Risk; it corresponds to areas with a high wildfire occurrence (i.*e. minimum* one wildfire every two years for pine trees; minimum one wildfire per year for oak forests; minimum three wildfires in four years for mixed forests) coupled with a high vulnerability. Mitigations and assessments are critically required.

4. Results

4.1. Wildfire ignition factors modeling

Three equations, each describing a type of forest, were created used Ordinary Least Squares approach. In pine forests, land surface temperature (LST) and proximity to roads factors are both negatively correlated against the wildfires' number, with −0.882 and −0.0035 coefficients' values, respectively. Proximity to recreation areas is positively correlated with the number of occurrence (Table 4). In oak forests, five of the seven factors used were negatives: LST, altitude, aspect, hardwood proportion, and proximity to agriculture land. Climatic drought and proximity to recreation areas have both a positive correlation, with 14.384 and 0.0004 coefficients' values, respectively (Table 5). In mixed forests, the majority of factors (i.e. LST, altitude, slope, proximity to agriculture land, and proximity to roads) show a negative relation with the wildfires' number (Table 6). Only aspect and proximity to recreation areas present positive coefficients, with 0.014 and 0.0005 values, respectively. While pine forests have only three factors in the model, oak and mixed forests included seven factors each. The model that combines all three equations is named the Three-Type Model (TTM). It is generated by applying each model, presented in Tables 4–6, for each forest's type. Then, the TTM is not a simple equation, but rather an application of three models above three forests' type. The output is the creation of the wildfire hazard, classified into four classes from low to high. In conclusion, these equations are as follows:

5. Pine forests

$$
\begin{aligned}
Y = {} & (-0.882)\text{xLST} + (-0.0035)\text{xProximity to roads} \\
& + (0.0017)\text{xProximity to recreation areas} + 29.505
\end{aligned}
$$

6. Oak forests

$$
\begin{aligned}
Y = {} & (-0.882)\text{xLST} + (14.384)\text{xClimatic Drought} + (-0.0031)\text{xAltitude} \\
& + (-0.013)\text{xAspect} + (-39.967)\text{xHardwood Proportion} \\
& + (-0.0013)\text{xProximity to agriculture land} \\
& + (0.0004)\text{xProximity to recreation areas} + 26.986
\end{aligned}
$$

7. Mixed forests

$$
\begin{aligned}
Y = {} & (-0.754)\text{xLST} + (-0.0081)\text{xAltitude} + (-0.164)\text{xSlope} \\
& + (0.014)\text{xAspect} + (-0.002)\text{xProximity to agriculture land} \\
& + (-0.0011)\text{xProximity to roads} \\
& + (0.0005)\text{xProximity to recreation areas} + 43.042
\end{aligned}
$$

7.1.1. Model validation

Actually, 201 regions were considered as reference areas for the model and chosen randomly. The others regions (i.e. 365 areas) were interpolated. A comparison between results obtained from initial models (TTM) and those reference regions were made. The contingency table is illustrated in Table 7.

With a total accuracy of nearly 84%, TTM appears to be a reliable model. However, it is essential to verify its importance over another model that studies the forest as one unit only – no type of forests included. It is the second approach used to validate our model. In

