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Assessing fire hazard potential and its main drivers in Mazandaran province, Iran: a data-driven approach

Hamed Adab · Azadeh Atabati · Sandra Oliveira · Ahmad Moghaddam Gheshlagh

Abstract Fires are a major disturbance to forest ecosystems and socioeconomic activities in Mazandaran province, northern Iran, particularly in the Hyrcanian forest sub-region. Mapping the spatial distribution of fire hazard levels and the most important influencing factors is crucial to enhance fire management strategies. In this research, MODIS hotspots were used to represent fire events covering Mazandaran Province over the period 2000–2016. We applied the ecological niche theory through the maximum entropy (MaxEnt) method to estimate fire hazard potential and the association with different anthropogenic and biophysical conditions, by applying different modeling approaches (heuristic, permutation, and jackknife metrics). Our results show that higher fire likelihood is related to density of settlements, distance to roads up to 3 km and to land cover types associated with agricultural activities, indicating a strong influence of human activities in fire occurrence in the region. To decrease fire hazard, prevention activities related to population awareness and the adjustment of farming practices need to be considered.

Keywords Structural fire hazard · Maximum entropy · MODIS active fire data · Anthropogenic factors

Introduction

Forests and other wooded land are very important worldwide, providing ecosystem services and refuges for terrestrial biodiversity, influencing employment, economic growth, human livelihoods, and well-being (Earl 1975; Shvidenko and Gonzalez 2005; Nilsson et al. 2011; Kibria et al. 2017). Fires are a major disturbance to forested areas, affecting millions of hectares of land every year, leading to disturbances on biodiversity, affecting the stability of ecosystem functioning and posing significant threats to human lives and livelihoods (Bowman et al. 2009; Özbayoğlu and Bozer 2012; Chandra and Bdishardwaj 2015). Forest vegetation is particularly sensitive to variations in climatic factors, such as extreme drought events (Bottero et al. 2017), which in turn make forests more susceptible to fire (Flannigan et al. 2006; Russo et al. 2017). Besides climate, other factors can strongly influence fire occurrence and spread, such as vegetation and fuel types, topographic conditions, proximity to roads and settlements or human activities (Flannigan et al. 2009; Kasischke et al. 2010; Bowman et al. 2011; Archibald et al. 2013; Chuvieco et al. 2014; Oliveira et al. 2017). Understanding the relationships between the spatial

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distribution of fires and their main drivers is vital to improve fire prevention and mitigation strategies. The influence of biophysical and anthropogenic factors in fire distribution and hazard levels has attracted wide international attention, fostering the development of assessment frameworks, fire danger and risk models based on GIS and the application of novel and advanced techniques worldwide (Chuvieco et al. 2014; Hantson et al. 2015; Šturm and Podobnikar 2017; Tien Bui et al. 2017; Connor et al. 2017; Oliveira et al. 2018). Despite these efforts, fire hazard and risk mapping tools, adapted to the specific features of different fire-prone areas in the globe, are still missing.

Machine learning, statistical techniques and experts' knowledge approaches are commonly used in fire hazard modeling and to analyze fire occurrence patterns at different spatial and temporal scales (e.g., from local to global, and short to long-term analysis (Oliveira et al. 2012; Tien Bui et al. 2016; Satir et al. 2016)). Approaches using presence-absence methods (PA) have been used to analyze the distribution of specific events or elements, based on presence data (ignition, in case of fires) at a certain location (pixel); interpretation about the probability of fire occurrence can be accomplished, for example, by fitting the presence–absence fire data to discriminant analysis, logistic regression and related models (MacKenzie et al. 2002; Adab 2017). Presence-absence methods (PA) have been shown to yield high accuracy in modeling predictive habitat suitability, ultimately determined by the quality of the data (Brotons et al. 2004). Maximum entropy (MaxEnt) is a presence-background method (PB) (Guillera-Arroita et al. 2014) based on the probability distribution of maximum entropy (Phillips et al. 2006) that applies presence-only data with the number of raster covariates to predict probability of suitability for occurrence of a target phenomenon. MaxEnt is particularly suited for modeling with presence-only data and verified absence is not required to fit the model (Renard et al. 2012), which are difficult to confirm because it depends on survey location (MacKenzie et al. 2002). The performance of presence-absence methods will be low if absence data at a particular location is caused by factors not included in the model, such as dispersal limitations, biotic interactions or incorrect assessment (Liu et al. 2005; Pearson et al. 2007).

In Iran, fires are a major disturbance to forest ecosystems (Shafiei et al. 2010; Jafarzadeh et al. 2017) and biomass burning is one of the main drivers of deforestation and degradation in the northern part of the country (Sobhani and Khosravi 2015). Even though historical forest fire statistics are not completely reliable and the fire data currently available are partial (FAO 2015; Jafarzadeh et al. 2017), the Global Forest Resources Assessment (FAO 2015) accounted for about 3400 ha of forests burned annually, between 2003 and 2012, and ca. 88,000 ha of burned land overall in the country per year. Previous studies were developed to analyze forest fire distribution, hazard and risk levels in Iran, at several scales and using different methodologies. At national level, Eskandari and Chuvieco (2015) obtained a fire danger assessment map based on a framework adapted from other countries, focusing on specific fire ignition and propagation factors; specific areas in the north and west of the country were found to be more likely affected by fires. Other authors applied Geographic Information Systems (GIS), remote sensing techniques and particular statistical analysis to uncover the relations between fires and influencing factors in the provinces of Gilan, Golestan, Ilam or Mazandaram (Mahdavi 2012; Mohammadi et al. 2014; Eskandari and Chuvieco 2015; Najafabadi et al. 2015; Abdi et al. 2016; Adab 2017; Pahlavani and Bigdeli 2017). These studies provided valuable indications on the potential drivers of fire at local and regional levels and on the applicability of different methods. Despite these efforts, the factors contributing to fire occurrence in Iran are still unclear (Eskandari and Chuvieco 2015; Abdi et al. 2018), also because forest studies in the country are still in an early stage; however, the existing studies indicate that anthropogenic factors are likely to have a strong contribution to fire hazard in the country (Adab 2017). Also, the country has not yet built a forest information system (FIS) or an exhaustive database on fire events, hindering the development of coherent fire hazard and risk models (Mahdavi and Naghdi 2007). Important gaps still exist regarding the development of technical and operational tools, based on advanced methodologies, GIS mapping and state-of-the-art scientific knowledge, to improve fire management strategies tailored to the country's needs and applicable to the different phases of fire management (prevention, suppression, mitigation or recovery). These circumstances introduce an obvious degree of uncertainty in the theoretical and applied research on fire modeling in Iran, which can lead to unexpected and imprecise results (De la Riva et al. 2004). Therefore, better information and deeper knowledge concerning fire occurrence distribution,

hazard and risk assessment and influencing factors, is still needed for Iran at different scales and timeframes. Modeling fire hazard levels is essential to provide effective tools for controlling or preventing forest fires. The main purpose of the present study was to improve the understanding of the environmental factors that potentially influence fire hazard levels in the province of Mazandaran, in Iran, which are still largely unknown. Notwithstanding the frequent forest fire activity (Adab et al. 2015), a comprehensive fire occurrence database is still not available for the province. For this reason, the assessment was based on MODIS active fire product. Different environmental covariates were obtained from different data sources with the purpose to provide quantitative estimations of fire hazard potential, measured in association with anthropogenic and biophysical conditions. In this research, we applied the ecological niche theory (EN), classically used for distributional possibilities of species, for predicting the potential geographical distribution of fire hazard, based on the presence of fire events occurred in different areas of the Mazandaran Province. The relative importance of the different environmental factors to fire hazard levels are discussed, in view of the potential implications to improve forest fire prevention and mitigation strategies in the region.

