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Estimating the probability of wildfire occurrence in Mediterranean landscapes using Artificial Neural Networks

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ABSTRACT

Wildfires are a major disturbance in the Mediterranean Basin and an ecological factor that constantly alters the landscape. In this context, it is crucial to understand where wildfires are more likely to occur as well as the drivers guiding them in complex landscapes such as the Mediterranean area. The objectives of this study are to estimate wildfire probability occurrence as a function of biophysical and human-related drivers, to provide an assessment of the relative impact of each driver and analyze the performance of machine learning techniques compared to traditional regression modeling. By employing an Artificial Neural Network model and fire data (2004–2012), we estimated wildfire probability across two geographical regions covering most of the Italian territory: Alpine and subalpine region and Insular and peninsular region. The high classification accuracy (0.68 for the Alpine and subalpine region and 0.76 for the Insular and peninsular region) and good performances of the technique (AUC values of 0.82 and 0.76, respectively) suggest that our model can be used in the areas studied to assess wildfire probability occurrence. We compared our model with a logistic function, which showed a weaker predictive power (AUC values of 0.78 for the Alpine and subalpine region and 0.65 for the Insular and peninsular region) compared to the Artificial Neural Network. In addition, we assessed the importance of each variable by isolating it in the model. The importance of an individual variable differed between the two regions, underscoring the high diversity of wildfire occurrence drivers in Mediterranean landscapes. Results show that in the Alpine and subalpine region, the presence of forest is the most important variable, while climate resulted as being the most important variable in the Insular and peninsular region. The majority of areas recently affected by large wildfires in both regions have been correctly classified by the ANN model as 'high fire probability'. Hence, the use of an Artificial Neural Network is efficient and robust for understanding the probability of wildfire occurrence in Italy and other similar complex landscapes.

1. Introduction

Fire disturbance is a key driver of many natural landscapes and for the delivery of ecosystem services (Johnstone et al., 2016; Molina and Herrera, 2019). However, wildfires have detrimental effects on natural resources and human life when they occur in urban interfaces (Argañaraz et al., 2017; Modugno et al., 2016; San-Miguel-Ayanz et al., 2013).

Reports of the European Commission suggest that over the past 30 years Europe has seen an increase of extreme wildfire events generating major socio-ecological impacts (Elia et al., 2016; Lozano et al., 2017; Paveglio et al., 2018). In Italy, the magnitude of the wildfire dilemma is similar to that of other Mediterranean countries (Carlucci et al., 2019; Mancini et al., 2018b). In 2017 alone, more than 7800 wildfires occurred in the peninsula burning over 162,000 ha. Statistics also reveal that the average number of wildfire casualties is 5 per year, while the mean number of injured is 39 per year (Union, P.O. of the E, 2018). Despite the continuous support of the European Commission and the efforts of national and regional government to improve fire management policies, these data depict a dramatic picture. The numbers remind us of the importance and urgency to integrate the emergency approach (e.g., fire suppression) with a more efficient preventive fire management strategy, specifically focused on favoring the development of fire-resistant and resilient landscapes (Moreira et al., 2020; Twidwell

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et al., 2019). To this end, landscape management agencies need to understand where wildfires are most likely to occur (i.e., wildfire probability) as well as the key drivers of current wildfires (Faivre et al., 2014; Guo et al., 2017; Pricope and Binford, 2012; Rodrigues et al., 2016).

The scientific community has developed many approaches to disentangle the multifactorial aspects that lead to wildfire probability in a specific landscape. For example, the first pioneering study by Chuvieco and Congalton (1989) suggests integrating geo-environmental data and logistic regression to assess wildfire probability. Preisler et al. (2004a) published a study presenting a probability-based model for estimating wildfire occurrences. Subsequent to these first studies wildfire probability estimation became an increasingly popular research theme, fostering a large variety of innovative approaches worldwide (Amatulli et al., 2013; Oliveira et al., 2012; Jaafari et al., 2017; Mancini et al., 2018a; Michetti and Pinar, 2019).

In this regard, the use of machine learning techniques (MLTs) can greatly improve the understanding of wildfire probability in complex territories as the Mediterranean (Jain et al., 2020). For example, Artificial Neural Network (ANN) models, in comparison to simpler models (e.g., linear regression), have the ability to explore a set of existing nonlinear relationships in the data leading to improved model accuracy (Yang et al., 2006).

Previous studies have employed ANNs to investigate fire danger (Bisquert et al., 2012; Pai et al., 2020), wildfire vulnerability (Dimuccio et al., 2011; de Bem et al., 2019), wildfire risk assessment (Li et al., 2009; Jafari Goldarag et al., 2016; Lall and Mathibela, 2016), burned area detection (Maeda et al., 2009; Gómez and Martín, 2011), pre- and post-fire vegetation (Debouk et al., 2013; Polinova et al., 2019), causes of wildfires (Rodrigues and de la Riva, 2014), and flame and smoke detection (Chetehouna et al., 2015; Hossain et al., 2019). However, the literature currently does not provide a satisfactorily large number of studies in which ANNs have been employed to estimate the probability of wildfire occurrence. Further,In many cases the scale of analysis is restricted to small geographical areas (Vega Garcia et al., 1996; Vasilakos et al., 2009; Ruiz-Mirazo et al., 2012; Safi and Bouroumi, 2013; Satir et al., 2016).

To fill these gaps, we developed an ANN model to estimate the probability of wildfire occurrence in the complex Mediterranean landscape of Italy. The Italian landscape represents a suitable testbed for our study given its wide variety of vegetation types, topographical and ecological features in heterogeneous urbanization contexts, and different weather conditions. The specific objectives of the study are: (1) to estimate the probability of wildfire occurrence as a function of biophysical and human-related drivers; (2) to assess the relative magnitude of each driver; and (3) to analyze the performance of the ANN model compared to traditional regression modeling.

Because of varying fire regimes and the difficulty in obtaining a robust model for the entire country, the Italian peninsula was divided into two main study areas: (i) the Alpine and subalpine region (ASR) and (ii) Insular and peninsular region (IPR). The models and relative validations were applied to each region. The findings represent a further step toward a better understanding of wildfire probability occurrence, which can be useful for other related studies across the globe.