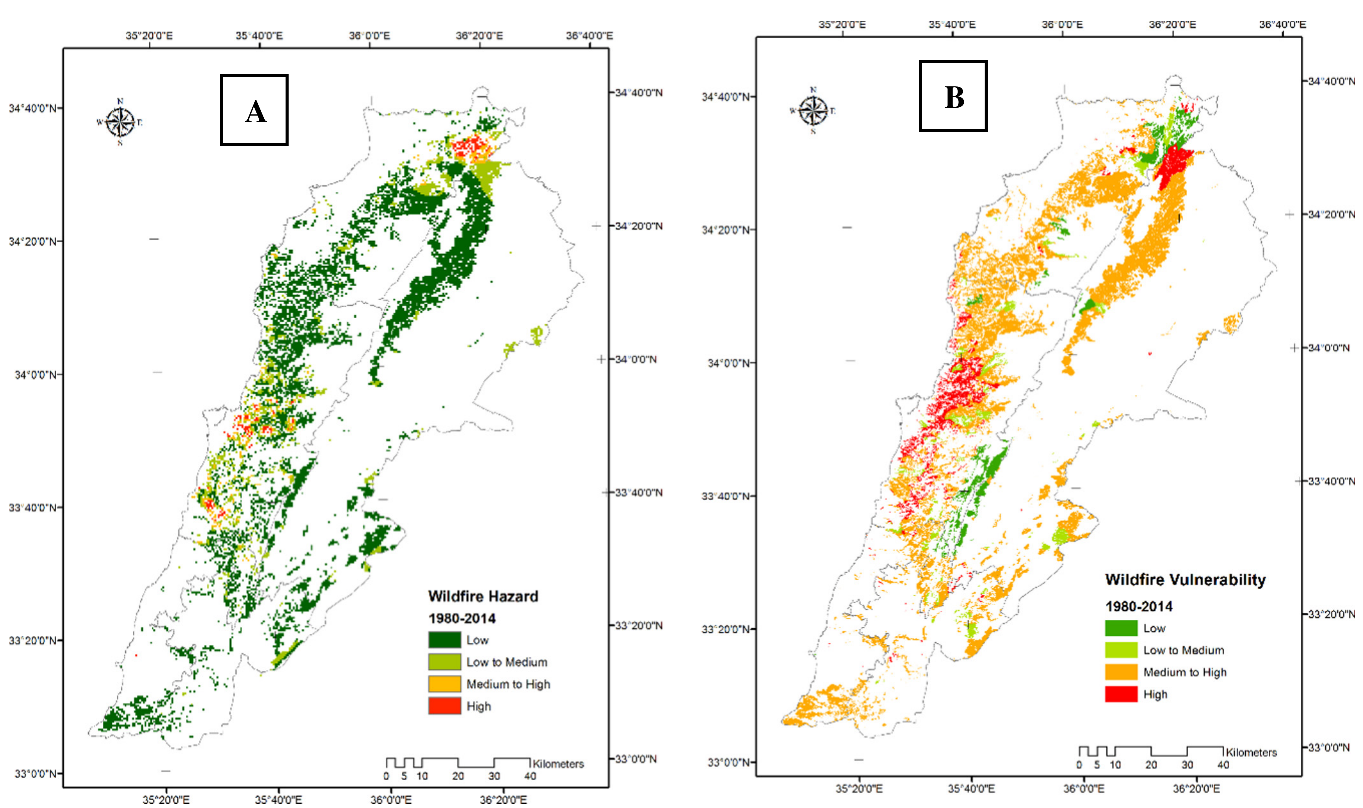

Fig. 7. Wildfire Hazard Map (A) and vulnerability maps (B) of Lebanon.

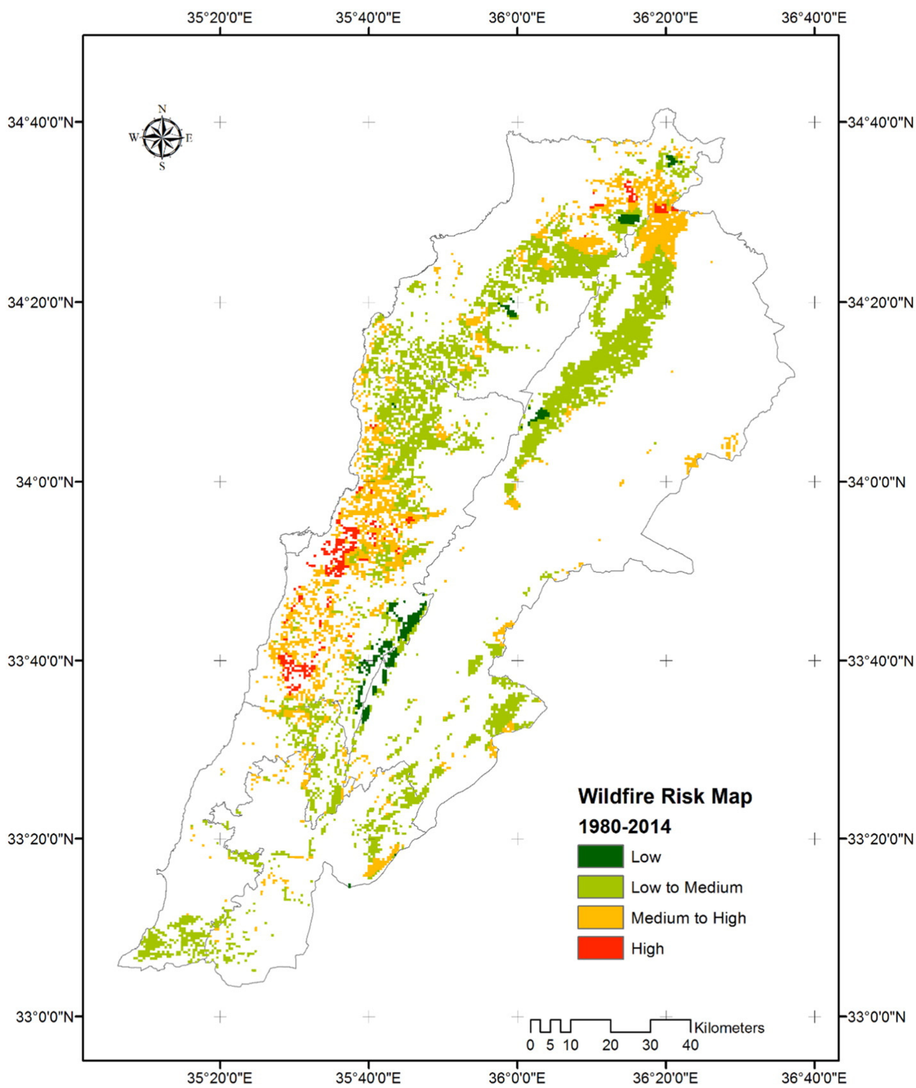

Fig. 8. Wildfire risk map of Lebanon.

consequence, the same procedure already completed for the TTM model has been followed. The best model, which is named One Entity Model (OEM), was identified. The model was based on the Ordinary Least Squares method. The equation is presented in Table 8. Two factors (i.e. climatic drought and proximity to recreation areas) are representing a positive relation, whereas, six other factors are showing a negative relation with the number of wildfires. The OEM model is as follows:

$$\begin{aligned} Y = {} & (-0.511)\text{xLST} + (15.372)\text{xClimatic Drought} \\ & + (-0.0041)\text{xAltitude} + (-0.014)\text{xAspect} \\ & + (-25.809)\text{xHardwood proportion} \\ & + (-0.0014)\text{xProximity to agriculture land} \\ & + (-0.0015)\text{xProximity to roads} \\ & + (0.0005)\text{xProximity to recreation areas} + 31.864 \end{aligned}$$

By proceeding with the same approach used to validate the TTM (i.e. 30% by 70% of the data), a contingency table has been created (Table 9). Random 30% of the total data were chosen. Total accuracy is decreasing in the OEM in comparison to TTM model (i.e. 84% vs. 73%).