Materials and methods

Study area

The study area corresponds to Mazandaran province which extends over 23,833 km^2 in the north of Iran and is located along the southern edge of the Caspian Sea (Fig. 1). This area experiences mild and humid climatic conditions (Emadi et al. 2016), with warm summers and cold winters (Peel et al., 2007); mean precipitation values are above the average of the country, about 500 mm annually, increasing in the north of the province (Molavi-Arabshahi et al., 2016). This area belongs to the Hyrcanian forests belt, stretched along the northern slopes of the Alborz mountains; these are mainly composed of temperate deciduous forests and have high species richness and biodiversity levels (Scharnweber et al. 2007; Akhani et al. 2010; Bani Assadi et al. 2015).

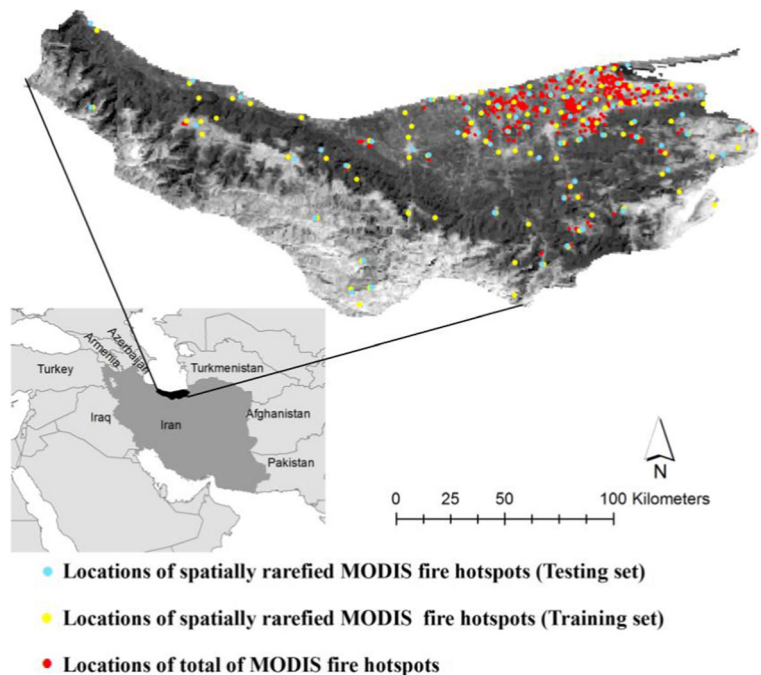Data collection and pre-processing

Fire occurrence data

The historical database on forest fire events which is available for Mazandaran Province was coordinated by government institutions and national NGOs, using different fire detection technologies (Jahdi et al. 2016), and subsequently given to the Forests, Range and Watershed Management Organization (Allard 2001). This database has recently integrated information on the location, time, ignition source, and burnt area of each fire ignition, but shows some spatial uncertainty in the fire records, derived from location errors or missing fire events, which may hinder the development of a robust analysis. In order to overcome these issues, MODerate resolution Imaging Spectrometer (MODIS) hotspots (also known as active fire product) were used instead for the study area. MODIS fire hotspots (Collection 6 - C6) used in this study included global daily coverage at 1 km spatial resolution (MOD14A1), which is also a rapid fire detection product for operational near-real time (NRT) use and it is also applied in forest fire-related studies (Justice et al. 2002). MODIS hotspots of all confidense levels were included, because the low confidense hotspots represent extra information which outweighs the potential problem of slightly higher commission errors (Hantson et al. 2013). This dataset has been improved over previous versions (Collection 5 – C5), with a reduced incidence of false alarms caused by small forest clearings and an improved detection of large fires with 1.2% global commission compared to 2.4% in C5 (Giglio et al. 2016).

As the study area is mostly covered by vegetation types that are likely to burn, all MODIS hotspots detected over the period 2000–2016 were retained. In the present study, a total of 726 active fire events were recorded by MODIS sensor in the Mazandaran Province in the period considered, which are integrated as the dependent variable in the model (Fig. 1).

Driving factors

In this research, the term "fire hazard" refers to the probability of a certain location to experience a fire each year (Richards et al. 1999). Fire ignition and spread are a result of the complex interaction between a variety of components. The factors influencing fire hazard levels were categorized into four groups, based upon their

Fig. 1 The location of the study area, Mazandaran province, northern Iran. Labeled red points represent the total number of fire occurrences detected by MODIS sensor prior to spatial filtering ($n = 726$) for the period from November 2000 to July 2016. The source of borders of Middle East countries is from GADM (www.gadm.org). The source of background image is from NASA Earth Observations (NEO) (https://neo.sci.gsfc.nasa.gov/)

• **Locations of spatially rarefied MODIS fire hotspots (Testing set)**

• **Locations of spatially rarefied MODIS fire hotspots (Training set)**

• **Locations of total of MODIS fire hotspots**

potential relation with fire occurrence: (1) climatic conditions; (2) topographic conditions; (3) land cover and land use types, and (4) anthropogenic factors, from which we obtained 18 explanatory variables. The technical specifications of each variable are detailed in Table 1 and a brief description of their potential relation with fire occurrence, based on literature, is presented below.

Climatic conditions

Climatic conditions are widely recognized as important factors influencing regional and local fire probability. Annual and interannual climatic variation for precipitation, temperature and drought influences fuel availability and conditions (Schoennagel et al. 2004; Littell et al. 2009) which are linked to the likelihood of fire ignition and to the probability of fire propagation (Archibald et al. 2013; Bedia et al. 2015; Hantson et al. 2015; Moreira et al. 2009; Oliveira et al. 2012; Syphard et al. 2008; Itziar et al. 2015). This is due to the effects of weather parameters on fuels moisture, fuel load and composition, including the amount of fine fuels (e.g., leaves, grasses, forest litter) and fuel-desiccating drought (Schoennagel et al. 2004; MacMillan and Shary 2008). Higher annual precipitation and lower temperatures increase vegetation productivity and

generate higher fuel loads in specific topographic and land cover conditions, such as grasslands and shrublands, which in turn will be available to burn in subsequent drier seasons (Oliveira et al. 2014; Nunes et al. 2016). The relative dryness of fuels is a direct effect of long-term dry conditions and is of greater significance in fire hazard (Renard et al. 2012). Climatic predictors are used in this study to explore their relative importance in driving fire occurrence in the study area (Wimberly and Reilly 2007; MacMillan and Shary 2008; Renard et al. 2012; Alvares et al. 2013; Guo et al. 2017; Tien Bui et al. 2017).

