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Integrating new methods and tools in fire danger rating

Christos Vasilakos[A], *Kostas Kalabokidis*[B,D], *John Hatzopoulos*[A], *George Kallos*[C] *and Yiannis Matsinos*[A]

[A]Department of Environmental Studies, University of the Aegean, University Hill, 81100 Mytilene, Greece.
[B]Department of Geography, University of the Aegean, University Hill, 81100 Mytilene, Greece.
[C]Department of Applied Physics, National and Kapodistrian University of Athens, Bldg PHYS-V, 15784 Athens, Greece.
[D]Corresponding author. Email: kalabokidis@aegean.gr

Abstract. Prevention is one of the most important stages in wildfire and other natural hazard management regimes. Fire danger rating systems have been adopted by many developed countries dealing with wildfire prevention and pre-suppression planning, so that civil protection agencies are able to define areas with high probabilities of fire ignition and resort to necessary actions. This present paper presents a fire ignition risk scheme, developed in the study area of Lesvos Island, Greece, that can be an integral component of a quantitative Fire Danger Rating System. The proposed methodology estimates the geo-spatial fire risk regardless of fire causes or expected burned area, and it has the ability of forecasting based on meteorological data. The main output of the proposed scheme is the Fire Ignition Index, which is based on three other indices: Fire Weather Index, Fire Hazard Index, and Fire Risk Index. These indices are not just a relative probability for fire occurrence, but a rather quantitative assessment of fire danger in a systematic way. Remote sensing data from the high-resolution QuickBird and the Landsat ETM satellite sensors were utilised in order to provide part of the input parameters to the scheme, while Remote Automatic Weather Stations and the SKIRON/Eta weather forecasting system provided real-time and forecasted meteorological data, respectively. Geographic Information Systems were used for management and spatial analyses of the input parameters. The relationship between wildfire occurrence and the input parameters was investigated by neural networks whose training was based on historical data.

Additional keywords: geo-informatics, GIS, natural hazards, neural networks, wildfires.

Introduction

Many countries facing forest fire problems have developed wildfire danger estimation systems in order to enable civil protection agencies to define high risk areas and plan the necessary preventive and preparedness actions (Deeming *et al.* 1977; Van Wagner 1987; Hoffmann *et al.* 1999). The majority of the systems are based, mainly, on meteorological data that are collected by weather stations (Deeming *et al.* 1977; Van Wagner 1987; Carrega 1991; Viegas *et al.* 1999). Nevertheless, these systems adopt a different approach to spacial–temporal resolution for which they are applied, and they use various correlations of the input parameters. Geographic Information Systems (GIS) are widely used in order to collect, manage, analyse and present spatial data that are taken into consideration in identification of wildfire pattern occurrence (Chuvieco and Congalton 1989; Chou 1992*a*, 1992*b*). The aim of the present research was to develop a fire ignition risk index as a part of a quantitative fire danger rating system based on parameters that are easily and quickly definable, in order to be usable in forest fire management activities such as (Kalabokidis 2001):

- Preventive measures that aim at the reduction of fire ignitions, e.g. personnel and volunteer training, effective legislation regarding property land development and law enforcement.
- Preparedness measures that promote the existence of an agency able to initiate promptly and effectively direct suppression of any forest fire at its ignition, with sufficient firefighting force for direct suppression, including dispatch systems for fire suppression, operation of lookout towers and patrols.
- Raising public awareness of oncoming fire risk, and accessing administrative response arrangements.
- Emergency situation assessment and evacuation of threatened areas if appropriate.

Study area

The island of Lesvos is located in the north-eastern Aegean Sea and covers an area of 1672 km^2 (Fig. 1). The climate is Mediterranean-type, with typical warm and dry summers and mild and moderately rainy winters. Annual precipitation averages 670 mm and the average annual air temperature is 18°C with large differences between maximum and minimum daily temperatures (Kalabokidis *et al.* 2004). The terrain is hilly and steep, with the highest peak at 960 m above sea level. Slopes greater than 20% dominate, covering almost two thirds of the island. Narrow alluvial plains are present in the lower parts and along the coast, having a shallow groundwater table. Arid lands are prominent in the western part of the island, in which acid volcanic rocks dominate. Vegetation of the area, defined on the basis of

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the dominant species, includes phrygana or garrigue-type scrubs in grasslands, evergreen-sclerophyllous or maquis-type shrubs, pine forests, deciduous oaks, olive tree orchards and other agricultural lands (Fig. 2). The soils of Lesvos have been widely cultivated, mainly with rain-fed crops such as cereals, vines and olives. Owing to low productivity, the majority of sites were abandoned 40–50 years ago. After abandonment, the area was moderately grazed and the growing shrubs were occasionally cleared by the use of fire. More than 420 fires, mainly human-caused, occurred from 1970 to 2001, resulting in $\sim$80 km^2 of burned area in total (Fig. 3). Even though the number of fires has increased during recent years, the burned area has been limited owing to the fire control undertaken by the Greek Fire Brigades, which use heavy aerial suppression in addition to ground-based equipment and personnel.

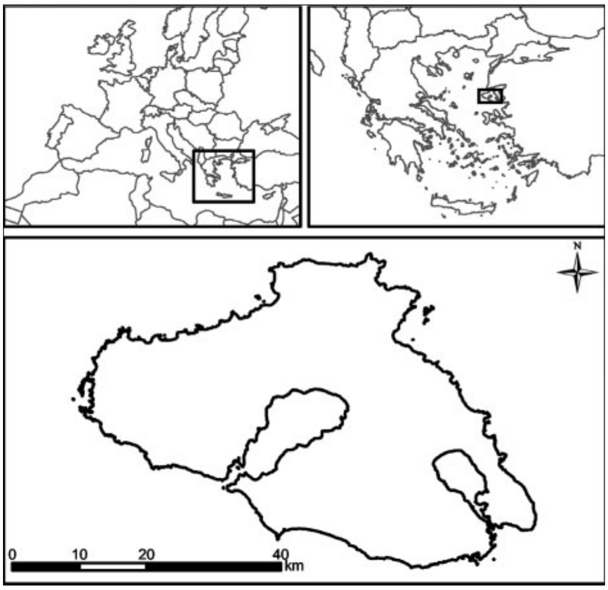

Fig. 1. The study area of Lesvos Island, Greece.