A normal distribution of the residual standard deviation could be recognized in the TTM model. There are 90 regions, of different forests' type, that contains a high residual standard deviation. They represent 15.9% of the chosen regions (Fig. 6). Low standard deviation of residuals is considered in regions presenting standard deviation values between −1.5 and 1.5.

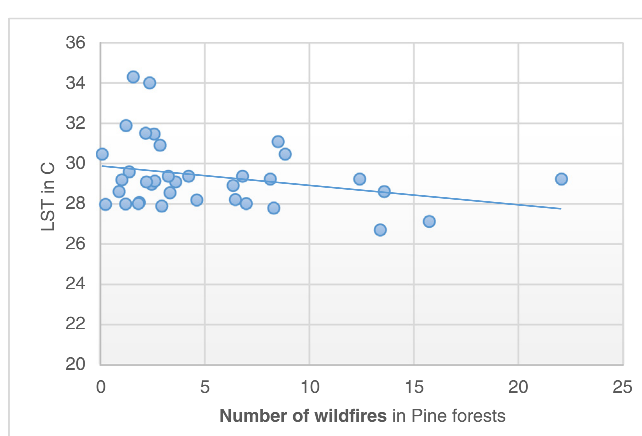

Fig. 9. Plotting LST and occurrence number in pine forests.

7.2. Wildfire hazard and vulnerability maps

Generating the wildfires' number map is essential to highlight areas that were at high risk while projecting the probability of occurrence of future events. Given the large temporal extent used in this study, factors that only had a temporary effect or are insignificant were eliminated. Extreme events have been excluded as well by taking average values based on different years – at least 10 years. Final wildfire hazard map, classified into four probability classes, is illustrated in Fig. 7 (A). Wildfire Vulnerability map describes the tendency of a forest to regain its normal state. It is illustrated in Fig. 7 (B).

7.3. Wildfire risk map

Wildfire Hazard and Vulnerability maps were combined to produce the Wildfire Risk map in Lebanon with a resolution of 1 km (Fig. 8).

8. Discussion

Model applied for the pine model shows a negative relation between land surface temperature (LST) and the number of occurrence of a wildfire. Actually, a negative trend line is clearly visible when plotting these two (Fig. 9). LST and air temperatures are generally correlated (Mostovoy et al., 2005); they can be estimated by applying a model (e.g. Benali et al., 2012; Cristóbal et al., 2008; Li et al., 2008), particularly because the studied regions exist in the same land-cover type (Jiang and Tian, 2010; Wan et al., 2004). Higher temperatures are expected to increase the amount of moisture that evaporates from land and water (Gleick, 2012; Vose and Klepzig, 2013), which will increase the probability of occurrence of a wildfire (Debano and Krammes, 1966; Running, 2006; Westerling et al., 2006). A paradox exists. However, this decrease is highlighted mostly for the number of occurrence above 5 (i.e. in classes low to medium, medium to high and high). It means that generally low probabilities regions are affected by natural/climatic factors. The others are mostly caused by human interferences. To solve this ambiguity, the standard deviation of the residuals (Fig. 6) was consulted. A high standard deviation means a bias in the model's prediction, which means an involvement of factors outside those used by the model. While climatic and natural factors are already included, anthropogenic factors are producing this bias. Actually, human-related selected variables reflect a steady relation between human and wildfires. While studies suggest that human interfere in 90 to 95% of total wildfires (e.g. Martínez et al., 2009; Running, 2006; Syphard et al., 2007; Vilar et al., 2010), it supposes to be a dynamic relation between human and wildfires: for instance, arson and prescribed fire. As a result, it appears that 5 out of 24 regions (i.e. 20.83% of total regions and 7.8% of the total amount of wildfires) of the low probability class are influenced by human, whereas 6 out of 14, representing classes 2, 3 and 4, are human-induced wildfires — 42.85% of the total regions and 59.62% of the total amount of wildfires. In sum, human has caused 47.16% of the total amount of wildfires in pine forests. A lower distance to roads produces a higher probability — which is shown by the model. It is related to the waste and pollution generated from citizen passing by and people walking.

For the oak trees' model, hardwood proportion and LST have negative correlation with the number of wildfires, whereas climatic drought shows a positive correlation. A denser vegetation cover reduces the wildfire probability (Graham et al., 2004; Schoennagel et al., 2004; Sweitzer et al., 2016). This is because a dense vegetation prevents solar radiation from penetrating into the forest and generates moister, which means less flammable conditions. The negative correlation between LST and number of wildfires is already explained in the pine model. After consulting standard deviation of the residuals (Fig. 6), 16 out of 219 regions (i.e. 7.3% and 5.5% of the total amount of wildfires) are classified as human-induced wildfires in the first class. The higher probabilities' categories (i.e. low to medium, medium to high, and high) are those most affected, representing 20 out of 24 regions (i.e. 83.33% and 89.13% of the total amount of wildfires). In sum, human has caused 42.01% of the total amount of wildfires in oak forests. More intense drought causes lesser water content in the vegetation cover. It encourages the ignition of a wildfire. The contradiction that exist is also related to the anthropogenic influences.