Topographic conditions

Topographic conditions influence fuel type distribution, composition and flammability and also have a big role on local climate variations (Parisien and Moritz 2009; Martínez-Fernández et al. 2013; Oliveira et al. 2014; Modugno et al. 2016). For example, elevation, slope and aspect are linked to plant composition in beech communities in unharvested beech forests in the north of Iran, because of their effects on decreasing air pressure, increasing ultraviolet rays, reduced temperatures and changes in precipitation conditions (Adel et al. 2014).

Forest fires may also be influenced by hydrogeological parameters (Tien Bui et al. 2016). As such, the

Table 1 Variables integrated in the maximum entropy model for assessing fire hazard, including the data source and a brief description. All variables were generated or resampled at 1-km resolution

Category	Code	Description of data	Data source
Explanatory variables			
Climatic conditions	WEI	Wind Exposition Index (dimensionless). Continuous	SAGA Climate and Weather module (Conrad et al. 2015)
	PIS	Potential Incoming Solar radiation (insolation) (kWh/m²). Continuous	SAGA Lighting module (Conrad et al. 2015)
	AP	Total Annual Precipitation (mm). Continuous	WorldClim, (Fick and Hijmans 2017)
	PDM	Total Precipitation of the Driest Month (mm). Continuous	WorldClim, (Fick and Hijmans 2017)
	AMT	Annual Mean Temperature (°C). Continuous	WorldClim, (Fick and Hijmans 2017)
	MTWM	Maximum Temperature of the Warmest Month (°C). Continuous	WorldClim, (Fick and Hijmans 2017)
	DAH	Diurnal Anisotropic Heating (dimensionless). Continuous	SAGA Climate and Weather module (Conrad et al. 2015)
	DI	Annual Dryness Index computed as annual mean temperature (°C)/annual mean precipitation (mm/year). Continuous	(S. Brown and Lugo 1982)
	Köppen	Köppen climate classification, computed by AP and AMT data that coincides with well-defined vegetation regions around the world (Alvares et al. 2013). Categorical	WorldClim, (Fick and Hijmans 2017)
Topographic conditions	Elevation	Elevation values obtained from Digital Elevation Model (DEM), at 1-km Resolution. Aggregated from ASTER 30 m Global Digital Elevation Model (GDEM), V2. Continuous	Global Data Explorer (GDEx), United States Geological Survey (USGS) (Tachikawa et al. 2011)
	Slope	Slope derived from DEM (%). Continuous	Calculated from GDEM, V2
	Aspect	Aspect derived from DEM (°). Categorical	Calculated from GDEM, V2
	TWI	Topographic Wetness Index (dimensionless). Continuous	Calculated from GDEM, V2. SAGA Hydrology module (Conrad et al. 2015)
Land cover/vegetation characteristics	LC	Land cover of Mazandaran Province, Globcover2009 V2.3 at 300 m Resolution. Categorical. A total of 14 different categories were retrieved: rainfed croplands (Code 14), mosaic croplands/vegetation (Code 20), mosaic vegetation/croplands (Code 30), closed broadleaved deciduous forest (Code 50), closed needleleaved evergreen forest (Code 70), closed to open mixed broadleaved and needleleaved forest (Code 100), mosaic forest-shrubland/grassland (Code 110), mosaic grassland/forest-shrubland (Code 120), closed to open shrubland (Code 130), closed to open grassland (Code 140), sparse vegetation (Code 150), bare areas (Code 200), water bodies (Code 210), and permanent snow and ice (Code 220).	GLOBCOVER project, European Space Agency (ESA) (Arino et al. 2007)
Anthropogenic factors	DisRo	Mean Euclidean distance to the primary roads (1-km). Continuous	Calculated from digital maps of topographic (The National Cartographic left of Iran (NCC), Iran)
	DisS	Mean Euclidean distance to the settlements, including hamlets, villages, towns and cities. (1-km). Continuous	Calculated from digital maps of topographic (The National Cartographic left of Iran (NCC), Iran)
	DenS		

Table 1 (continued)

Category	Code	Description of data	Data source
		Heatmap densities of settlements, including hamlets, villages, towns and cities. (km²). Epanechnikov kernel shape. Scaled kernel size. Continuous	Calculated from digital maps of topographic (The National Cartographic left of Iran (NCC), Iran)
	DisRi	Mean Euclidean distance to the rivers (1-km). Continuous	Collected from Forests, Range and Watershed Management Organization (FRWO), Iran)
Dependent variable			
Fire occurrence	Fire events	Derived from MODIS 1-km MCD14ML (2000-16), Collection 6. Point format shapefiles (.shp)	Fire Information for Resource Management System (FIRMS), National Aeronautics and Space Administration (NASA)

Notes: All climate variables consisted of 30-year means (1970–2000) for WorldClim version 2. Code represents labels for every predictor variable name in the dataset, SAGA GIS (System for Automated Geoscientific Analyses)

Topographic Wetness Index (TWI), a steady-state wetness index that quantifies topographic control on hydrological processes (Sørensen et al. 2006), was included in the analysis. TWI measures the potential soil moisture (Krishna P Vadrevu et al. 2006) which can influence the moisture of dead fuel beds (Matthews 2014). Topographic features also play an important role on the distribution of human activities and the presence of people can increase the probability of fire ignition (Parisien et al. 2016; Nami et al. 2018). Lowland areas with gentle slopes are more attractive to human activities and, therefore, are more densely populated, have a higher concentration of built-up structures and more agricultural fields (Reed et al. 1999; Xu et al. 2006; Armién et al. 2009). TWI and topographic features (elevation, slope and aspect) were derived from a Digital Elevation Model (DEM) at 30 m resolution, resampled to 1 km (Table 1).

Land cover/vegetation

Land cover is a key variable driving the patterns of wildfire occurrence at the landscape level and is used as a proxy of vegetation characteristics. Specific types of land cover (e.g., shrublands or conifer plantations) are considered more fire-prone than others (e.g., wetlands, agricultural areas or recently burned patches) in certain environments, due to differences in fuel load composition and vegetation structure, which subsequently affect flammability levels, fire spread and intensity (Barros and Pereira 2014; Carmo et al. 2011; Grégoire et al. 2013; Moreira et al. 2009; Oliveira et al. 2014; Pereira et al. 2014; San-Miguel-Ayanz et al. 2012; Silva et al. 2009). Land cover also reflects human activities, as is the case of agricultural uses such as annual crops, permanent crops and agro-forestry systems, which are usually less fire-prone than wildland areas (Moreira et al. 2009). For this research, specific land cover types were retrieved (Table 1), according to their potential association with the spatial patterns of fire occurrence in the province.