Data and methodology

The fire ignition risk scheme presented is part of a Fire Danger Rating System (FDRS) that has been developed within the framework of the European Union research project *AUTO-HAZARD PRO*, and has been designed as a potential evolution of the empirically derived fire danger mapping of Greece (Kalabokidis 2004). The main outcome of the proposed subsystem is the Fire Ignition Index (FII), based on three different indices: the Fire Weather Index (FWI), the Fire Hazard Index (FHI) and the Fire Risk Index (FRI). Each of these indices is dynamic, i.e. they vary according to time and space. The correlation between fire occurrence and the parameters that are incorporated into the above indices is based on fire history data and has been modelled by the use of artificial intelligence methods and neural networks, in particular. The training of neural networks makes them a powerful tool to be used for any specific geographic extent if similar spatial and fire history databases are developed, as in the present case study. Furthermore, the neural networks can be re-trained for each study area by adding new fire data after the end of the fire season. In Fig. 4, the work methodology is depicted as well as

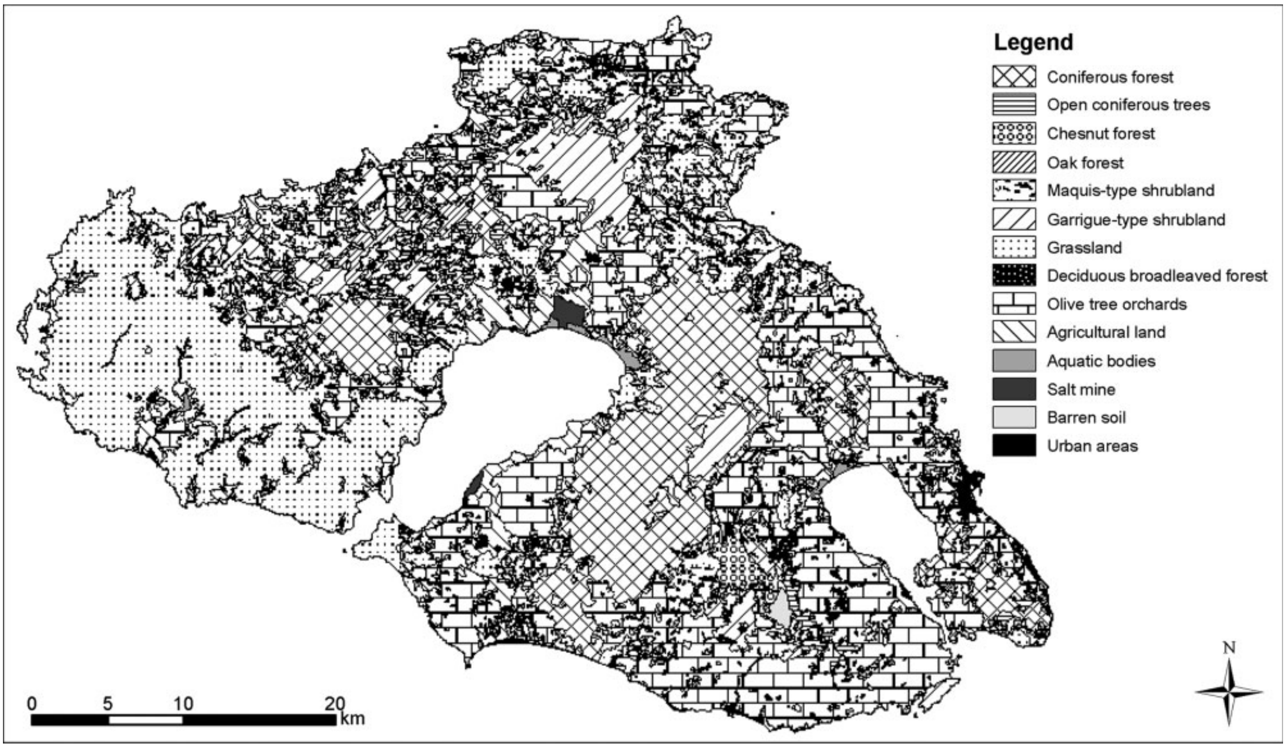

Fig. 2. Land cover types of Lesvos Island, Greece, derived from QuickBird satellite data by visual interpretation.

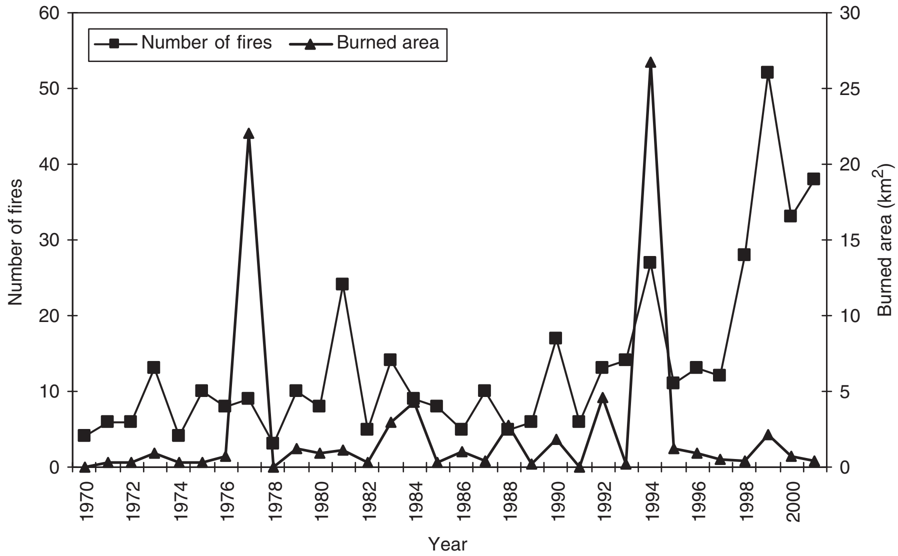

Fig. 3. Number of fires and burned area on Lesvos Island, 1970–2001.