LST and slope exhibit negative correlations in the mixed forests. Temperature effect is already discussed in pine model. And by referring to standard deviation of the residuals (Fig. 6), 21 out of 218 regions (i.e. 9.63% and 10.38% of the total amount of wildfires) were human-induced wildfires in the first class. In the higher classes, 22 out of 67 regions (i.e. 32.83% and 53.79% of the total amount of wildfires) are characterized by wildfires caused by human. In sum, people affected 41.2% of the total amount of wildfires in mixed forests. A steep slope increases the speed at which a fire burns (Holden et al., 2009; Lecina-Diaz et al., 2014; Lentile et al., 2006; Rothermel, 1972; Sullivan et al., 2014). This is due to the increase of oxygen flow in the inflamed area. Furthermore, slope inclination can alter soil infiltration properties by reducing the amount of interception materials that protect soil against the impact of rain drops and runoff. Therefore, greater slope reflects a larger probability of ignition of a wildfire. It appears that it is not the case in the model. Humans are to blame.

As a result, 42 out of 461 regions (i.e. 9.11% and 7.9% of the total amount of wildfires) are wildfires caused by human interferences, in the low probability of occurrence class. For the higher classes (i.e. low to medium, medium to high and high probability of occurrence of a wildfire), they correspond to 48 out of 105 regions (i.e. 45.71% and 67.51% of the total amount of wildfires). In conclusion, 15.9% of total forest selected regions and 43.46% of the total amount of wildfires are caused by human actions. It is important to note that the first class probability describes a region that a wildfire occurs with low ability for recurrence. On the other hand, higher classes, even with smaller total area (i.e. 18.55% of the total area), are regions that wildfires might have occurred over twice a year, posing a serious issue. Controlling human actions is normally a difficult task, but needed to prevent the deterioration of the Lebanese forests.

In addition, the model used, named TTM, has shown an enhanced representation of a Mediterranean-climate forests — by diving it into three main trees' types. It is recommended, however, to reproduce the model for other types of vegetation and verify the total accuracy of the model. Including other factors, if available, might also seem beneficial. Nonetheless, with an accuracy of 84%, this model could be portable to other Lebanese and Mediterranean-climate woodlands.

Even if it is a human-induced wildfire in Mount-Lebanon and north of Akkar, the affected regions are at risk. Only some reserves, like Shouf natural reserve, and some reforestation areas, where human affects positively, show a low risk of wildfire. They represent nearly 56 km^2. Low to medium corresponds to the largest class – 1272 km^2 – which are all over the Lebanese territory. The third class, with approximately 802 km^2, is localized mostly in Mont-Lebanon region. It represents a high density governorate, where pressure on forest is high, mainly due to urban expansion. By consulting the residual standard deviation (Fig. 6), the regions where the risk of wildfire is high are as well representing a high human interference, accused of ignition of wildfires. It is important to educate and encourage citizens of these regions to protect and support forests sustainability. Beginning with these high-risk regions shall be the key to prevent and battle this phenomenon.

Building a model where human behaviors are included is hard, mainly because of his unpredicted activities and actions. Defining the wildfire risk in Lebanon, with an accuracy of 84% based on cross-data validation was important. It was vital as well because of its spatial resolution (i.e. 1 km), which facilitate the prediction and assessment of wildfires, in comparison to other villages-scale risk maps produced in Lebanon in 2007. The usage of fourteen factors in the model has improved the risk' study and removed the ambiguity concerning ignition causes. A wildfire-ignition model was created and could be portable. It shall help the conservation of the Lebanese and Mediterranean forests. However, assessing the accuracy of the model versus the next five years, or in other Mediterranean regions, might be needed. Multitude of data sources and representations might cause some difficulties and generate some errors if not processed wisely. While a creation of one-source datasets seems far reached, mainly because of the incorporation of a dozen of factors, an automation of the fetching and processing procedures is needed. This is because the wildfire is an interactive phenomenon that needs constant update. For future studies, using higher resolution datasets, if possible, might enable to generate more detailed maps of the wildfires' risk in Lebanon. This map may help decision-makers to maintain a sustainable development without affecting natural resources.

9. Conclusion

Whatever human-induced or natural wildfires, this phenomenon has its impact on the forests in Lebanon, and in the Mediterranean region. In fact, 15.9% of total forest selected regions and 43.46% of the total amount of wildfires are caused by human interferences. Unstandardized factors of ignition of wildfires have been used worldwide, with some ambiguities on the hazard, vulnerability and risk concepts. Then, we begin by collecting fourteen different factors that assumed to cause the ignition of a wildfire, from 1980 to 2014. Producing a model from these factors, predicting future wildfire hazard with an accuracy of 84%, was our first goal. This model could be portable to other Mediterranean-climate regions. It has been followed by the generation of the wildfire hazard and vulnerability maps. The combination of these two outputs generates the wildfires' risk map of Lebanon, which was our second goal. This map could be consulted by the Lebanese authorities to prevent and pre-suppress wildfire occurrence in Lebanon, as well as to pinpoint at the most critical areas.

While the Lebanese forest is chosen as an example or pilot area, in this paper, we propose a new system of monitoring wildfires in the Mediterranean countries. This system is based on a model to project hazardous areas combined with the vulnerability to wildfires.

Acknowledgments

We would like to express our sincere thanks and appreciation to Pr. Juli G. Pausas for his constructive and helpful comments.