Anthropogenic variables

Incorporating human-related parameters in fire occurrence analysis is important, since the spatial distribution of fires in different regions of the world is closely related to human presence and activities, although with differing trends (Bistinas et al. 2013; M. Krawchuk and Moritz 2014; Hantson et al. 2015). The data on cause

of ignitions is still unavailable for Iran, but sparse fire studies found that the majority of fires in recent years were human-caused (Mohammadi et al. 2014), whereas lightning is still relevant as an ignition source in certain mountainous areas (Eskandari and Chuvieco 2015). The proximity of populated settlements to forests may increase their susceptibility to fire and the probability of human-caused ignitions (Satoh et al. 2004). As well, socioeconomic settings and the technological development verified in recent decades have led to an overall increase in the number of visitors to forest and woodland ecosystems, due to increased movements of people and vehicles, the spread of tourism and recreational activities and an increased accessibility to forested areas (Guo et al. 2017). Distance to roads reflects the accessibility to forest areas and increases the possibility of fire occurrence (Guo et al. 2017; Armenteras et al. 2017). In the study area, most of the land located near rivers was allocated to traditional home gardens and vegetable gardens, and therefore can contribute to increase tourism activities (Mohammadi et al. 2014). For these reasons, it is of primary importance to include such anthropogenic variables (distance to rivers, distance to primary roads and density of cities) in fire hazard assessment.

Statistical analysis

MaxEnt modeling of fire occurrences

The principle of the MaxEnt model relies on the estimation of the probability distribution of maximum entropy. Occurrences are predicted by finding the distribution that is most spread out (i.e., closest to the uniform), while taking into account a set of constraints (the environmental conditions) of known locations (Chen et al. 2015). MaxEnt iteratively compares the conditional density function of given covariate grids (predictor variables) at presence locations to the marginal density (a background grid consisting of the mean observations) of covariates across the entire study region. Conditional probability is then derived from these two probability densities as sampled from a large number of grids, which gives the relative environmental suitability for presence of a fire for each point in the study area. The MaxEnt represents a list of functional forms (i.e., linear, quadratic, threshold, hinge, product, and categorical) to describe occurrence responses (for fire, in this study) to environmental conditions. Functional forms assist us in fitting highly complex responses by using function

types that cannot be modeled with regression techniques, such as generalized additive models (GAM) (Chen et al. 2015). Linear and quadratic features are used when sample size is low (< 20) (Kumar and Stohlgren 2009). MaxEnt can be trained to fit complex relationships between occurrences and environmental variables, and in this study auto feature type was used to simplify interpretation, since understanding the more complex and multifaceted relationships is still hard to accomplish (Louzao et al. 2012).

Spatial autocorrelation

A spatial correlation may exist between MODIS active fire data, which are collected as points. Ignoring this spatial correlation may yield a biased estimation of the model parameters and misleading inferences; including spatially independent occurrence from neighboring sites in a model can reduce residual error and improve the model estimation (Boria et al. 2014). Therefore, spatial filtering should be conducted before executing the MaxEnt model. Average Nearest Neighbor distances among fire points were calculated to measure the spatial autocorrelation distance between each fire feature and its nearest neighbor's location, and subsequently fire points were rarefied using the Rarefy Occurrence Data at SDMs (Species Distribution Models) tool performed in ArcGIS 10.3 (Brown 2014; Brown et al. 2017).

Regarding presence data, autocorrelation of clustered occurrence points was detected using Moran's I ($I = 0.21$) and Average Nearest Neighbor (z-score -31.2). The expected value of the nearest neighbor distance (7512 m, z-score 3.4) was used in this study to define the spatial resolution of rarefied occurrence data, which corresponds to the average distance between nearest points when these are randomly distributed throughout the study area. From these procedures, 105 points representing fire events were retrieved (training set), to predict fire distribution with the minimum spatial correlation between points (Moran's $I = 0.044$) (Fig. 1). Using the same procedures, 62 points of fire events, out of 621, were selected for the testing set in the fire model (Moran's $I = 0.039$) (Fig. 1).

Output transformations

MaxEnt provides four output transformations (floating point files) for model values in raw, cumulative, logistic and complementary log-log (cloglog). These output

formats are monotonically related to each other, but their scaling properties are totally different from each other, and have different meanings (Baldwin 2009). For many modeling applications, such as the one presented in this study, the probability of fire presence is a relevant result. This probability of presence is given by the logistic and cloglog format. The cloglog gives an estimated value between 0 and 1 of probability of presence, with higher values demonstrating more favorable conditions for fire occurrence. Therefore, cloglog output is more easily interpreted overlapped with the other transformations, when imported into a GIS to map fire likelihood (Kadej et al. 2017).

Model evaluation

In every hazard assessment, it is important to identify how each predictor variable affects the presence of the estimated event, in this case fire, which variable has the largest effect on the model and in what manner these different variables influence fire occurrence likelihood. The relative importance of the predictor variables in the model was tested using three approaches: heuristic (percent contribution), permutation (permutation importance) and jackknife metrics. Caution must be taken in employing heuristic methods because strong multicollinearity among variables can affect the results by adding misleading importance to correlated predictors; a jackknife approach (leave-one-out cross-validation) for evaluating variable importance is recommended, because each variable is excluded at a time when running the model with the remaining variables (Baldwin 2009). The jackknife approach was also used to measure the performance of the individual predictor variables in the model. The model's ability to correctly discriminate the positive (test points) and the negative (pseudo-absence points) cases was evaluated with the receiver operating characteristic (ROC) analyses (Renard et al. 2012). The area under the curve measured by ROC provides a single metric of model performance that is independent of any particular choice of threshold (Phillips et al. 2006). AUC values range between 0.5 and 1, with 1 reflecting a perfect discrimination between presence and absence, and 0.5 indicating a random performance without discriminative power. Predictor variables are also important in what concerns their high training gains when used alone in a model; additionally, a predictor variable can be considered a significant contributor if the training gain is low when the variable

is deleted from the model (Miller et al. 2012). Therefore, in order to compare the importance of the 18 predictor variables (Table 1), AUC statistic was employed and three different models were produced and compared with AUC values: (1) using all predictor variables; (2) using only one variable at a time and (3) systematically dropping out one variable each turn.

The Cohen's kappa (κ) index measures the reliability of a classification model quantitatively, indicating an agreement between the observed and the predicted values (Cohen 1960). Kappa values are interpreted as follows: $\kappa \leq 0$ as indicating no agreement and $\kappa = 0.01$–0.20 as none to slight, $\kappa = 0.21$–0.40 as fair, $\kappa = 0.41$–0.60 as moderate, $\kappa = 0.61$–0.80 as substantial, and $\kappa = 0.81$–1.00 as almost perfect agreement, using 0.5 as a threshold (Monserud and Leemans 1992). In this study, 105 points were randomly selected from the background, equivalent to the training dataset, for computing Cohen's kappa index via the MedCalc® statistical software.

Model validation

Model validation is a necessary step to assess the predictive performance of a model, considering that the validation error represents an unbiased estimate of a model's predictive power. A common approach to validation is to randomly split the dataset into two portions: a training set and a testing set, thus generating quasi-independent subset data for testing the model (Kumar and Stohlgren 2009; Lezama-Ochoa et al. 2016). The MaxEnt model developed in this research used a training dataset composed of 105 points of presence data. The predictive ability of the model was then assessed by cross-validation without duplicates (Lentz et al. 2008) using the 62 points of presence data set aside initially for testing purposes and, as such, not included in the training phase (Renard et al. 2012). A set of 10,000 random points representing background (or pseudo-absence) points were sampled to create the background distribution which fits the model (Phillips et al. 2006). MaxEnt limits model complexity and, hence regularization was used in this study to reduce model over-fitting through a process for achieving optimal MaxEnt model, similar to the Akaike Information Criterion (AIC) (Anderson and Gonzalez Jr. 2011); further details on this process can be found in (Phillips et al. 2006). ArcMap 10.3® was used to process the outputs of the MaxEnt model, mapping

the predicted fire occurrence likelihood levels in a raster format.