2. Materials and methods

2.1. Study areas

Italy is located at a northern latitude between 36° and 47°30′ and an eastern longitude between 5°30′ and 18°30′, extending for the most part into the Mediterranean Sea (Fig. 1). The territory covers an area of approximately 301,330 km², 23% of which is classified as lowland, 42% as upland, and 35% as mountainous landscape. Italy is crossed by two important mountain chains – the Alps in the North and the Apennines in the south-central region. This orography gives rise to a climate gradient from North to South, ranging from Mediterranean warm to temperate cool. Most of the remaining region is surrounded by the Mediterranean Sea creating conditions for the presence of a wide variety of flora and fauna species. Forest resources in Italy extend over 10.9 million ha (RAF, 2019). According to Habitat Directive no. 43/92 of the European Commission, 32% of forest lands cover the Alpine biogeographical region, 16% the Continental region, and 52% the Mediterranean region.

Italy is one of the southern European countries most affected by wildfires. Its fire regime changes while proceeding from North to South (Conedera et al., 2018). In the ASR, the majority of wildfires in recent decades have mainly occurred in the first three months of the year (from January to March), reaching a peak in March of 1000 events (Fig. 1-a). This winter fire regime is due to the continental climate characterized by cold-dry winters, fully cured vegetation and frequent episodes of strong warm-dry winds (foehn) that further dry out vegetation and make it fire prone (Valese et al., 2014). On the contrary, in the IPR wildfires mostly occur in summer (third quarter of the year), reaching a maximum of about 14,000 events (Fig. 1-b). During this season the climate is of the Mediterranean type characterized by minimum precipitation in July, dry winds from North Africa and high temperatures causing the loss of fuel moisture, hence increasing the probability of fire ignition and spread (Michetti and Pinar, 2019).

2.2. Response variable

To estimate the response variable, we used historical wildfire georeferenced polygons derived from the Comando Unità Forestali, Ambientali e Agroalimentari (CUFAA), Carabinieri Force, and forest services of Autonomous Regions. The response variable represents wildfire occurrence (presence/absence) in each 1-km² grid cell of the two study regions. If the fire polygon or a portion of it fell in a 1-km² cell we considered it as presence of wildfire, whereas if it did not it was considered as absence of wildfire occurrence. We opted to use the 2004 to 2012 time period for our study, which displays the most harmonized data throughout Italy. The Liguria region, the Valle d'Aosta region and the Autonomous Province of Bolzano were excluded from the analysis due to the difficulty in obtaining a complete spatial and temporal dataset of wildfire events for the entire territory.

2.3. Biophysical explanatory variables

One of the most important steps in probability analysis is building a set of explanatory variables based on their potential relation to the response variable (wildfire occurrence) and data availability (Table 1). Therefore, we collected human-related and biophysical variables and transformed each variable into a continuous scale at a 1-km² resolution grid (Elia et al., 2019; Guo et al., 2016).

To characterize land cover, the Corine Land Cover initiative 1:100,000 (2012) was adopted, which ensured a complete mapping of the Italian landscape at the fourth hierarchical level (CLC, 2012). We aggregated the land cover classes by creating eight variables, each corresponding to a specific group of land use such as agriculture, wetland, waterland, forest, grassland, shrubland, otherland, and urban. We then calculated the presence (percentage) of each group within the 1-km² grid cells.

Another important variable affecting the probability of wildfire occurrence is tree cover (Satir et al., 2016). In Mediterranean coniferous forests tree cover might be positively related to crown fire behavior, while dense broadleaved forests could hamper fire spread due to the high moisture content in the understory and the limited presence of flammable grasses and shrubs. We derived tree cover from the Copernicus Land Monitoring Service (https://land.copernicus.eu/). The product consisted of status layers (for 2012) showing the level of tree cover density in a range from 0 to 100%; these layers were then converted into a 1-km² resolution grid scale.

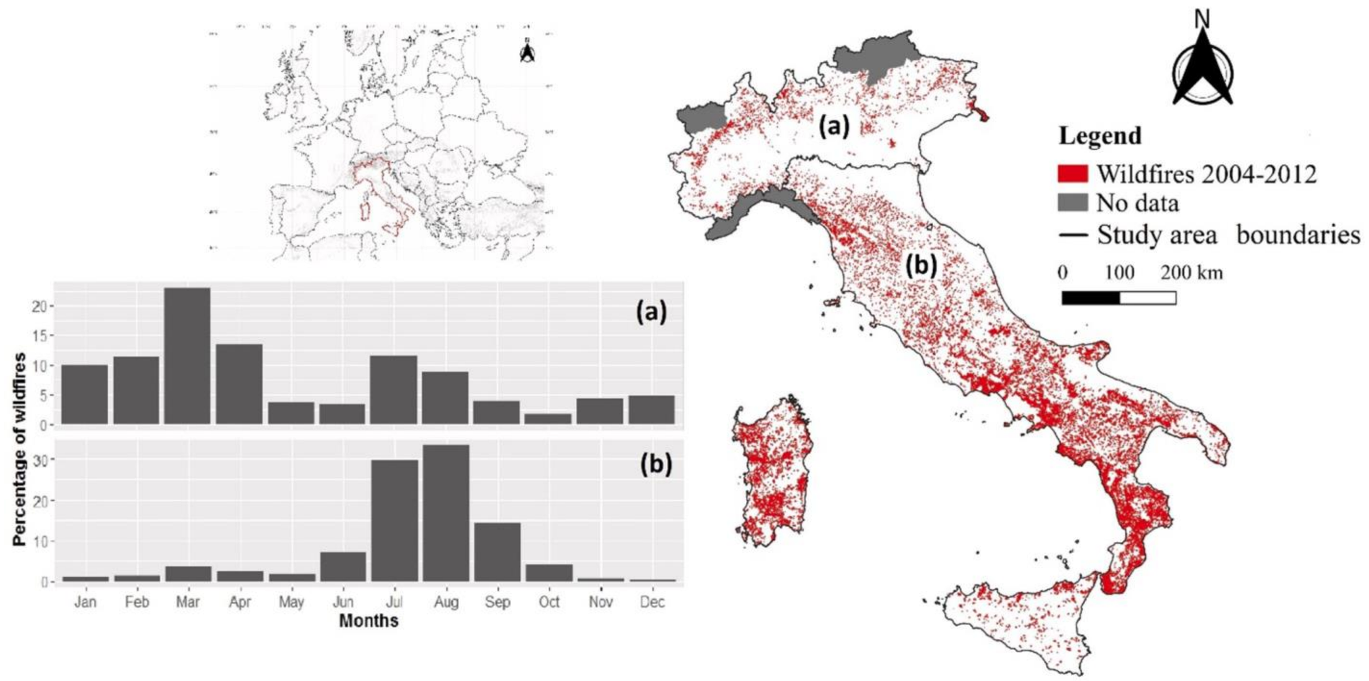

Fig. 1. Location of the study areas in Italy (black line indicates the boundaries of the Alpine and subalpine region and Insular and peninsular region) within the Mediterranean Basin, and map of wildfires during the period of investigation. The histograms show the number of fire events (percentage) across months for each study area: (a) Alpine and subalpine region; (b) Insular and peninsular region.