Appendix I. Plotting the number wildfires and the other factors

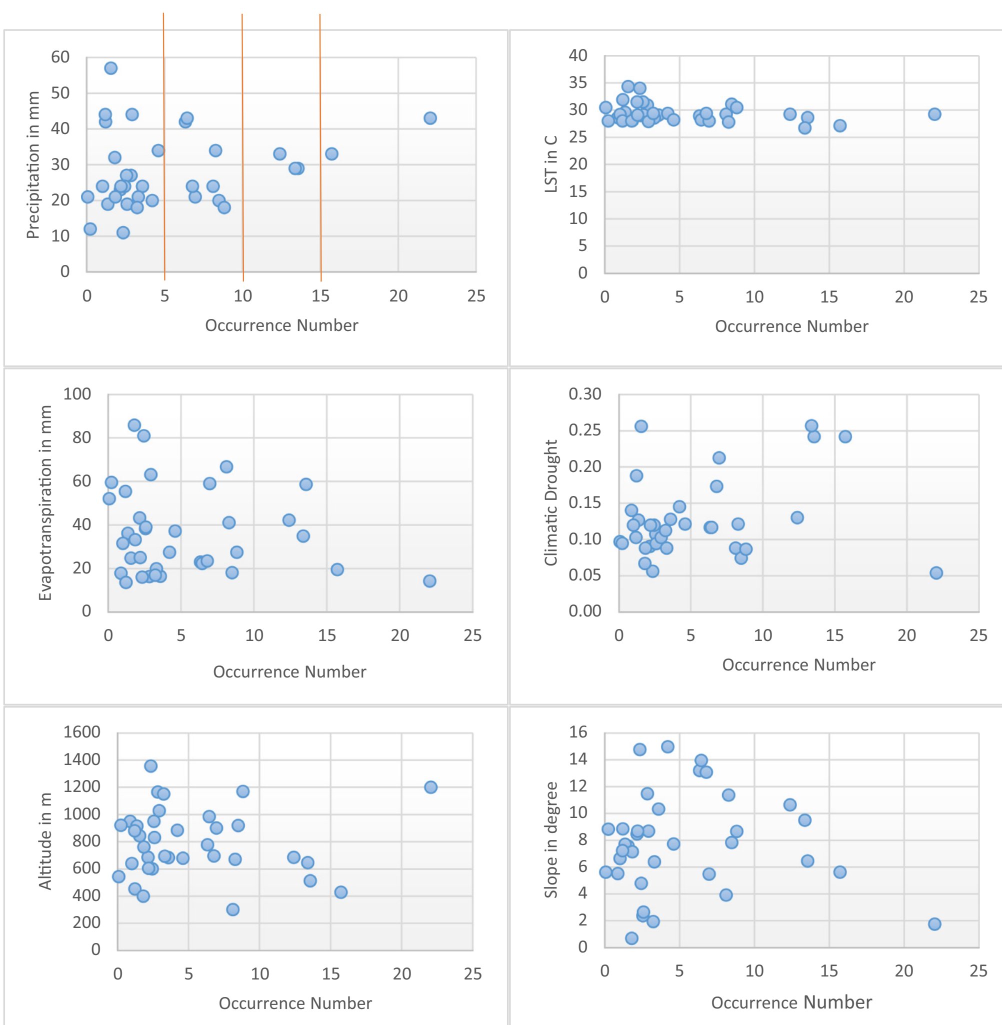

Fig. A1. Pine forests.