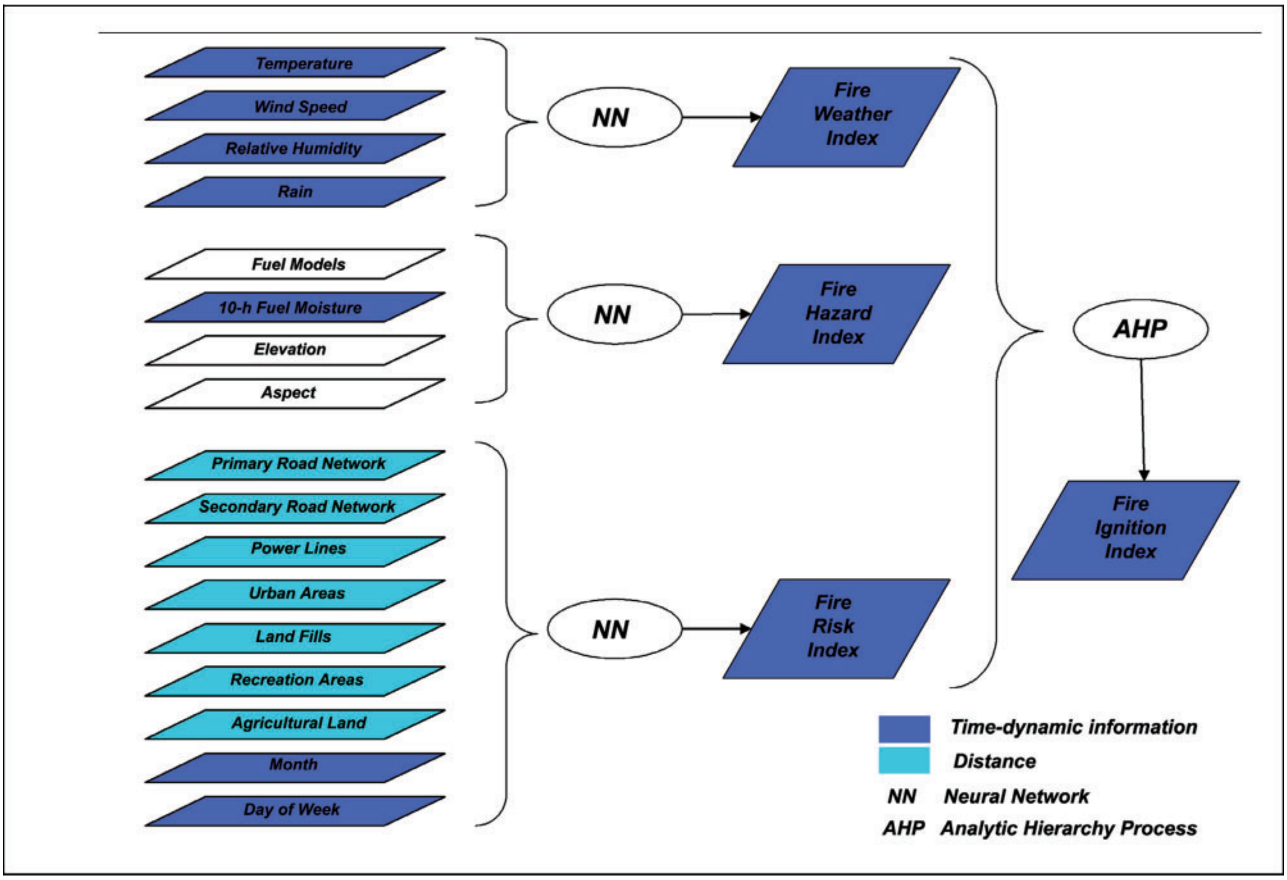

Fig. 4. Flowchart of methodology.

the parameters considered for the estimation of each index such as meteorological conditions, distance from human presence, vegetation and topography. These parameters have been chosen in such a way as to be easily defined, thus enabling the system for immediate operational use at a local level. The composition of the final index using the three individual indices was undertaken by multi-criteria analysis methods and according to Analytic Hierarchy Process (AHP).

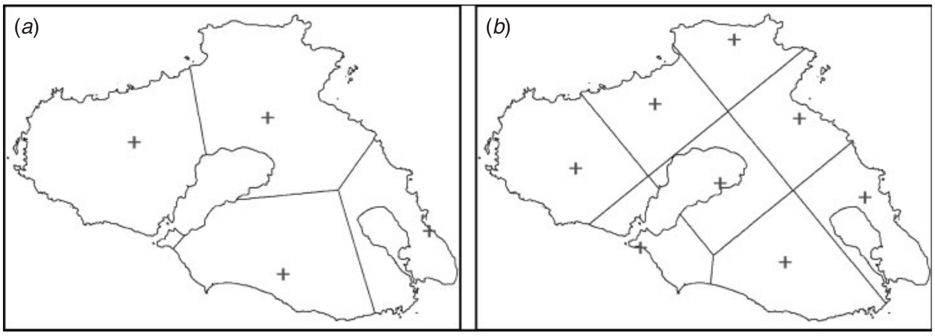

Fig. 5. Thiessen polygons of (*a*) 4 (+) Remote Automatic Weather Stations, and (*b*) 8 (+) points of forecasted weather data from SKIRON/Eta model.

Fire Weather Index: conception, structure and data collection

The Fire Weather Index contains the correlation between fire weather parameters and fire ignition. The FWI includes the meteorological conditions such as air temperature, relative humidity, wind speed and the existence of rainfall during the previous 24 h from the time the index is calculated. It is based on meteorological data collected by four Remote Automatic Weather Stations (RAWS). The actual FWI (and hence the actual FII) is calculated by using RAWS data. The forecasted FWI is estimated based on meteorological data derived from the SKIRON/Eta model with 5-day horizon (Kallos *et al*. 1997; Papadopoulos *et al*. 2001). The main assumption is for the spatial distribution of the meteorological conditions using the above point measurements. The method of the Thiessen polygons was applied for the present study considering that the point measurements derived from the weather stations and the SKIRON/Eta model are sufficient to describe the surface weather conditions (Fig. 5). For a better description of the wind field, a higher resolution model (e.g. 1–2 km) is required. Because this was not feasible owing to technical–economical reasons, wind fields with horizontal resolution ability of 10 km (considered to cover the present application sufficiently) were used.