Topographical variables were selected for their relevance to wildfire occurrence based on previous research and data availability. The topographical features of a landscape heavily affect species composition, the microclimate and fire behavior (e.g., stack effect) (Syphard et al., 2008). Furthermore, previous studies (Gralewicz et al., 2012) have found that the higher the altitude, the fewer the occurrences of wildfires. Elevation and slope were derived from the Digital Elevation Model at European level (Reuter et al., 2007) and reclassified at a 1-km^2 resolution grid scale.

With regard to climatic variables, we used an index combining information on different weather parameters in the period of investigation (2004–2012). Data on maximum wind speed, maximum temperature and relative humidity in the two study areas were collected daily. Climate data for the months of January, February, March and April were obtained for the ASR, while the same data for June, July, August and September were collected for the IPR. Consequently, for each region we estimated a mean value of the three climatic parameters for the entire time period of investigation. Once the parameters were collected, a Fire Climate Index (FCI) was estimated for each 1-km^2 cell of the two study areas (Fig. 2) based on previous studies (Barbero et al., 2015; Fox et al., 2015; Hamadeh et al., 2017; Satir et al., 2016; Sharples et al., 2009). This index was calculated using the following formula:

$$\textit{Fire}\ \text{Climate}\ \textit{Index} = \max(U)/\textit{FMI} \tag{1}$$

where U represents the wind speed (km h^{-1}) and FMI stands for the fuel moisture index. The FMI was developed by Sharples et al. (2009) using the following formula:

$$\text{FMI} = 10 - 0.25\,(\text{T} - \text{H}) \tag{2}$$

where T is the temperature (°C) and H stands for the relative humidity (%).

All the data were downloaded from the SCIA (National System for the collection, processing and dissemination of climate data) website (http://www.scia.isprambiente.it/wwwrootscia/Home_new_eng.html)

Table 1
Overview of the explanatory variables selected to perform the study.

Data	Input	Source	Output	Coding
Climate	Relative humidity (%) Absolute maximum temperature (°C) Maximum wind (m/s)	SCIA	Fire Climate Index	
Anthropogenic	Road maps Rail maps Settlement locations Population	Open Street maps Gallego, 2010	Distance from roads, settlements and railways Population density map	Road_dist, Urban_dist Rail_dist, Pop_density
Topographic	DTM Slope (%)	National Geoportal	Digital elevation map Slope map	Elev, slope
Landscape	Corine Land Cover Tree cover density (%)	Copernicus Program	Corine Classes Percentage Tree canopy Percentage	Urban, Agric, Shrubland, Forest, Wetland, Waterland, Grassland, Otherland, Cover_tree

DTM = Digital Terrain Model; SCIA = National System for the collection, processing and dissemination of climate data.

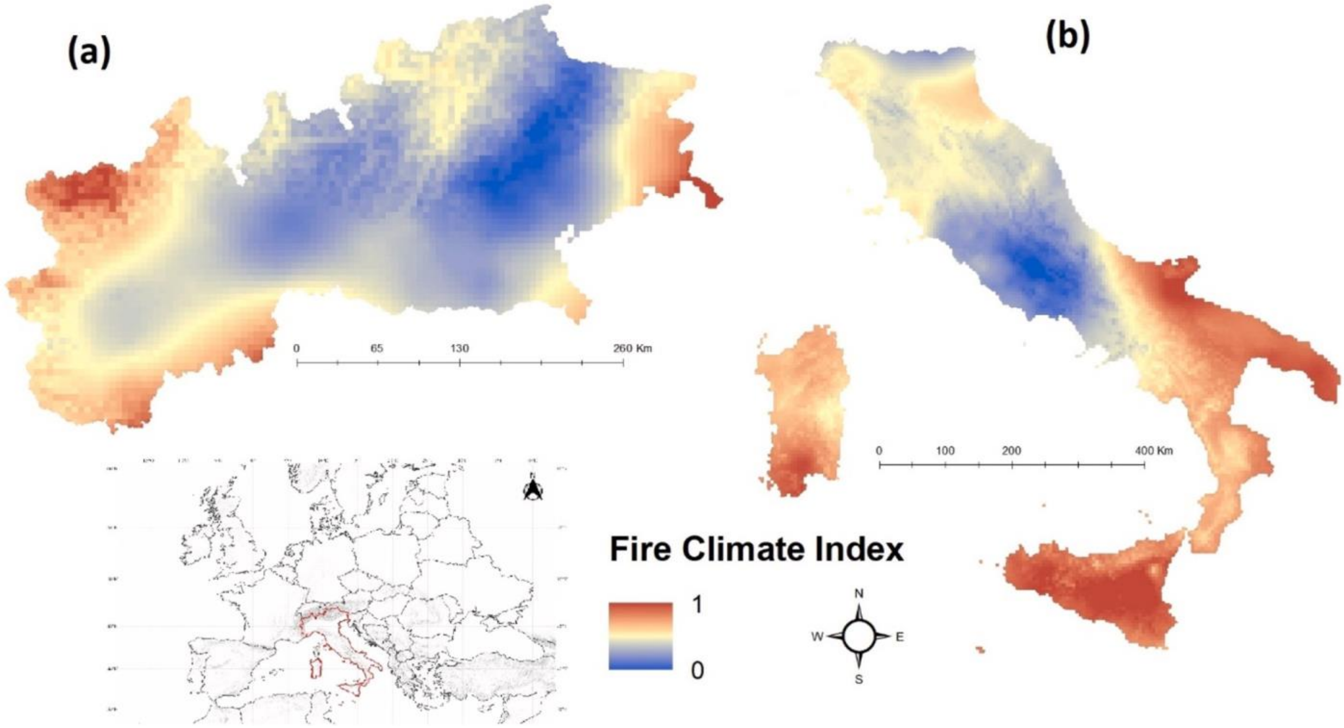

Fig. 2. The Fire Climate Index estimated for each km^2 cell within the two study regions: (a) Alpine and subalpine region; (b) Insular and peninsular region.

of the Italian Institute for Environmental Protection and Research (ISPRA). The website provides main climatic parameters that can be downloaded and displayed in the form of tables, diagrams and maps.