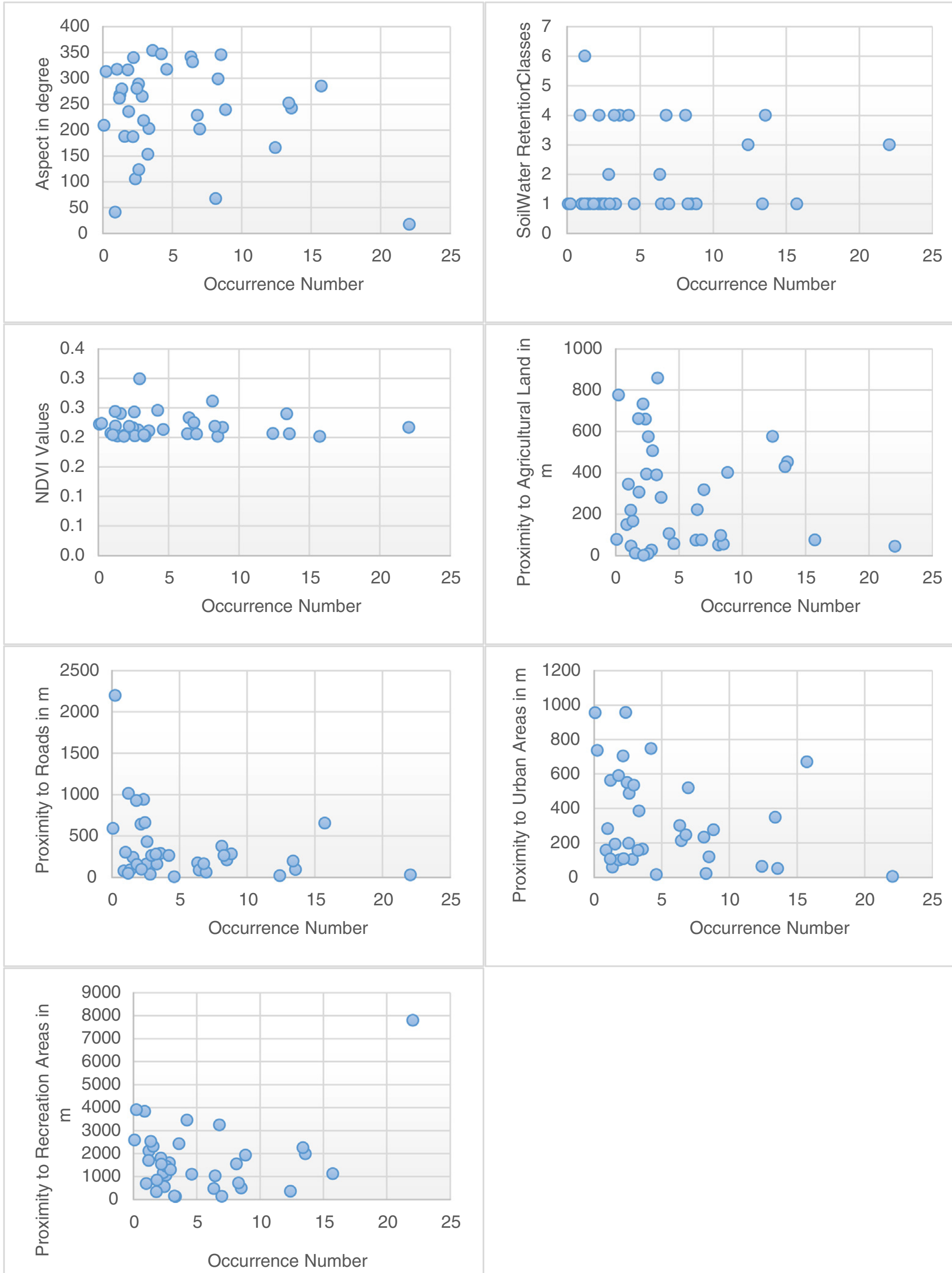

Fig. A1 (*continued*).

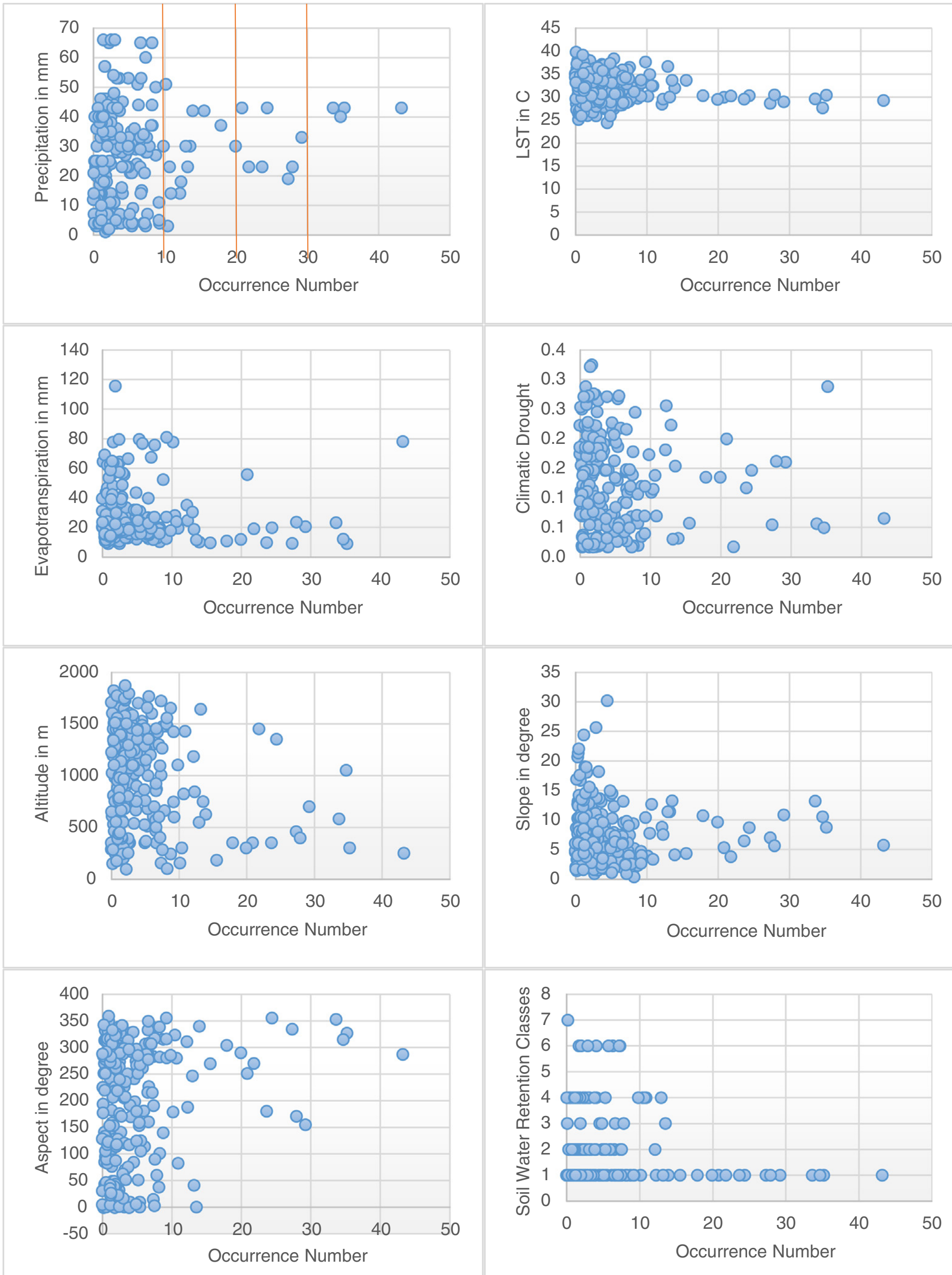

Fig. A2. Oak forests.