Fire Hazard Index: conception, structure and data collection

The Fire Hazard Index refers to fire ignition probability based on topography and vegetation. FHI includes fuel models, 10-h fuel moisture content, terrain elevation and aspect. Areas with the same vegetation type have the potential of a different risk due to terrain and quantity of vegetation. This variation in vegetation may be accounted for in the different fuel models (Deeming *et al*. 1977). To create the spatial layer of fuels on the island of Lesvos, CORINE land cover types were matched to the 13 BehavePlus2 fuel models (Andrews *et al*. 2003). Five fire behaviour parameters (i.e. Rate of Spread, Heat per Unit Area, Fireline Intensity, Flame Length and Reaction Intensity) for each model were then calculated, under the assumption that the equally weighted sum of these parameters considered as flammability could be examined for any effect in a fire ignition scheme (Kalabokidis *et al*. 2004). The input conditions were the worst – average environmental values for the study area: 1-h fuel moisture content (FMC) of 5%, 10-h FMC of 6%, 100-h FMC of 7%, live FMC of 70%, wind speed of 15 km h^{-1}, wind direction of 0° applied for 0, 15, 30, 50 and 100% of slopes.

The 10-h fuel moisture (DFMC) was also included in the calculation of FHI. When the fire ignition scheme was initialised for the real-time calculation of FII, the 10-h fuel moisture value (as systematically measured in RAWS) was taken into account. In order to run the sub-system in a forecast mode, the expected fuel moisture was calculated based on the forecast relative humidity (RH) provided from the SKIRON/Eta model. Observations from RAWS were used to model the 10-h fuel moisture with RH, resulting in the function ($R^2 = 0.784$):

$$\mathrm{DFMC} = -1.0232 + 0.4882\times\mathrm{RH} - 0.0125\times\mathrm{RH}^2 + 0.0001\times\mathrm{RH}^3$$

In order to examine whether and how fire ignitions are influenced by terrain elevation and aspect, both variables were included in the FHI scheme. Terrain elevation was retrieved from the 20-m contour interval of maps with scale 1:50 000 whereas aspect was calculated from elevation through GIS.

Fire Risk Index: conception, structure and data collection

The human factor is of great importance in danger estimation, especially in the Mediterranean countries where it is one of the primary causes of forest fires either by accident or arson. The FRI refers to the fire risk at a particular area due to human presence. The spatial analysis of human risk is quite complex, owing to the difficulty of spatially illustrating human activities. The prime method used to delineate human risk is the correlation of the spatial distribution of fire ignition with the proximity to human activities (Chuvieco and Congalton 1989; Chuvieco and Salas 1996).

The parameters taken into account for the calculation of FRI were distances from main and secondary road networks, power lines, urban areas, landfills, recreation areas (i.e. camping sites, swimming beaches and other sites with temporary human presence, especially during the fire season), agricultural land, and month and day of the week. The month was included in the model based on the rate of fires ignited during each month from 1970 to 2001, and the day of the week with a binary value (weekend or not).

In Fig. 6, the structural system parameters presented are more or less permanent and don't alter on a short-term basis, and most