2.4. Human-related explanatory variables

Most wildfires in Italy are linked to human activity. For example, fires may ignite as a result of pasture renewal or the burning of stubble and then spread to nearby forest patches. These practices demonstrate the need to include human-related variables in our analytical model to explain the presence of anthropogenic activity. Based on previous studies (Lein and Stump, 2009; Maingi and Henry, 2007; Ricotta and Di Vito, 2014) and the available data, we opted to consider three main human-related predictors: major roads, railways, and distance from human settlements (e.g., houses, industrial areas, airports) (Table 1). The layers were extracted from the Open Street Map website on a scale of 1:50,000. From these layers we derived the raster distance from major roads, the distance from railways and from settlements resampled at a 1-km^2 resolution grid. All the datasets were processed for the ASR and IPR.

2.5. Pre-processing and model selection

For each study region, a predictive model of wildfire probability occurrence was built using MLTs. Pre-processing is an essential step in machine learning consisting of normalization, data split and balancing of the database. The data were normalized in a range from 0 to 1 to homogenize the entire dataset. Before fitting the model, the original dataset was divided into training (70% of data) and testing (30% of data) sets. Because our dataset was strongly unbalanced with a major absence of wildfires (0) and a minor presence of wildfire occurrences (1), the training set of each area was subjected to an under-sampling technique, i.e. Random Over-Sampling Examples (ROSE). This technique consists in randomly under-sizing the most represented class (Liu et al., 2009; Menardi and Torelli, 2014). Subsequently, the training set was used to train the model algorithm while the test set was used for its validation.

Among the MLTs we chose to employ ANNs, which are mathematical models of supervised learning (Abiodun et al., 2018). ANNs take inspiration from modeling the human brain and try to replicate its structure. Nodes or neurons are the basic units of neural networks. They combine data inputs with coefficients, or weights, which amplify or reduce the importance of inputs according to the algorithm. For each node, the sum of the inputs multiplied by their weights passes through an activation function which determines how this signal influences the results. The selection of the optimal values for the weights is referred to as the "training phase", where the model is trained using a resilient back propagation algorithm with weight backtracking.

For ASR the "*neuralnet*" package of R was applied. We employed one hidden layer and a logistic activation function [Eq. 3] setting the value between 0 and 1.

$$AF = \frac{1}{(1 + exp(-x))} \tag{3}$$

In this case the training set, consisting of 64,547 observations of which 61,448 were classified as absence and 3099 as presence, was under-sampled as previously mentioned to reduce the number of non-occurrences to 3099.

In this case the training set, consisting of 64,547 observations of which 61,448 were classified as absence of wildfires and 3099 as presence of wildfires, was under-sampled as previously mentioned to reduce the number of wildfire non-occurrences to 3099. For the IPR it was necessary to apply a deep neural network due to the size of the area and large amount of data. In this case, we used "*keras*" package for R (https://cran.r-project.org/web/packages/keras/index.html). Two hidden layers were employed, and a sequential model was created containing two activation functions: the *Relu* function for the intermediate hidden layers, and the *Sigmoid* activation function to obtain output from 0 to 1. The optimization algorithm used was *Adam* (Adaptive Momentum estimation), and binary cross-entropy was used as loss of function. In this case the training set consisting of 143,200 observations, of which 118,129 were classified as "absence" and 25,071