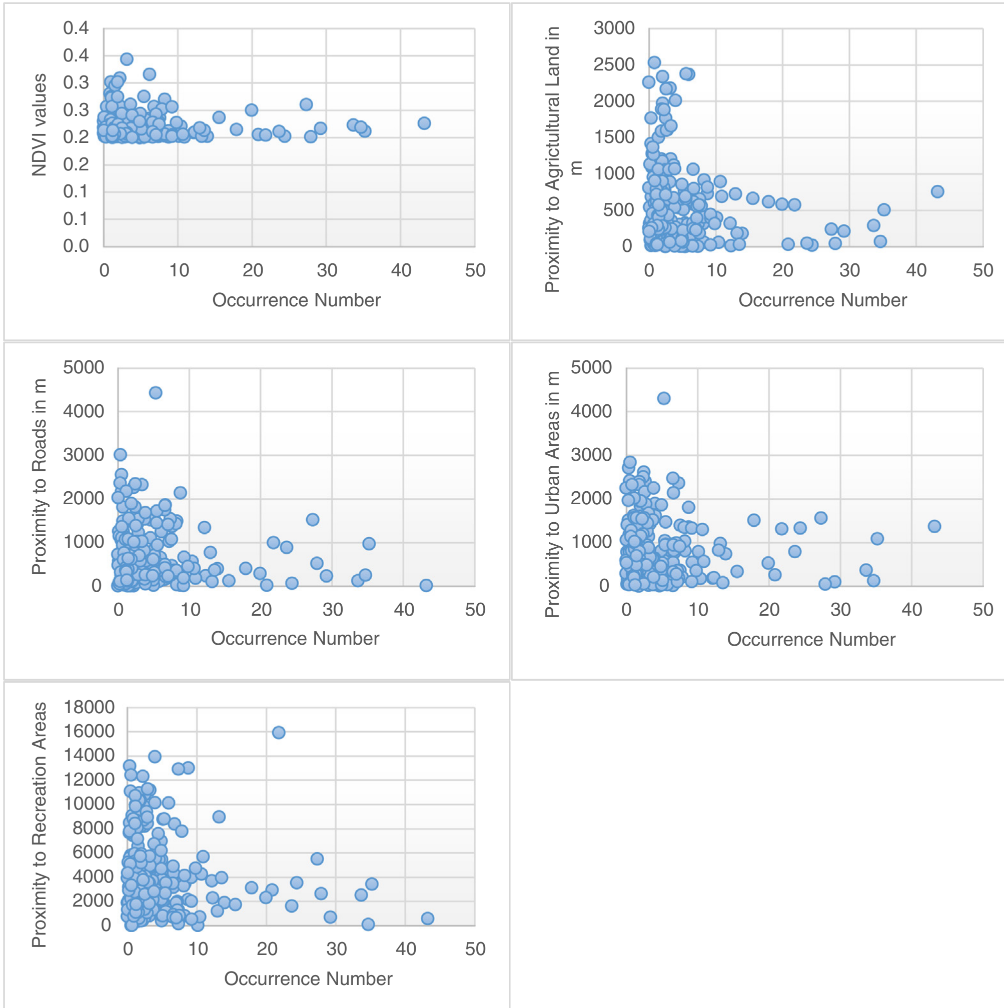

Fig. A2 (*continued*).