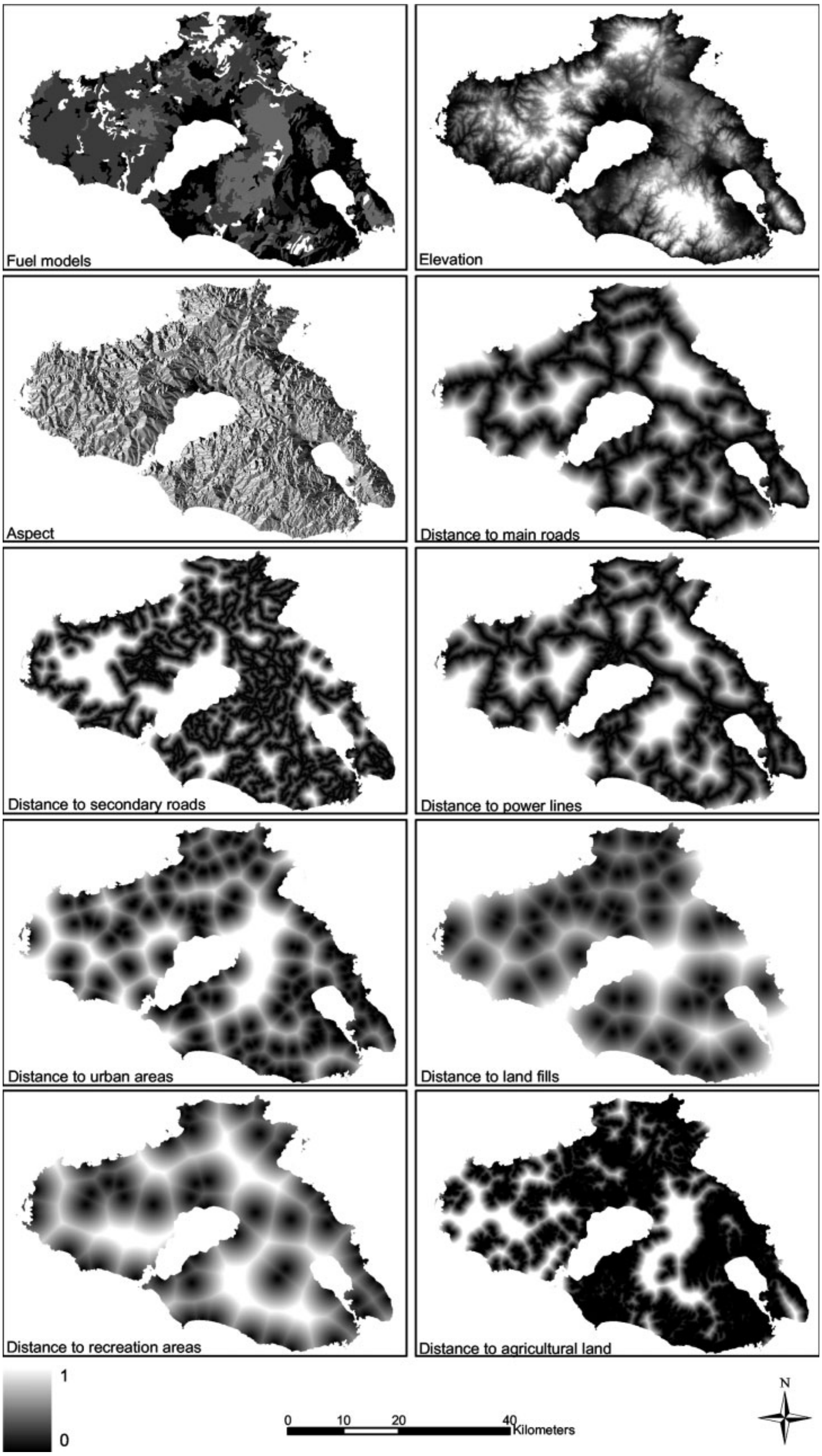

Fig. 6. Structural parameters of the system linearly stretched in domain 0–1.

Table 1. Number of fires in training (Tr.) and validation (Val.) datasets for each index
FWI, Fire Weather Index; FHI, Fire Hazard Index; FRI, Fire Risk Index

	FWI – Tr.	FWI – Val.	FHI – Tr.	FHI – Val.	FRI – Tr.	FRI – Val.
Total sample	64	27	91	25	322	121
Fire ignitions	27	17	45	12	202	66
Non-fires	37	10	46	13	122	55

of them are based on straight-line distances from human activity. More than 20 scenes of the very high resolution remote sensing data coming from the QuickBird sensor (pixel size 2.8 m) were used for direct mapping (by visual interpretation) of the road network and the urban and agricultural areas. To replace the few clouded areas, Landsat-ETM imagery was used with 30 m pixel size at multispectral channels and 15 m at panchromatic.

Fire Ignition Index: conception and structure

FII is a composite index representing the accumulated ignition risk of an area based on the probability of a fire starting based on weather, hazard and risk indices. As no type classification was considered in the wildfires that were taken into account, FII calculated the index of a fire ignition regardless of its severity. For better comprehension and acceptance of the final map by end-users, the FII was classified into five categories of low (0–40), medium (41–60), high (61–80), very high (81–90) and extreme danger (91–100). These classes in our application do not necessarily represent the kind of precautionary measures that should be taken vis-à-vis the fire danger, but they are only a qualitative characterisation of FII. The above FII ranges were selected by analysing the 2003 and 2004 fire seasons to calibrate the specific classes to visually identified areas where fires ignitions occurred. More specifically, the classes were initially selected to have equal range for the year 2003 and the fires that occurred were mapped for each day. According to the results, the fire ignition was reclassified in order to have the maximum number of fires and the smallest area in the higher classes.

Data collection and pre-processing

A total of 420 fires that occurred during the period 1970–2001 on the island of Lesvos were mapped and the historical data necessary for the training of neural networks were collected with the help of interviewed residents, experts and Global Positioning Systems. The variables that refer to distances from a parameter for each ignition point were calculated by GIS. Training and validation samples were created from the total historical data of the fires, to be used in the neural networks for each index. Owing to the absence of daily meteorological data, with the exception of some of doubtful credibility, fires that occurred during the 1997–2001 period (May–September) had to be used for the training of the FWI and FHI (with uneven numbers of fires because some daily weather data were also missing during this period). For the training of FRI, all the fires having occurred during May to September (1970–2001) were used, i.e. a total of 268 fires (Table 1). In order for the resulting model not to become biased in favour of fires, a randomly selected subset of 70% of all fires was used in every training of FRI. For the simulation of the system's operation and its better validation, the 102 fires having occurred from May to October 2003 were mapped, and the values of all the parameters taken into consideration during training were collected. October was included in the validation database of 2003 because 42 out of 102 fires were ignited during this month. The specific fires were used in the validation stage as well as in the resulting interpretation stage only for fire causes on Lesvos Island. For proper training, random points simulating the non-fires for the specific time during the year 2003 were created. After having verified that there had not been any fires at the points above at the specific time, meteorological conditions were collected as well as the rest of the parameters according to the methodology followed for the fires during 1970–2001 (Fig. 7).

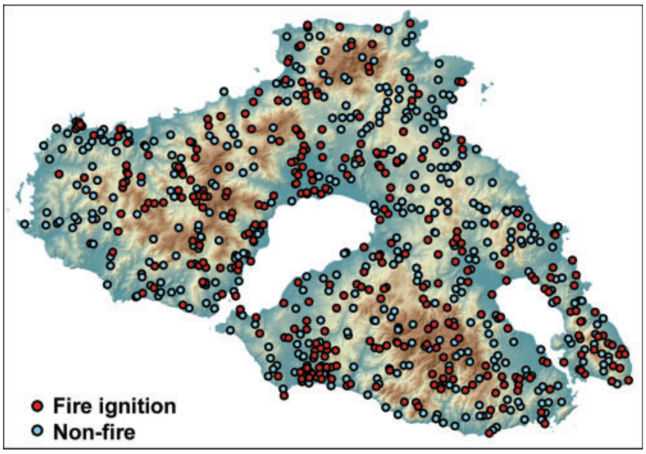

Fig. 7. Fire ignition points and non-fire points during years 1970–2001.

Neural network training

The development of artificial neural networks or simply neural networks (NN) began over 50 years ago as part of scientists' attempts to better comprehend the human brain and simulate some of its abilities. There is no widely accepted definition of the NN. Neural Networks are simply a means of processing data based on the human brain model using the main concepts of its function. The NN are based on a collection of units similar to neurons trying to perform similar procedures, and are particularly useful for pattern recognition and modelling complex problems for which the explicit form of the relationships among certain variables is not known (Fausett 1994). NN have been partly used for spatial fire ignitions forecasts (Vasconcelos *et al*. 2001).