Results

The MaxEnt model generated an ASCII file of predicted fire presence locations, indicating a relative measure of fire proneness of the landscape at 1 km resolution. The cloglog outputs are shown in Fig. 2. The likelihood of a pixel being affected by a fire was expressed within the range of 0 and 1, with higher values representing increased probability and more favorable conditions for fire presence. High fire hazard potential (probability ≥ than 0.8) was found in the northeast area of the province and near coastal and urban areas, whereas inland sites, away from the coast and inside mountainous ranges, experienced very low probabilities (probability ≤ 0.1).

According to the relative contributions of the environmental variables to the MaxEnt model (Table 2), Köppen, LC, Elevation and DenS were the strongest predictors of fire distribution, with 21.9, 19.9, 11.2 and 8.4% contribution, respectively. The variables with a lower percentage of contribution were DisRo, Aspect, DisRi and PIS.

The Cohen's kappa index was 0.6, representing 60% better than random chance, and a slightly better agreement between the maximum entropy model and the training data. Regarding the performance of the MaxEnt model using ROC and AUC, the sensitivity (true positive rate) for the training data was 77.4%, indicating that over 77% of the fire points were correctly classified by

the model, whereas 71.2% of no-fire points were also correctly classified. The overall analysis of the AUC (Fig. 3) shows that the model presents a high goodness-of-fit (AUC = 0.85) with the training dataset, while the AUC is 0.79 when applied to the independent testing dataset, indicating that the model's predictive power is 79% and low p values. Overall, the maximum entropy model performs well on both the training and testing datasets and showed a reasonable overall accuracy.

Figure 4 shows the results of the jackknife test regarding the order of importance of the predictor variables in the model. Density of settlements was the strongest contributor to the MaxEnt model for the study area; if excluded from the model, its overall performance is considerably reduced (Fig. 4). Among all predictor variables, land cover and distance to roads rank second and third in importance, and the remaining variables show similar levels of importance (AUC values). The cumulative contribution of these 18 variables is 79%.

The influence of each predictor variables on fire hazard potential was further investigated by producing response curves. The shape of the response curves can provide some details on the patterns of distribution of fire occurrence, as follows. Figure 5 shows the relationships between the three strongest predictors and fire hazard potential based on jackknife test (Adab et al. 2016). Fire hazard potential is negatively related to distance to roads (DisRo), indicating that fires are more likely to occur closer to roads and urbanized areas. For density of settlements, fire hazard potential reaches a

Fig. 2 Forest fire hazard map for Mazandaran province using the MaxEnt complementary log-log (cloglog) output from environmental variables. The predicted spatial distribution of fire probabilities across the forest landscape, with values ranging from 0 to 1 (grayscale color) is depicted by white to black colors. Black colors show a higher potential fire hazard while the white colors indicate lower potential
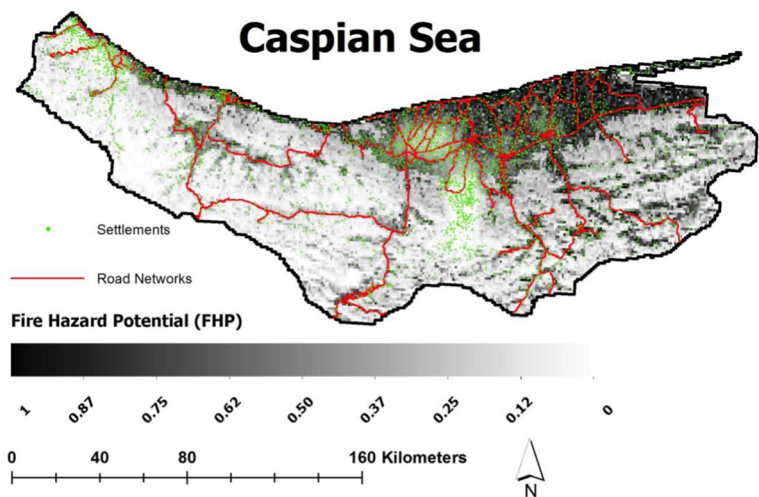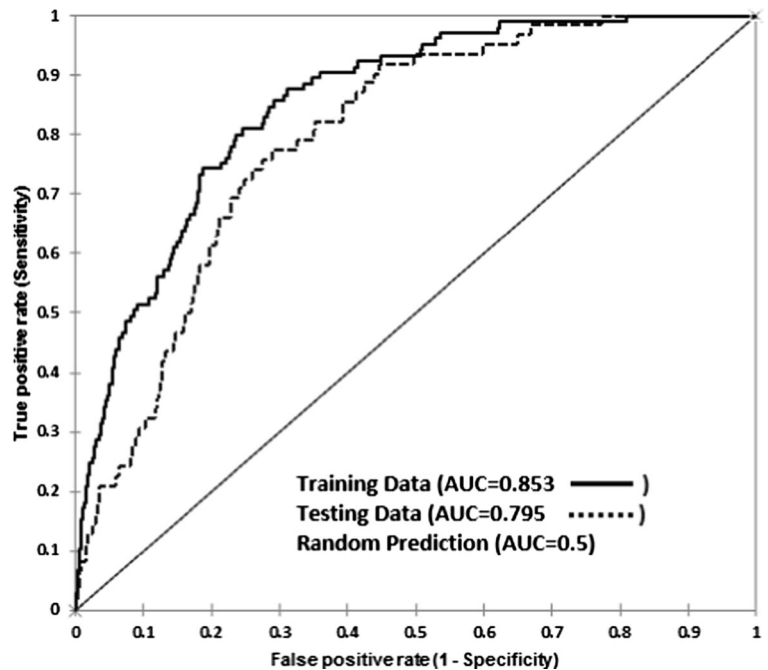
Table 2 Relative contributions of the of predictor variables to the forest fire hazard model. The highest predictive power is Köppen, followed by LC, Elevation, and DenS. For details about variables acronyms, see Table 1

X	Contribution (%)	Permutation importance
Köppen	21.9	5.4
LC	19.6	13.9
Elevation	11.2	4.5
DenS	8.4	13.8
Slope	7.1	3.9
TWI	6.6	1.9
DAH	5.5	8.5
DI	2.8	5.1
WEI	2.8	3.5
PDM	2.6	8.5
MTWM	2.5	0.1
AMT	2.2	13.4
AP	2.2	1.2
DisS	2.2	6.3
DisRo	1.3	6.6
Aspect	0.6	0
DisRi	0.5	2.2
PIS	0.1	0.9

peak and then decreases as the values go up. The probability of fire presence was highest when DenS was 0.26

(number of settlements equal to 43 in 1 km^2) (Fig. 5a) and DisRo was less than 3000 m (Fig. 5b). The importance of land cover variables indicates that fires are most likely to occur on specific forest types, namely closed to open mixed broadleaved and needleleaved forest (0.86), but also on rainfed croplands (0.83) and in areas with mosaic croplands/vegetation (0.78) (Figs. 5c and 6). On the contrary, fires are less likely to occur on closed broadleaved deciduous forest (0.23) and closed to open shrubland (0.26).