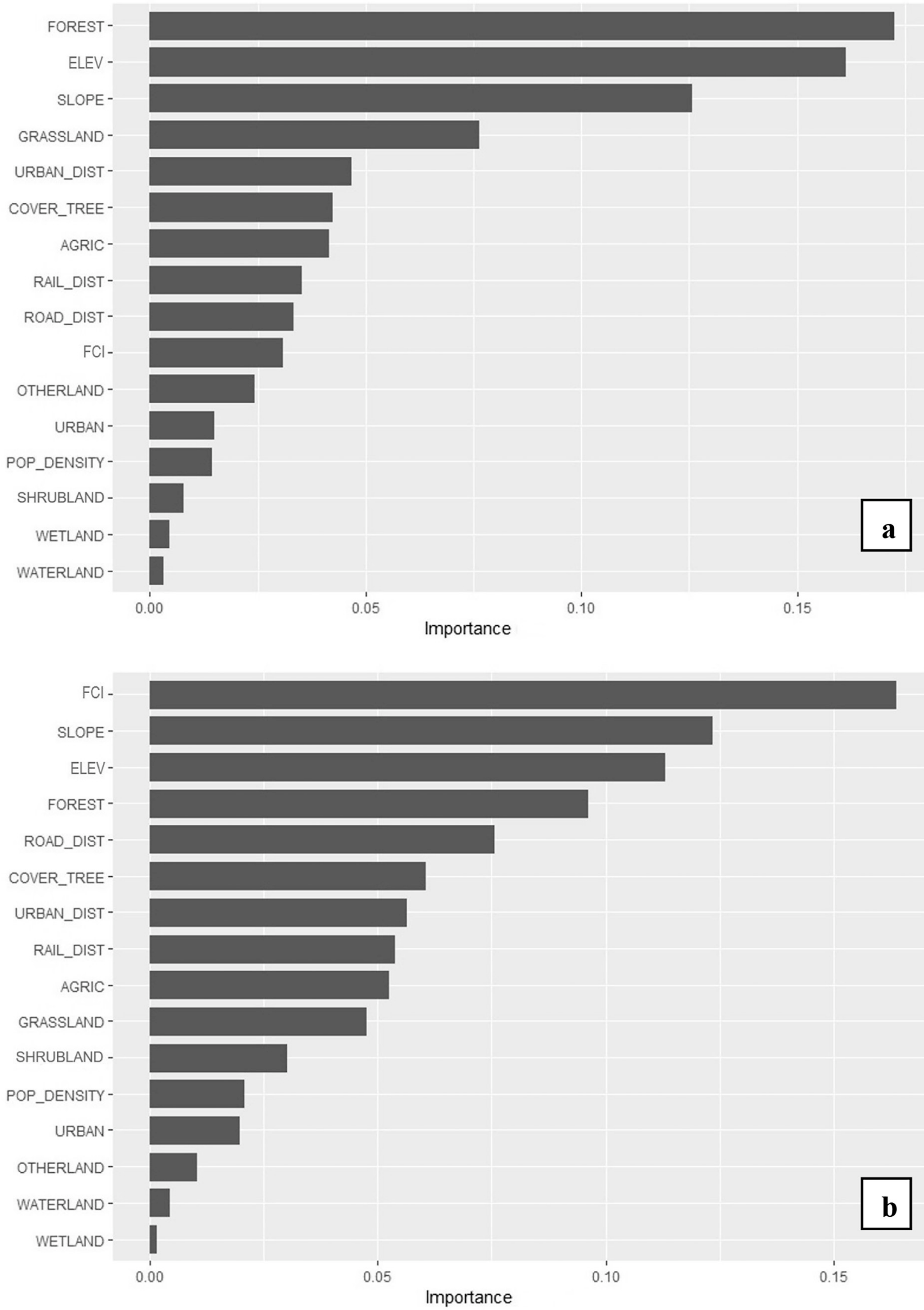

Fig. 3. Explanatory power of the variables through model isolation for the (a) Alpine and subalpine region and (b) Insular and peninsular region. Variable names are also found in Table 1.

as "presence" of wildfires, was under-sampled with the same technique to reduce the number of wildfire non-occurrences to 25,071.

2.6. Model performance and variable importance assessment

The model performances were assessed using the confusion matrix and Receiver Operating Characteristic (ROC) curve test method. The area under the curve (AUC) was employed as it is one of the most common statistical methods adopted to estimate model fitting (Guo et al., 2017; Jiménez-Valverde, 2012; Vilar del Hoyo et al., 2011). For AUC values ≥0.7 the predictors indicated good performance in predicting the dependent variable (Elia et al., 2019). Accuracy was also considered in assessing the correct classification; results were then compared and validated as a function of their accuracies.

The ANN models were validated through cross-validation. Model calibrations were performed five times on random subsamples of the training and test sets and the metrics estimated for each subsample. In addition, we attempted to describe the explanatory power of the topographic variables by isolating them in the overall models (Fig. 3). Variable importance can be estimated by observing how much the score, AUC in our study, decreases when a feature is not used in the model calibration process. Importance is represented by subtracting the estimated AUC value without the considered variable from the total AUC of the all variables.

Lastly, we developed a logistic model with our dataset and compared the results with the ANN models on the basis of the AUC parameter for each study area. We also developed probability maps for both models and discussed them from a management perspective.

3. Results

3.1. Artificial neural networks and variable importance

After the ANNs were constructed and trained using the test set (70% of the total dataset), the remaining 30% of the data was used to assess ANN performance. Table 2 summarizes the performance metrics for the ANN model used to estimate the probability of wildfire occurrence for each study region. Overall, the performances of the ANNs across each study area were robust. Of the two areas, the ASR recorded the highest AUC value (0.82) and lowest accuracy value (0.68) in contrast to the IPR, respectively.

The cross-validations confirmed model robustness (Table 3). The results showed similar metrics values among the five subsamples of training and test set models for each study area, indicating that the overall model did not show explicit overfitting.

In the ASR the presence of forest showed the highest importance with a value of 0.17, followed by the topographic variables, Elevation and Slope with values of 0.16 and 0.13, respectively (Fig. 3-a). In addition, the human-related variables exhibited a lower value of importance in comparison to the IPR. For example, by eliminating road distance the AUC decreased by a value of 0.03, which is less than that of the IPR (0.07).

In the IPR, the FCI and topographic variables, Slope and Elevation, yielded high importance values, i.e., 0.16, 0.12 and 0.11, respectively, which were greater than for the remaining predictors (Fig. 3-b). The other variables related to land cover and human-related drivers exhibited a lower value of importance (~0.02) for population density and urban lands.

Table 2
Performance metrics of the Aerificial Neural Network model for each study area.

	AUC	Accuracy
Alpine and subalpine region (ASR)	0.82	0.68
Insular and peninsular region (IPR)	0.76	0.76

AUC = area under the curve.

Table 3
Performance metrics in five random subsamples of the training and test sets for each study area.

	AUC		Accuracy	
	ASR	IPR	ASR	IPR
Sample 1	0.82	0.76	0.69	0.78
Sample 2	0.82	0.76	0.69	0.80
Sample 3	0.83	0.76	0.69	0.79
Sample 4	0.82	0.76	0.68	0.78
Sample 5	0.82	0.76	0.70	0.79

AUC = area under the curve.
ASR = Alpine-subalpine region.
IPR = Insular and peninsular region.

3.2. Probability of wildfire occurrence

The high classification accuracy and good performances of ANNs suggest that ANN models can be used in the two studied regions to estimate wildfire probability (Fig. 4). In the ASR, the model highlighted the high probability of wildfire occurrence throughout the entire esalpic mountain belt of the southern European Alps, starting from the Maritime Alps at the western-most side to the southern limestone Alps in the Eastern Alps. Interestingly, the model discriminated between higher wildfire probability in the lower esalpic part of the Alpine valleys and a lower probability in the higher inland area, a gradient that is particularly marked in the Eastern Alps. Furthermore, the model consistently correlated recurrent extensive wildfires with several well-known hotspots such as the slopes surrounding major Alpine lakes of the Insubric region and the coast of the Gulf of Trieste at the eastern-most side of the Alpine region. The map also exhibited high wildfire probability occurrence across the southern slopes of the lower Susa valley in the southwestern Alps where in the summer of 2017 the largest wildfire in Italy occurred.

With regard to the IPR, an increasing North-South gradient in wildfire probability occurrence was evident with some isolated hotspots. This gradient is mostly due to southern summer climatic conditions that trigger dramatic increases in temperature, dryness and wind speed compared to northern areas. However, the ANN model effectively detected relevant isolated hotspots in central-north Italy, such as the hills west of Florence, the Conero reserve south of Ancona, or the mountain ridge of Monti Pisani, which features one of the most flammable forests in the Tuscany region; here, in 2018, the largest fire event of the last 30 years took place. Notably, the model correctly classified the area in the IPR with the highest wildfire probability, which comprises the mountain ridge of Monti Aurunci, (the highest fire recurrence rate in Italy, i.e., three fire events during the study period), and high fire-prone areas such as the Tyrrhenian coast from Cilento to Calabria and the Ogliastra region of the island of Sardegna. Similarly, the model effectively identified isolated hotspots such as Vesuvio National Park, where in 2017 a large wildfire burned 44% of the protected area (Espinosa et al., 2018), and the coastline south of Peschici, where in 2007 one of the most dramatic and largest wildfires occurred in Italy's history in terms of human fatalities.