The calculation of the three initial indices was undertaken through the use of an NN, and more specifically a Multi-Layer

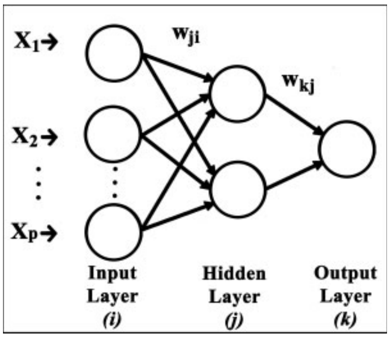

Fig. 8. Backpropagation neural network with one hidden layer and one output neuron.

Perceptron (MLP) that had been trained through the method of error back-propagation. This is the most popular method for training an NN with multiple processing layers. Different variations of the error back-propagation method have been developed but it was promoted, and became popular, by Rumelhart and McClelland (1986). The basic architecture of MLP with i input nodes, one hidden layer with j units and the output layer with k nodes is shown in Fig. 8. During training, the network initiates the learning process through the random values of its weights. The computed output is then compared with the actual output of the input vector Xp and the weights are corrected so as to minimise the error function (gradient descent). The same process is repeated many times so that the error is gradually diminished until it becomes small and tolerable.

In order to evaluate the performance of the NN, the Mean Square Error (MSE) function was used:

$$\mathrm{MSE} = \frac{1}{n}\sum_{k}(t_k - d_k)^2$$

where t_k is the desired outcome, d_k the actual outcome in the output layer and n the total number of the training samples. The logistic function that follows was used as an activation function, which is necessary for the implementation of non-linearity in the network:

$$f(z) = \frac{1}{1 + e^{-z}}$$

This function approaches 1 for big positive values of z, and 0 for big negative values of z, and is appropriate for the occurrence or not of fires, as the dependent variable has a binary value 0 or 1 (Jordan 1995; Sarle 1997). Moreover, the use of this continuous, differentiable and monotonically non-decreasing function as the activation function allows for the interpretation of the result as a probability (Hampshire and Pearlmutter 1990; Bishop 1995). Finally, the logistic function was also used in the output neurons in order to avoid effects from noisy data that didn't conform to the identity function or any other linear function (Masters 1993).

The training procedure of the network in Fig. 8 can be summarised in the following steps:

- Initialisation of weights w
- Feeding the network with the input vector $x = (x_1, x_2, \ldots, x_i)$
- The input for each hidden unit is given by the equation $z\_in = \sum_i x_i w_{ji}$
- Calculation of the output of each hidden unit with $z_j = f(z\_in)$, where f is the logistic function presented above
- Then, the input of each output unit is given by $y\_in = \sum_j z_j w_{kj}$
- Calculation of the output of each output node with $y_k = f(y\_in)$, where f is the logistic function presented above
- Weight correction (i.e. for weights connecting output layer with the previous layer) with $\Delta w_{kj}(t+1) = -r\frac{\partial E}{\partial w_{kj}} + \Delta w_{kj}(t)$, where r is the learning rate and controls the rate and the speed of the training.

The network was re-fed with new input data and the process was continued for t iterations, known also as epochs, until the error was minimised. In order to ensure that the trained network would approximate target values that were not included in the training dataset, a validation dataset was used that included cases that were not used in training. Usually, the training was stopped when the error started to increase in the validation dataset despite the fact that the error could be still decreasing in the training set. This was an indication that the network had a good generalisation and an overfitting to the training dataset had been avoided.

Analytic hierarchy process

FII is calculated by multicriteria analysis of the three individual indices, according to the weighted average method:

$$\mathrm{FII} = \sum_{j=1}^{n} w_j a_{ij}$$

where n is the number of decision criteria, a_{ij} is the actual value of the ith alternative in terms of the jth criterion and w_j is the weight of importance of the jth criterion. By applying the above formula to the present study, the Fire Ignition Index (FII) was calculated with:

$$\mathrm{FII} = w_a\mathrm{FWI} + w_b\mathrm{FHI} + w_c\mathrm{FRI}$$

The vector of weights w was calculated by the Analytic Hierarchy Process (AHP), as proposed by Saaty (1980). More specifically, the AHP was used for the calculation of the three indices' weights after a pairwise comparison among the indices using a relative importance scale. The strength of importance was expressed on a ratio scale from 1 to 9 in order to quantify the linguistic choice. A preference of 1 indicates equal importance between two indices, whereas a preference of 9 indicates that one index is 9 times more important than the one with which it is being compared. These pairwise comparisons were initialised by the decision makers that were experts in the importance of each criterion to another, and a decision matrix (comparison table) was constructed, which in the present study had dimensions of 3×3. The comparison table has the following basic properties: $a_{ii} = 1$ and $a_{ij} = 1/a_{ji}$ where a_{ij} is the strength of importance of criterion i compared with criterion j. For the calculation of the weights of each criterion, the right principal eigenvector from the comparison table was calculated. The eigenvector can be approached using the geometric mean of each table line, i.e. multiplying the elements of each line to each other and then calculating the n-th root, where n equals the number of elements in

Table 2. Training and validation results of neural network training
FWI, Fire Weather Index; FHI, Fire Hazard Index; FRI, Fire Risk Index; MSE, Mean Square Error

	FWI	FRI	FHI
Number of hidden layers	1	1	1
Number of nodes in hidden layers	6	8	4
Training epochs	100	1000	1500
MSE training sample[A]	0.122	0.121	0.091
MSE validation-1 sample[A]	0.130	0.157	0.120
MSE validation-2 sample[B]	0.177	0.073	–
Correct classification of fire ignitions in training sample[A]	93%	87%	91%
Correct classification of non-fire points in training sample[A]	59%	50%	69%
Correct classification of fire ignitions in validation-1 sample[A]	88%	89%	75%
Correct classification of non-fire points in validation-1 sample[A]	60%	38%	76%
Correct classification of fire ignitions in validation-2 sample[B]	65%	91%	–

[A](FWI and FHI: 1997–2001, May–September; FRI: 1970–2001, May–September).
[B](May–October of 2003).

each line. Afterwards, the geometric means were normalised by dividing them by their sum (Triantaphyllou and Mann 1995).