Discussion

Main drivers of fire hazard potential at regional level (Mazandaran province)

The assessment of fire hazard levels in the North of Iran is crucial to further understand the spatial distribution of fire occurrence likelihood and its main influencing factors. We developed a modeling procedure to quantify fire hazard potential at regional level by applying the MaxEnt method, integrating multiple layers of geospatial-based data potentially related to fire occurrence in Mazandaran province and a roadmap is provided for the study area as guidelines for fire hazard reduction.
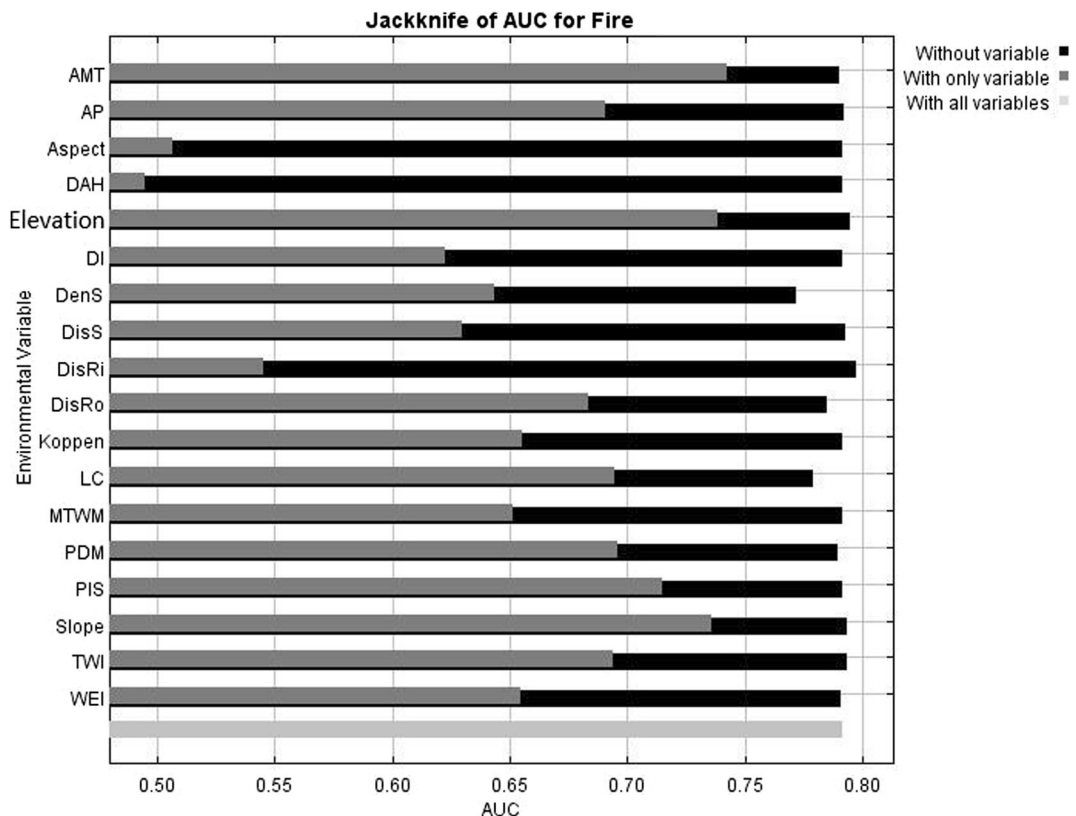
Fig. 3 The receiver operating characteristic (ROC) curve and area under the ROC curve (AUC) for the maximum entropy. AUC for training data reaches 85% and for testing data is 79% which are higher than 0.5 of a random model

Fig. 4 Estimations of variable importance using Jackknife test for the final MaxEnt model output. For each variable, bars indicate the area under the ROC curve (AUC). The light gray bar represents the full-model AUC when using all variables, the dark gray bar represents the gain of AUC when the specific variable is used in model and black bars represent the AUC of models without the specific variable, and a lower gain shows that the specific variable has more information that is not present in other variables

Fire hazard potential was highest in the northeast of the province. From the models obtained, with or without jackknife permutation and including single or multiple variables at a time, it was found that anthropogenic variables, particularly density of settlements and specific land cover types related to farming activities, were the most relevant drivers. Regarding the density of settlements, the study area is characterized by many small settlements and villages, with forest and agricultural landscapes neighboring them. Hazard levels in the study area declined when settlements density reached a certain threshold (0.26), (Fig. 5), a trend that is consistent with the results of other studies (Syphard et al. 2007). The probability of man-made ignitions is influenced by population density (Mahdavi 2012; Penman et al. 2013; Oliveira et al. 2014), but the effect in fire occurrence and burned area is positive only up to an intermediate threshold of population density, since the amount of available fuel decreases in more populated areas (M. A. Krawchuk et al.

2009; Bistinas et al. 2013). Another global analysis showed the effect of increasing population on the reduction of fire frequency, except for very sparsely populated parts, where the effect is slightly positive (Knorr et al. 2014).