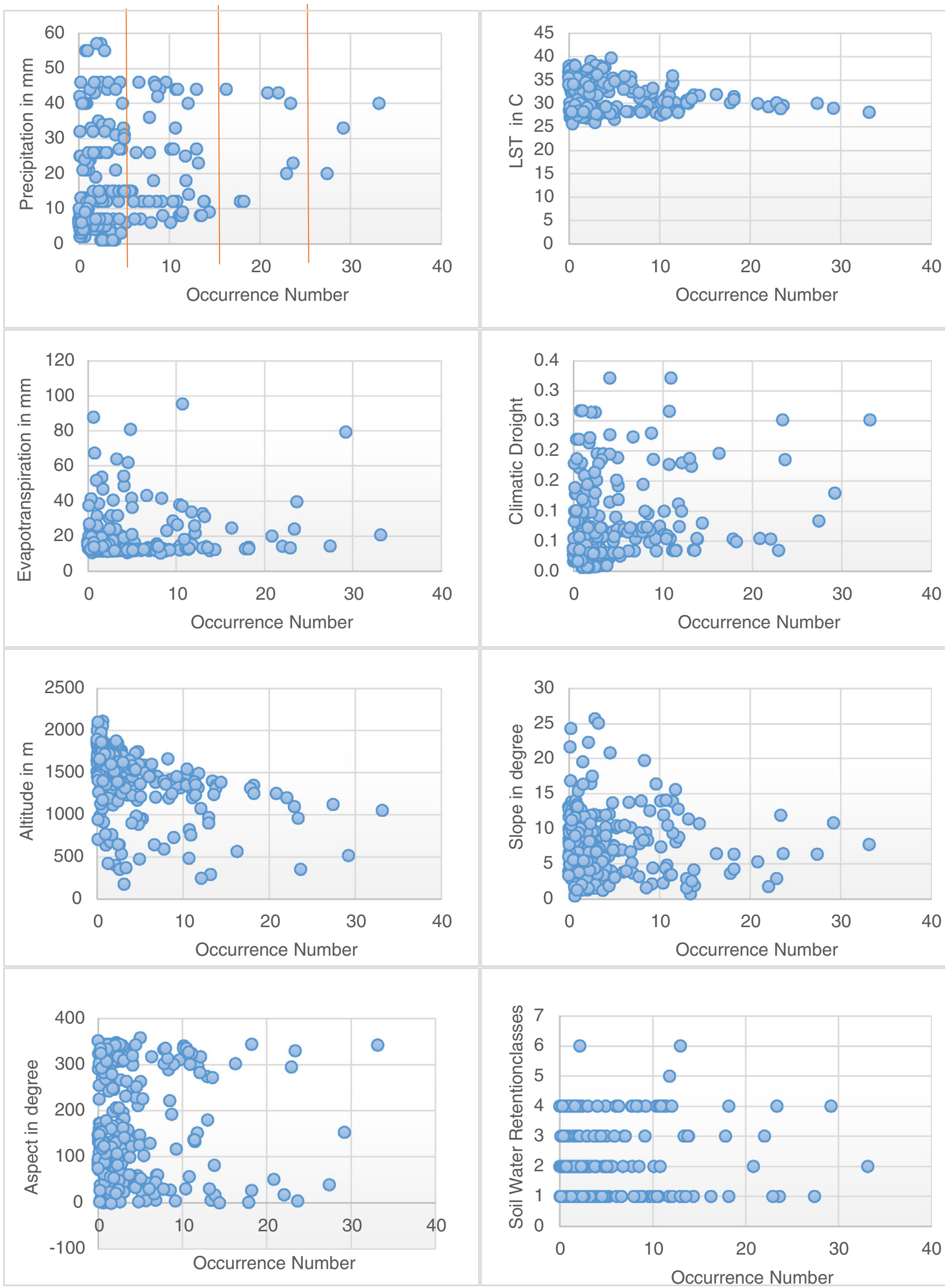

Fig. A3. Mixed forests.

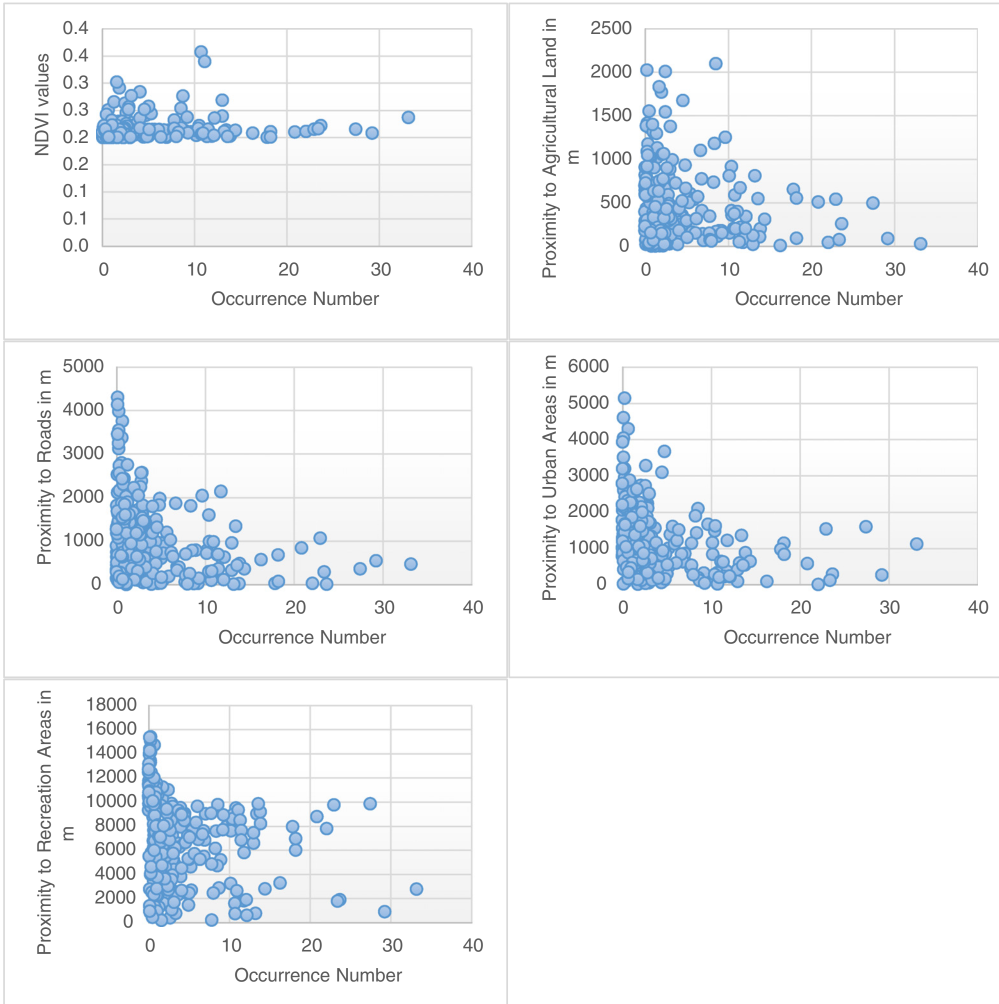

Fig. A3 (*continued*).

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