In reality, the comparison table is not considered consistent. Saaty (1980) recommends that in order to evaluate the table's credibility, the use of Consistency Index, CI, and Consistency Ratio, CR, are applied, dividing the CI by a Random Index, RI, which equals 0.58 for the 3×3 table. When CR is small enough, then the comparison table is considered consistent. The value 0.1 is used as a criterion. In case of $CR > 0.1$, then the re-evaluation of pairwise comparisons that have been chosen in the comparison table should be considered.

Results and discussion

Multiple tests were performed in order to select the final structure of the neural networks for each index. Despite the NN's modelling flexibility, the possibilities of directly measuring the variables' influence are limited. The resulting weights of the trained networks cannot be directly examined; thus it was impossible to interpret weights *v.* inputs importance or fire causes. In order to evaluate the performance of the training, the correct classification rates of training and validation samples were used, i.e. actual fires classified as fires and non-fires classified as non-fires. Also, the MSE of the training and the validation datasets was monitored during training; the process was continued until the MSE of the training or the validation dataset started to increase.

A learning rate $r = 0.1$ was chosen, whereas the output neuron was considered activated in case of an output value above 0.5. The FWI function was more easily approached, whereas the FRI had better classification percentages regarding the 2003 fires (Table 2). The training for the three networks was stopped before the MSE for validation sets of the period 1997–2001 started to increase. The error of the 2003 validation set was calculated with the trained network because only fire records were included.

More specifically, the chosen network of the calculated FWI classified correctly 93% of the fires of the 1997–2001 training sample and 88% of the fires of the 1997–2001 validation sample (Table 2). On the other hand, 59% of the non-fire points for the training sample and 60% of the non-fire points for the validation sample were correctly classified. In almost 100 epochs in the training process, the network missed its generalisation in the 2003 validation sample, whereas in the case of more than 700 epochs, the generalisation in the 1997–2001 validation sample was missed as well; this meant an over-fitting of the function on the training sample. When adding a second hidden layer, the network became more sensitive in local minimums, whereas in 400 epochs, there was a better classification of the 2003 fires. However this network with a second hidden layer was not selected owing to an under-estimation of the non-fires in the training sample.

The network used by FRI was trained in 1000 epochs. For more epochs, it missed its generalisation in the 1970–2001 validation sample. The correct classification percentages are judged to be satisfactory although there was an over-estimation due to the low percentage of correct classification regarding non-fires in the 1970–2001 sample. More specifically, the correct classification of non-fire points for the training sample was 50% and for the validation sample was 38%. The latter means that for 62% of the points that were not expected as a fire, an ignition probability more than 50% was computed (Table 2). It is worth mentioning the great percentage (91%) of the correct classification of the validation sample regarding the 2003 fires. This meant that 91% of the fires having occurred in Lesvos during the period of May to October 2003 broke out in areas where the network output was more than 50% for the FRI, i.e. the 2003 fires had human presence and activity as a main cause. This is also confirmed by the cross-examination of files of the Fire Department regarding the many human-caused fires on Lesvos Island in 2003.

The training process of the FHI enhanced the conclusion above, because the MSE of the 2003 validation sample showed very high values, whereas the correct fire classification percentage was low. Thus, the training was based completely on the fires of the 1997–2001 period and was terminated before missing the generalisation in the validation sample. The 91% of the fires and the 69% of the non-fires in the training sample were correctly classified, whereas the 75% of the fires and the 76% of the non-fires in the validation sample were correctly classified (Table 2).

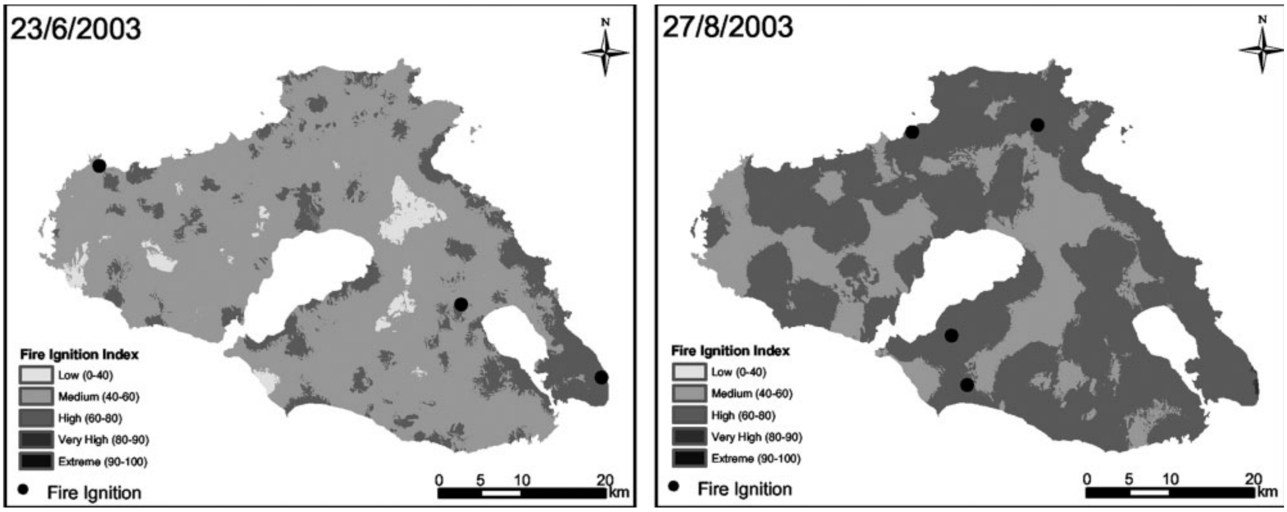

Fig. 9. Fire Ignition Index (FII) mapped and fires ignited on 23 June 2003 and 27 August 2003.