Among all land cover types existing in the study area, closed to open mixed broadleaved and needleleaved forest, rainfed croplands, and mosaic croplands/ vegetation (i.e., cropland (50–70%) and grassland/ shrubland/forest between 20 and 50%) significantly influenced fire hazard potential. The contribution of the closed to open mixed broadleaved and needleleaved forest to fire hazard is likely related to their specific fuel load and composition, particularly the bulk of fine fuels produced (Agee et al. 1976; Small and Bush 1985; Stohlgren 1988; Dimitrakopoulos 2002). Also, the higher presence of tourism activities due to recent improved accessibility to these forests could increase the possibility of human-caused ignitions (Caldararo 2002; Ajin et al. 2016).
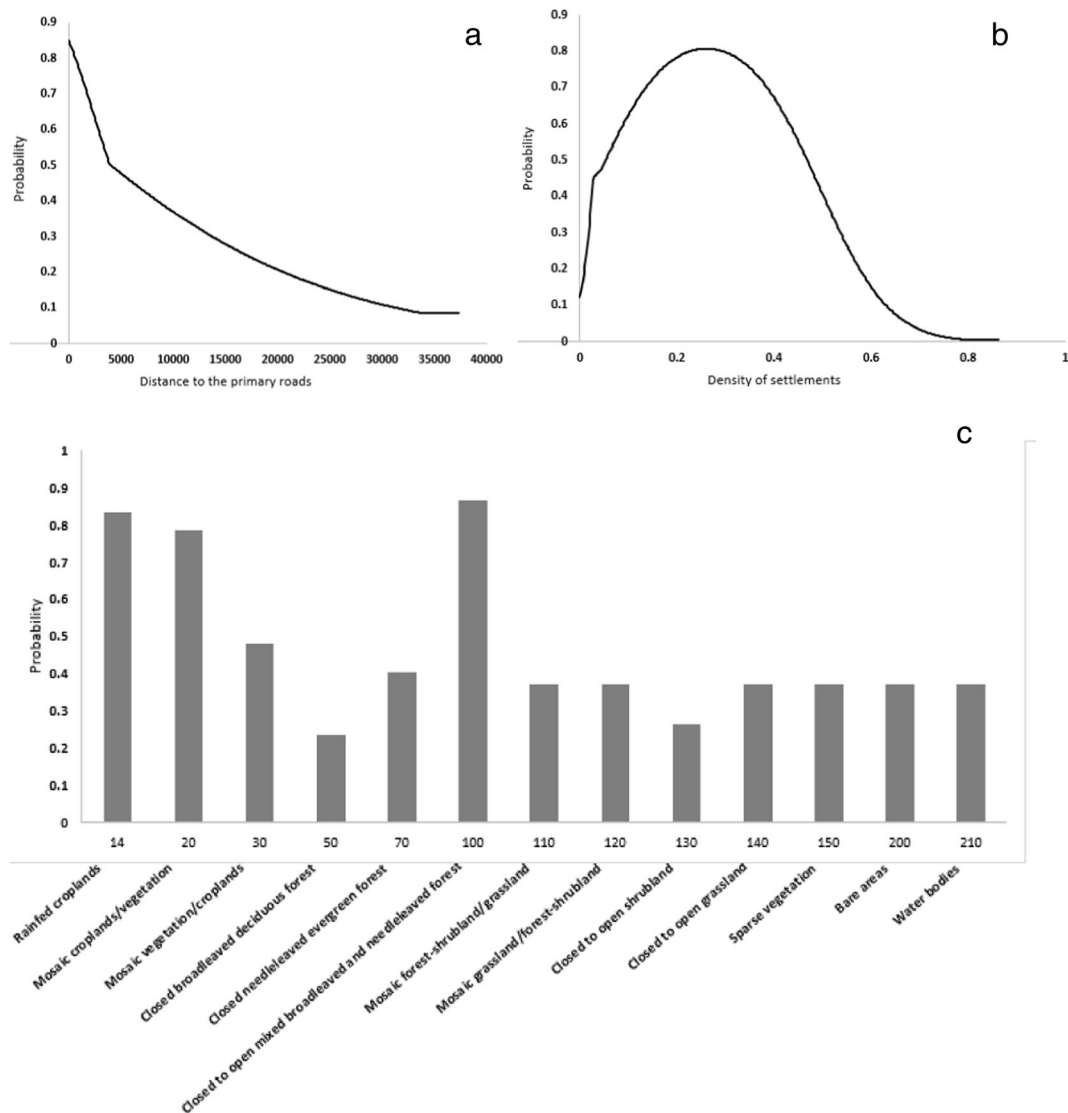
Fig. 5 Relationships between third highest predictors and the probability of presence of fire occurrence in Mazandaran province that included only the corresponding variable. **a** Distance from roads (meter) (DisRo). **b** City/settlement densities (scaled size) (DenS). **c** Landcover. Black lines are the response curves of fire occurrence to predictors. The y-axis shows the logistic probability of fire presence; higher value of logistic probabilities indicates higher fire hazard

The presence of croplands/natural vegetation as a relevant variable indicates the potential influence of ignitions related to agricultural activities, which can spread to other vegetated areas nearby, a pattern also found in Southern Europe and the Middle East (San-Miguel-Ayanz et al. 2012; Ganteaume et al. 2013; Giglio et al. 2013). In Golestan Province in Iran, Adab (2017) has also argued that the mosaic croplands/vegetation class provides the greatest amount of fuel to burn, followed by rainfed cropland. Indeed, fire is widely used as a tool for shifting cultivation and converting forest to agricultural land in many countries (Ketterings and Bigham 2000; Ruiz-Mirazo et al. 2012). In total, 321 and 171 hotspots were detected on mosaic croplands/vegetation and rainfed croplands, respectively, which cover over 600,000 ha of land in Mazandaran province. At the global level, as evaluated from MODIS data, agricultural fires accounted for ~ 9% of the global annual fires (Korontzi et al. 2006), with most biomass burning occurring in savannas (48–51%), and cleared areas used for agriculture showing the highest mean probability of fire occurrence, which increased even
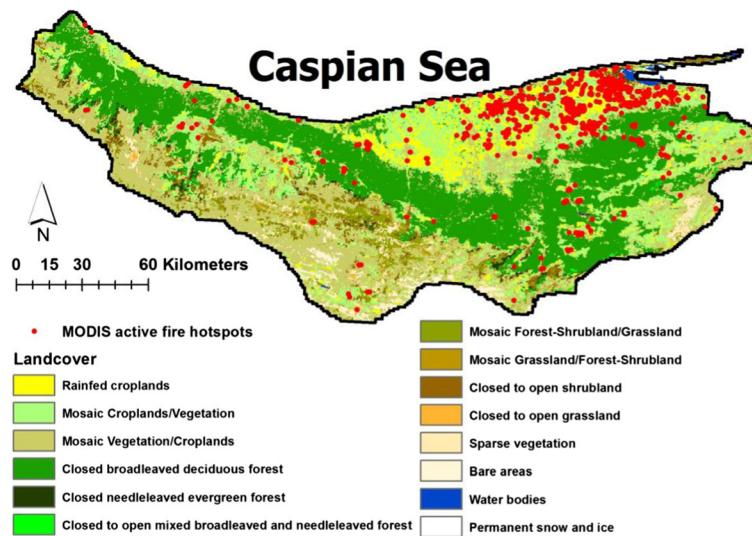
Fig. 6 Map showing the distribution of fire-affected area into land cover types. 14—rainfed croplands, 20—mosaic croplands/vegetation, 30—mosaic vegetation/croplands, 50—closed broadleaved deciduous forest, 70—closed needleleaved evergreen forest, 100—closed to open mixed broadleaved and needleleaved forest, 110—mosaic forest-shrubland/grassland, 120—mosaic grassland/forest-shrubland, 130—closed to open shrubland, 140—closed to open grassland, 150—sparse vegetation, 200—bare areas, 210—water bodies, 220—permanent snow and ice (without presence of MODIS active fire data)

further under drought conditions (Devisscher et al. 2016). Particularly in Iran, previous studies have shown that land cover/land use (LULC) is a relevant parameter for predicting fire occurrence in the Caspian Hyrcanian forest ecoregion, and also in arid and semi-arid ecosystems (Bashari et al. 2016; Adab 2017; Nami et al. 2018). This is due to a longer dry period each year that increases the amount of dry fuel available to burn, thus increasing the probability of an ignition turning into a large fire (Agee 1996).