3.3. Comparison with the logistic model

As stated above (section 2.6), we developed a logistic (Logit) function to compare our ANN models (Table 4). Based on the AUC parameter, the ANN models showed a higher predictive power than the Logit function in each of the two study areas. The major difference was found in IPR, where the AUC value of our ANN models was 0.76 versus

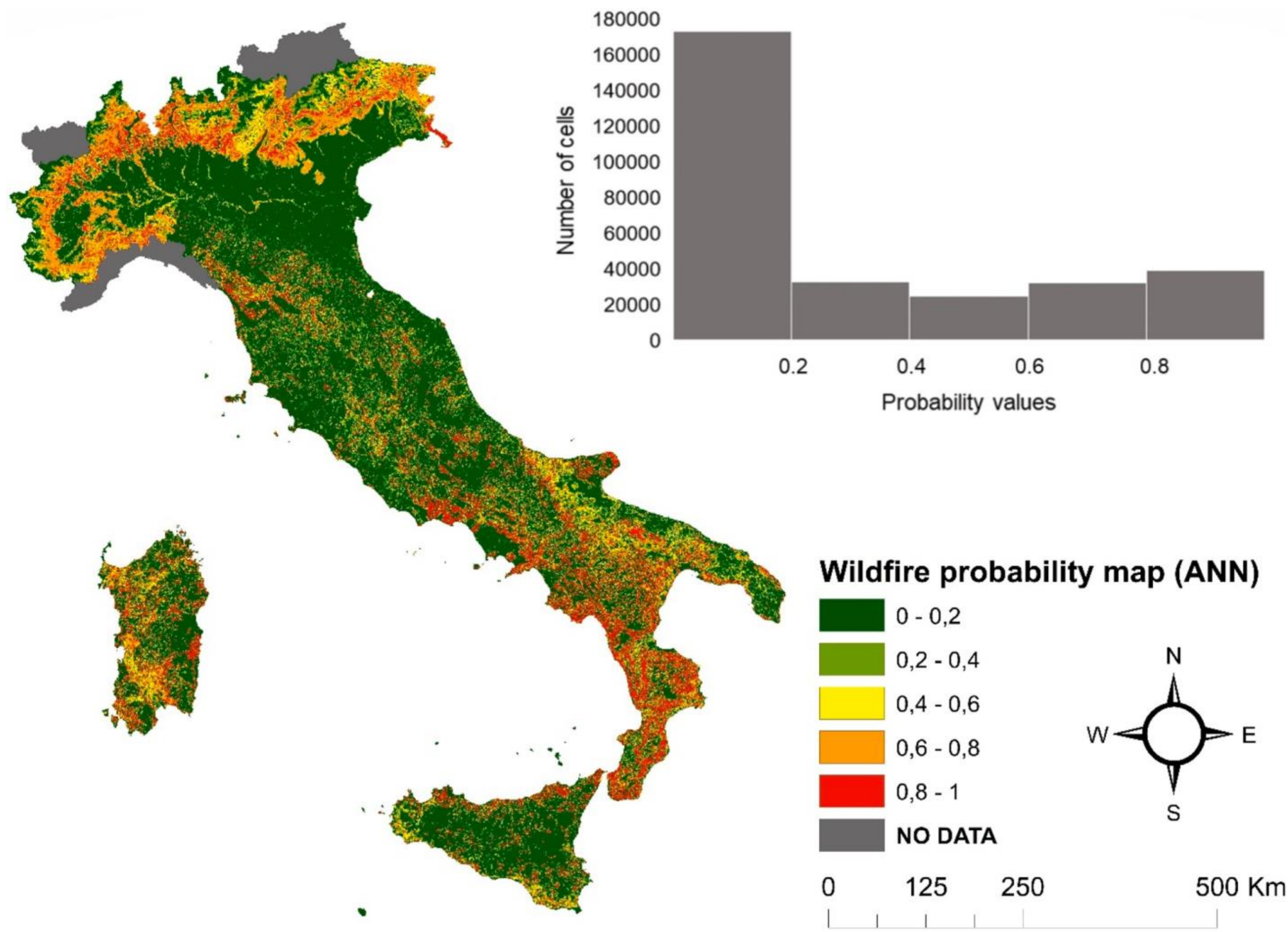

Fig. 4. Map of wildfire probability occurrence generated by the Artificial Neural Network (ANN) model across the entire peninsula of Italy merging the Alpine and subalpine region and Insular and peninsular region. The histograms indicate cell distribution according to the probability of wildfire occurrence.

Table 4
Comparison between the logistic and ANN models using the AUC parameter.

	AUC	
Model	**ASR**	**IPR**
ANNs	0.82	0.76
Logit	0.78	0.65

AUC = area under the curve; ANNs = Artificial Neural Networks; ASR = Alpine and subalpine region; IPR = Insular and peninsular region; Logit = logistic.

0.65 for the Logit function. More information about the Logit function (e.g., coefficient of explanatory variables and relative *P*-values) is available in the Supplementary materials (Tables S1 and S2).

With regard to the ANNs, the map generated by the Logit model (Fig. 5) revealed remarkable differences in estimations of wildfire probability occurrence. The Logit model seemed to overestimate the values across the landscape. For example, the logistic map suggested an average probability value of 0.35 for the Pianura Padana. However, the area is mostly dominated by agriculture and few wildfires were recorded in the past due to lack of forest fuel prone to wildfire occurrence. On the contrary, the ANN map showed that the same area exhibited an average probability value of 0.06, which is much lower. This finding suggests a more accurate performance of the ANN in discriminating areas with high probability from areas with low probability of wildfire occurrence.

4. Discussion

Using novel approaches to understand the main predictors of wildfire occurrence is crucial in the context of broader wildfire risk assessment (Jaafari et al., 2019; Lafortezza et al., 2015; Polinova et al., 2019). Hence, the aim of this study was to increase our knowledge of wildfire probability occurrences in Italy using MLTs. Previous studies have also employed MLTs for estimating wildfire probability in Mediterranean areas. However, our investigation is one of the first to apply ANN models at a regional scale to better understand the impact of biophysical and human-related drivers on the probability of wildfire occurrence in the complex Italian landscape.