The weight vector of FII that resulted from AHP had no direct relation with fire causes but it was calculated based on the relative importance of each index compared with others, intuitively assigned by the authors. We assigned a moderate (weak to equal) importance of FRI over FWI, a weak importance of FRI over FHI, and a weak importance of FWI over FHI. The choices are based on the specific fire history of the area and taking into consideration that fire ignitions, regardless of the resulting burned area, were dependant mostly on human factors, i.e. from July to October, the records of the area show an equal distribution of fire ignitions for each month. The choices also are based on the fact that FWI and FHI cannot be relatively strong indicators of an FII as they affect mostly fire spread.

The comparison table, which had a 0.0268 CI and a 0.0462 CR, was created to calculate the FII. Consequently, using the weight vector that came up, the FII was calculated through the function:

$$\mathrm{FII} = 0.3325 \times \mathrm{FWI} + 0.1396 \times \mathrm{FHI} + 0.5278 \times \mathrm{FRI}$$

In Fig. 9, the FII is presented for the dates 23 June 2003 and 27 August 2003, when three and four fires occurred respectively on the island of Lesvos. To create the maps, the actual weather conditions of the specific days were used. All the fires occurred in areas where the FII was more than 50. The comparative risk in relation to some other areas was much larger. More specifically, the FII (23 June 2003) for the three fires was 56, 59 and 72 respectively. Regarding area classification, 4% of the area was classified as 'low', 79% classified as 'medium' and 17% classified as 'high'. The four fires of 27 August 2003 had FIIs of 65, 66, 68, and 71, respectively, whereas 29% of the area was classified as 'medium', 70% classified as 'high' and 1% classified as 'very high'.

The map-outcomes in Fig. 9 might be useful to the Fire Departments and state authorities as an important decision-making tool for prevention and suppression of forest fires. An operational validation of FII under realistic conditions was performed during the fire period of 2004, although only 28 fires occurred on Lesvos Island as opposed to the 102 fires that burned during 2003. The reduction of fire events was mainly due to the high alertness of the public authorities (i.e. fire department, police, etc.) during the 2004 Athens Olympics. During this period, the FII map was produced daily, valid for the next day, and distributed to the local Mytilene–Lesvos Fire Department and the General Secretariat for Civil Protection of Greece. The operational use had the following results: from June till September 2004, 12 out of 28 fires were ignited in areas classified as 'Medium Danger', which averaged 63% of the total area, and 16 occurred in 'High Danger' areas, which averaged 35% of the total area. The remaining 2% of the area was classified as 'Low Danger'. No areas were classified as 'Extreme Danger', whereas, rarely, very small areas were classified as 'Very High Danger' for the 2004 fire season owing to actual weather conditions. The validation of 2004 confirmed that fire ignition in Lesvos is dependant mainly on human factors. Human risk factors are shown from fire history records on Lesvos Island. According to the 1970–2001 fire history records for Lesvos Island, the causes of 55% of wildfires were determined. Human negligence was responsible for 62% of wildfires erupted from known causes; 16% were arson, 10% were lightning fires, 6.5% were caused by activities of the army, 2.8% were garbage disposal-related and 1.7% were from electric powerline malfunctions. Our methodology, and especially the FRI, can describe spatially the previous causes except for lightning and army fires. As the parameters are not dynamic *per se*, our results can be used in mid- to long-term forest management regarding fire prevention and planning. The trained NN is consistent with what would be the understanding and expectation of experienced forest fire staff and of history that the main factor in forest fire ignition is human presence and activities. In general, Lesvos Island seems to have a clear equation of people equal fire on a long-term basis. This fact explains the low correctness in classification rates of non-fire points; 50 and 62% of the non-fire points of the training and the validation samples, respectively, were classified as expected fires with more than 50% probability.

Conclusion

The aim of the present research was to develop an operational large-scale quantitative fire ignition risk scheme as a component of a fire danger rating system, with the ability for short-term forecasting of wildfire danger to support better and realistic prevention and pre-suppression planning. The proposed scheme is based on multiple layers of information from the quantitative and systematic analysis of the spatial distribution of fire ignition points. Some of the parameters that were taken into consideration are vegetation, topography, weather conditions and human geography of the study area.

High-resolution QuickBird satellite data were used for direct mapping by visual interpretation of land cover boundaries, a methodology with a high level of confidence and accuracy in a local-to-regional scale. Innovative methodologies of automatic object recognition could be also used with a main disadvantage being the specialised technological know-how that is required.

The neural network showed a significant ability to discover patterns in data that are so obscure as to be imperceptible to standard statistical methods. The input data of natural phenomena usually exhibit significant unpredictable non-linearity and variability, but the robust behaviour of a neural network makes it perfectly adaptable to environmental models and these sort of data. The time required for processing the input tabular data during the training and the input of raster data during the calculation of indices was limited, suggesting that these processes could be used in an operational mode within an integrated process, e.g. a landscape fire danger prediction system.

The ability of NN to be trained makes them a powerful function approximator for a fire ignition scheme. Compared with other operational systems that are based on data-driven specificities of each target area, NN can be trained to develop the specific equation representing the fire ignition pattern scheme of each area. If the training sample is changed with another one from the same area (Lesvos Island), the results should not change significantly if both training procedures are successful. That would mean that a generalisation was achieved. If a sample from another area is used for NN training, then the results are likely to change, reflecting the wildfire ignition pattern in that area. One of the disadvantages of NN is the difficulty of interpretation of model output in order to identify the most important input variables that affect it. Because of this, NN have often been characterised as a 'black box'.

Future work, based on the present research, is geared towards performing sensitivity analysis on the trained networks in order to rank variable importance. This can provide useful outputs in a quantitative fire ignition system because forest fire management activities can then be focused on preventive measures that specifically target the reduction of fire ignitions based on the most important variables. Validation will also be continued over the next years, after corrections and optimisation of the whole procedure take place. Fire ignitions of recent years, for which actual weather data from RAWS exist, will be used exclusively in new trainings of NN. Spatial computational methods of weather variability will be included in the methodology as well as new fuel type mapping, as available.

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