Climatic variables, represented by Köppen categories (Humid Temperate Cfa), showed the highest importance in the overall model (without jackknife permutation); annual mean temperature alone provided evidence of increased fire occurrence by 74% in Mazandaran Province, affecting all classes of land cover, likely related to the effects on moisture content on live and dead fuels (Adab et al. 2016). Climate parameters such as temperature and moisture play a substantial role in vegetation growth and, hence, in fuel loads (Dwyer et al. 2000) that can determine the potential to start and spread a fire during a dry period (Dwyer et al. 2000). The northeastern side of the study area is uniformly covered by humid warm-temperate climate and temperature is highest in July, coinciding with the areas where more fuel accumulates. Other studies have found that climate with long periods of moisture stress contributed to fuels dryness

conditions (Dwyer et al. 2000) which can sustain fire occurrence in arid and semi-arid ecosystems in Iran (Bashari et al. 2016).

In this study, distance to roads showed a low contribution in the first model (without jackknife permutation), contrarily to what was found in the other models (with jackknife permutation), where DisRo ranked second in importance, likely due to the association with the presence of people, as ignition agents, and their accessibility to vegetated areas. In the latter, fire hazard potential levels were higher at shorter distances to roads, but started to level off at 4 km; this is consistent with the results of other studies (Romero-Calcerrada et al. 2008; Penman et al. 2013; Rodrigues and de la Riva 2014; Devisscher et al. 2016). Contrarily, other research found that distances to roads did not contribute significantly to fire hazard, as found by (Renard et al. 2012) in the Western Ghats of India the dual influence of distance to roads in fire hazard seems to show strong regional variations, a pattern that should be further explored in future research (Zhang et al. 2016).

Several studies have identified that fires are closely correlated with topography (e.g., elevation, aspect and slope) (Carmo et al. 2011; Martínez-Fernández et al. 2013; Oliveira et al. 2014; Satir et al. 2016), opposite to what was found in this research. Our findings indicate that the topographic features of northern Iran do not

seem to influence fire hazard levels, a pattern that was also found in other studies done for Iran (Abdi et al. 2016; Adab 2017). Overall, the importance of different explanatory variables on forest fire hazard highly depends on the characteristics of the study area and on the scale of analysis (Arpaci et al. 2014).

Model performance

Fire hazard potential was analyzed based on a presence-only data and MaxEnt was found a suitable method, considering that absence data is not required to fit the model (Renard et al. 2012). Massada et al. (2013) argued that a presence–absence modeling approach may be more suitable in areas with long-term fire records and where only a small part of the area can sustain a fire. We used MaxEnt, a popular method in ecological niche models (ENMs) because fire is presence-only data and this method has previously shown higher predictive accuracy than generalized linear models (GLMs), General Algebraic Modeling System (GAMs), BIOCLIM, or Genetic Algorithm for Rule Set Production (GARP) in other fields such as biodiversity assessment and species distribution mapping (Hernandez et al. 2006; Franklin 2010). MaxEnt is able to cope well with sparsely, irregularly sampled data and minor location errors (Kramer-Schadt et al. 2013). Even though MaxEnt has outperformed in comparison with other methods (Renard et al. 2012), it may lead to over-fitting if many input variables with too few occurrence records are integrated in the model (Kramer-Schadt et al. 2013). In the absence of comprehensive and complete national or regional databases, the use of MODIS hotspots is a reasonable option, because MODIS thermal sensors provide a considerable long-term database collection with minor location errors (1000 m^2 in size). Global commission error (false alarms) for the MOD14 Collection 6 daytime was 1.2%, compared to 2.4% in Collection 5 and Middle East commission error rates for MOD14 Collection 6 was 2% (Giglio et al. 2016). The commission errors (false alarms) for the Middle East are usually associated with perimeters of hot, arid, and sparsely vegetated or barren regions most commonly associated with deserts (Giglio et al. 2016). Although caution is needed regarding the use of worldwide datasets, given the potential error in terms of spatial location (Parente et al. 2016), MODIS active fire data and MERIS GlobCover product, both with medium spatial resolution (1 km or 500 m) have been widely used to test and validate fire hazard models at different scales, when local or higher resolution data is lacking or when data are only available for partial time periods (Krishna PRASAD Vadrevu and Justice 2011; Renard et al. 2012; Eskandari and Chuvieco 2015). The use of the MaxEnt methodology allowed to develop models based on datasets that contain only fire presence data (Elith et al. 2006; Arpaci et al. 2014), an approach that requires additional work to further examine the consistency of global databases in comparison with national or regional ones, to ensure that the analysis of the spatial distribution of forest fires in the study area is not hindered by data limitations and by the characteristics of fire ignition and area burned registry.

Practical implications to fire management

In this study, fire hazard potential maps show where a fire is most likely to occur in Mazandaran province. Overall, our findings revealed that land cover types associated with agricultural activities, represented by rainfed croplands and mosaic croplands/vegetation, and the human presence evidenced in settlements density and distance to roads, are the most important factors influencing fire likelihood in the study area. These findings can contribute for defining fire prevention and mitigation strategies adjusted to the province's fire conditions. These strategies may include zoning regulations defined by legal instruments, to restrict the intensity of urban development in hazardous areas, as well as a timely allocation of public resources and support systems in areas that are more fire-prone (Eshliki and Kaboudi 2012; Mirzaei 2013). Additionally, fuel reduction measures over fire-prone areas should be a priority, mainly surrounding settlements and corridors in hazardous zones (Curt and Delcros 2010; Marchal et al. 2017). The implementation of specific fuel management measures, particularly changing vegetation structure and creating fuel discontinuities around buildings and other built structures, can help reduce fire hazard in these areas and mitigate potential fire impacts. Their implementation will have to be evaluated according to land ownership, available public resources and existing legal regulations.

Furthermore, considering the influence of agricultural land uses in fire hazard levels in the regions, strategies to adjust agricultural practices should also be considered, such as training farmers to improve the use of fire and increase safety measures. As well, prevention

measures focusing on public awareness, to reduce igni-
tions and to improve population preparedness in case a
fire occurs, are of utmost importance; in fact, current
international initiatives stress the need for a stronger
community participation in disaster preparedness, miti-
gation and recovery, regardless of the phenomenon
(fires, earthquakes, floods) that occurs (UNISDR 2015).

Conclusions

This paper showed how biophysical and anthropogenic
predictors interact to estimate potential fire hazard at the
landscape level in the north of Iran. The maximum
entropy method was successfully used to analyze forest
fire distribution in Mazandaran Province and to display
areas of higher fire hazard. We found that density of
human settlements, land cover types associated with
farming activities and distance to roads were the most
influencing factors of high hazard fire potential. Annual
mean temperature was also found relevant in one of the
models tested, whereas topographic conditions do not
seem to influence fire hazard in the province. Consider-
ing the relevance of agricultural land use types and
settlements density in fire hazard distribution, strategies
to improve people's awareness and communities pre-
paredness should be prioritized. Further work is needed
regarding the integration of other variables potentially
associated with fire likelihood in the region, such as
evapotranspiration, dead and live fuel moisture or the
location of tourism sites that are not yet available in a
compatible format and scale. Additional research is also
required to further examine the consistency of global
datasets for modeling fire hazard at local and regional
levels. This study aimed to improve the understanding
of fire drivers in Mazandaran province, which can con-
tribute to provide better mapping tools and further en-
hance decision-support systems used by fire managers
and other operational organizations.

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