Consistent with other studies (Oliveira et al., 2012; Syphard et al., 2008; Vilar et al., 2019), our model suggests that the probability of wildfire occurrence is affected by both biophysical and human-related drivers and that a non-linear trend exists between them and the variable response. For example, Oliveira et al. (2012) adopted a MLT (Random Forest) to explain fire density in Europe. The authors found a non-linear relationship between predictors and fire density and suggested that a non-parametric model could be more suitable to explain the response variable.

The comparison between the ANN model and logistic function (see Table 4) showed a more robust predictive power for ANNs in both study

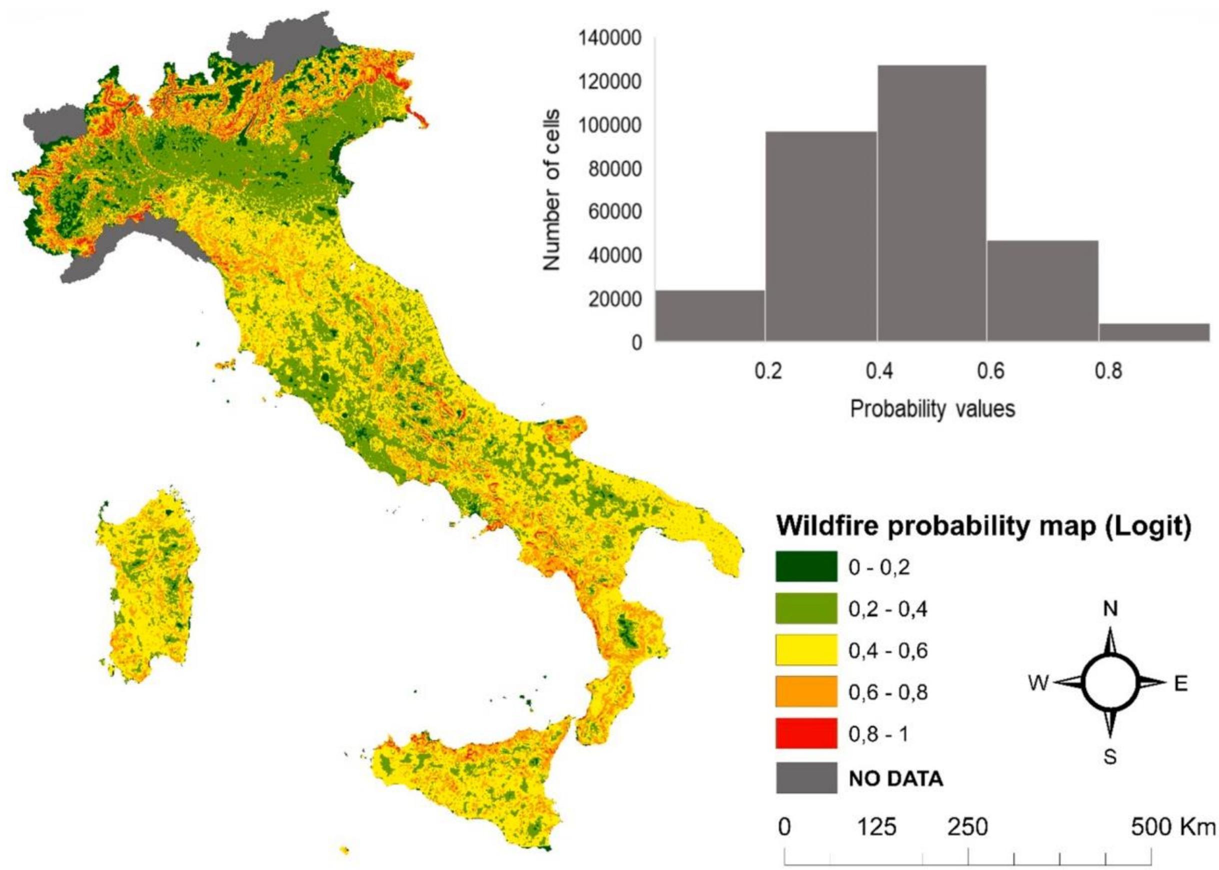

Fig. 5. Map of probability of wildfire occurrence generated by the logistic (Logit) model across the entire territory of Italy by merging the Alpine and subalpine region and Insular and peninsular region. The histograms indicate cell distribution according to the probability of wildfire occurrence.

areas, while logistic regression demonstrated weaker predictive power between the response variable and predictors. More specifically, our results indicate a better performance (i.e., higher AUC) for ANNs compared to the logistic function, suggesting the ability of ANNs to depict the spatial variability of wildfires in Italy based on high landscape heterogeneity (i.e., biophysical and human-driven variability) and fire regimes. Our results are consistent with those of previous studies focusing on differences between the logistic function and ANNs. For instance, Jafari Goldarag et al. (2016) found that accuracy was low (50.84%) for logistic regression compared to ANNs (92.3%) in developing fire prediction maps in Iran. In predicting fire occurrences in Brazil, de Bem et al. (2019) found AUC values of 0.77 and 0.75 using an ANN approach and logistic regression, respectively. Bisquert et al. (2012) used the ANN approach to investigate fire occurrences in Galicia (Spain) and found an average accuracy of 75%. Other authors as well have proven the soundness of ANN in estimating wildfire occurrences. For example, two studies in Lebanon (Hamadeh et al., 2015) analyzed the effects of climatological data on forest fire occurrences. Their results are consistent with ours, since they found an accuracy and an AUC value of 94% and 98%, respectively. Similarly, Sakr et al. (2011) demonstrated the robust capacity of ANN to correctly estimate the probability of fire occurrence with an accuracy of 90%.

4.1. Probability of wildfire occurrence and variable importance

In the Italian peninsula characterized by different ecological features and patterns of urbanization, environmental and anthropogenic elements play differently across the ASR and IPR study areas. Therefore, it is crucial to collect a comprehensive set of biophysical and human-related drivers (Prasad et al., 2008). The topographic variables of the ASR and IPR displayed a common pattern in terms of importance. Slope and elevation significantly influenced the probability of wildfire occurrence ranking high as variables of importance in both study areas (Fig. 4). This is most likely correlated to the positive influence of slope (e.g., chimney effect) and altitude on fire behavior and spread (Butler et al., 2007). Furthermore, it is rare to find wildland plains with flammable vegetation in Italy; the majority of wildfires occur in mountainous areas or in areas where the slope is steep. Previous studies have highlighted the strong influence of elevation on fire occurrence (Ajin et al., 2016). Wildfire occurrences in areas at a high altitude can be directly influenced by consistent sun exposure and increased lightening (de Bem et al., 2019). Our results are consistent with those of Mancini et al. (2018b), who found that elevation significantly influences both fire frequency and incidence in Italy (.

The study results also show that the two land cover variables proportion of forest and grassland present high importance values in the ASR. This region is characterized by dense forest cover of relatively flammable fuel complexes, such as understory of chestnut, oak, and pine plantations, which dry out during the winter because of minimal precipitation and foehn winds (Valese et al., 2014). As expected, the forest variable was important in both study areas, most likely due to the substantial amount of fuel available to burn and to the continuity and connectivity of forested landscapes. This finding has highlighted the importance of one of the main drivers of fire regimes in Italy, which in the last century has been forest expansion consequent to agriculture and grazing abandonment in mountainous and hilly areas (Bovio et al., 2017). Grassland was the more important variable in the ASR. Grasslands are mostly composed of flash fuels and are easy to ignite, thus their association to fire occurrence is somewhat predictable. In fact, during the winter season the herbaceous layers in this region are severely dried by the freezing winds blowing from northern Europe, thus becoming prone to fires.

The presence of shrublands was surprisingly less important than the above-mentioned land cover variables in both study areas, a finding that contrasts with previous studies. For example, Sebastián-López et al. (2008) considered shrubs as the principal predictor of fire danger in their model for southern Europe. Other studies (Moreira et al., 2011; Nunes et al., 2005) have provided evidence that shrubland is usually the land cover which is most fire prone in Mediterranean ecosystems. In our study areas, the presence of shrubland was less representative than forest and grassland and therefore exhibited lower predictive power. However, this outcome may contrast with local results suggesting that shrublands are more prone to burn if adjacent to roads and urban areas (Elia et al., 2020).

From a climatic perspective, FCI was recognized in the analysis as the most influential variable in the IPR. Conversely, the FCI did not attribute much importance to the ASR, ranking 10th as a variable of importance among all (Fig. 3-a). As expected, in the IPR during the fire season dry and hot summers make fuel prone to ignition and create flammable conditions. In addition, strong warm winds from North Africa push wildfires and in many cases lead to extreme and dangerous outcomes.

Some predictors did not exhibit much importance individually, and therefore it was easier to assess their impact on probability of wildfire occurrence within a group of variables. For instance, human-related variables such as distance from roads, railways and human settlements had an evident impact on the maps derived by the model. Proximity to the above-mentioned variables increases the probability of wildfire occurrence, even in areas of low population density (Bar Massada et al., 2013). The gradient of higher wildfire probability in the lower esalpic part of the Alpine valleys toward a lower probability in the higher inland area is a typical feature of fire regimes in the Alps (Valese et al., 2014), which is partly related to decreasing population density and lower foehn intensity in the upper valleys. Unexpectedly, the ANN model ranked 5th as a variable of importance among the different anthropic predictors for each study area. In the ASR, the human-related variable urban distance ranked 5th mostly due to the fact that the majority of wildfires originate close to the urban interface at the bottom of valleys, but then propagate and spread up the slopes affecting forests at higher elevations than most inhabited areas. Moreover, in this region a significant portion of fires originate from pastoral burns to maintain grazing areas (Ascoli and Bovio, 2013) at the top of mountain ridges distant from urban areas.

In the IPR, the first human-related variable considered was road distance. Many authors have pointed out how road distance can affect wildfire occurrences in the Mediterranean region. Others still (Cardille et al., 2001; Faivre et al., 2014; Gralewicz et al., 2012; Jaafari et al., 2018) have found significant correlations between wildfire occurrences and proximity to roads. Maingi and Henry (2007) estimated that in the US (Appalachian counties of Eastern Kentucky) distance to roads explained 54% of the total variation observed in wildfire occurrences. Elia et al. (2020) found that distance to roads influenced the likelihood and frequency of wildfires in southern Europe.

4.2. Management implications

Wildfire prevention, suppression and mitigation are critical issues for forest managers and decision makers because of the stochastic variability of the phenomenon across space. A deeper understanding of the wildfire phenomenon will inform about where wildfires are likely to occur and the drivers guiding potential new occurrences. This need has stimulated research efforts on wildfire probability studies, especially in Italy where the landscape is characterized by heterogeneous ecosystems from North to South and from coastlines to mountainous hinterlands.

Once areas with the highest wildfire probability are detected by ANN models, forest managers can use the resulting maps to prioritize fire management interventions (Elia et al., 2014). Additionally, by adopting these maps decision makers can develop civil protection plans, particularly in areas where natural and human systems mix (e.g., wildland urban interfaces) and with a high probability of wildfire occurrence.

5. Conclusions

In this study we applied an ANN model to estimate the probability of wildfire occurrence in Italy using a comprehensive set of biophysical and human predictors. The findings demonstrate that in a complex landscape such as the Italian peninsula, characterized by a large variety of anthropic and environmental features, the use of ANNs is efficient and statistically robust for understanding the probability of wildfire occurrence. Our model, in fact, suggests that the importance of a single variable differs along the North to South gradient, which underscores the high variability of fire drivers in a changing landscape. In addition, compared to the logistic function the ANN model produced a higher AUC value and demonstrated greater accuracy when evaluating wildfire probability.

Wildfire probability estimation using ANN models in the Mediterranean Basin still offers wide room for improvement. Although our method has been applied to a given landscape (Italy) and over a certain time period (2004–2012), it has the potential to be employed for longer periods of time and in cross-regional areas. This would require an adaptation of the ANN algorithm, thus involving a wide range of network architectures. Additionally, we recommend further investigation of the relationship between explanatory variables and the probability of wildfire occurrence by focusing on new predictors (e.g., socioeconomic) or by further examining those used in the present work.

A further intent of our work was to corroborate prior studies in the field of machine learning techniques to understand wildfire probability occurrence. For this purpose, the operational use of the above-mentioned algorithms might be worth investigating in the future. A key role in this regard is played by the scientific community for both the development of new models and the transmission of knowledge to the operative world (e.g., for fire risk assessment in Regional Fire Management Plans in Italy, Art. 3 – Law 353/2000), that still favors traditional approaches rather than models with “black boxes” as ANNs (Yang et al., 2006).

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eiar.2020.106474.

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