Applications of Statistics and Probability in Civil Engineering – Faber, Köhler & Nishijima (eds) , CRC Press, Proc. ICASP11, Zürich, 2011

Effect of Weather Conditions, Geography and Population Density on Wildfire Occurrence: A Bayesian Network Model

P. Papakosta & D. Straub
Engineering Risk Analysis Group, Technische Universität München, Munich, Germany

ABSTRACT: Occurrences of wildfires are related to weather conditions and human intervention and can only be predicted probabilistically. In this paper, the potential of Bayesian Networks for such predictions is investigated. A Bayesian Network is constructed, which expresses the effect of weather conditions, land cover and human presence on the rate of wildfire occurrences. The model is based on both temporal and spatial data. The parameters of the model are inferred from data obtained for the Greek Mediterranean island of Rhodes. Initial results show a dependence between human population density and wildfire occurrence. The selected indicator for weather conditions, a commonly used fuel moisture index, is found to be ill-suited for predicting wildfire occurrence on Rhodes, possibly due to the specifics of the Mediterranean climate. Future work is needed to identify and include relevant influencing factors, which is facilitated by the Bayesian network modeling approach.

1 INTRODUCTION

Wildfires are common in geographic areas where the climate is sufficiently moist for vegetation growth but also features extended dry hot periods, such as the Mediterranean area, Southeast Australia, Central and Southern California, or South Africa. Long periods of drought and hot temperatures, combined with strong winds and unmanaged biomass, make such areas naturally fire-prone. Besides climate, human interventions also play an important role in the occurrence of wildfires. Humans have used fire for their interests throughout history and the result is observable in the mosaic landscapes of the Mediterranean. The regeneration of pastures, land use change, suppression of natural vegetation to implement crops, land clearing activities or revenge are all human motives that caused and still cause wildfires (Leone et al. 2009).

Although wildfire incidents have always accompanied vegetation growth, statistical evidence suggests an increase in the severity of wildfires during the past three decades (FAO (Food and Agricultural Organization of the United Nations) 2001, Joint Research Center (IES) 2006). In the Mediterranean, long periods of high above-average temperatures and draught, especially in the summer months, have produced large fires with severe impacts on vegetation, animals, crops, human lives and properties. Record temperatures occurring during recent summer periods (Southeast Australia 2009, Russia 2010) lead to extreme wildfire events that were associated with huge socio-economical costs. In addition, scenarios of global warming suggest that wildfires will become more frequent and more intense in the future (Wotton et al. 2003, Flannigan et al. 2005, Munich RE 2010).

When modeling wildfires, it is commonly distinguished between the ignition and the behavior (including the spread) of the wildfires. This paper focuses on the occurrence of wildfires, which here is defined as the event that a fire has ignited and has spread to an extent that it is registered. Therefore, to model the occurrence of a fire it is necessary to consider factors leading to ignition as well as its initial spread.

The research on wildfire occurrence addresses the questions on when, where and why wildfires are triggered and start to grow. The answer to these questions requires understanding of the interrelations among biotic and abiotic factors and multidisciplinary approaches are thus needed for modeling fire risk. Multiple authors have investigated the role of weather conditions and fuels on fire occurrences, including (Chou & Chase 1993; Chuvieco et al. 2004; Wotton & Martell 2005; Camia & Amatulli 2009). A statistical approach is presented by Preisler et al. (2004), who use logistic regression to produce fire probability maps for the state of Oregon. In their study, the following variables are identified as having a significant impact on the probability of wildfire occurrence: spatial location; seasonality; elevation; 1000-h fuel moisture; dry bulb temperature; state of weather (e.g. clear skies, broken clouds, thunderstorm).

The interdisciplinary approach to natural hazard risk modeling can be supported efficiently by Bayesian networks (BN). Based on acyclic graphs, BN enable to model the probabilistic dependence among a large number of variables influencing the risk. The causalities expressed by the arcs between the variables make BN not only convenient for graphical communication of the interrelations between the influencing factors (qualitative part), but also include, through conditional probability tables, a quantitative probabilistic model (Jensen & Nielsen 2007). In other words, the graphical representation of the dependence structure among stochastic variables makes it easy to understand intuitively and facilitates the consistent modeling of complex problems involving many variables. For these reasons, BN are increasingly applied for risk assessment of natural hazards, e.g. for rock-fall hazards (Straub 2005), avalanches (Grêt-Regamey & Straub 2006), tsunamis (Blaser et al. 2009) and earthquakes (Bayraktarli et al. 2005, Bensi 2010, Kuehn et al. in press). Dlamini (2009) developed a BN model for wildfire occurrence, which is used to analyze the influence of 12 biotic and abiotic variables on wildfire occurrence in Swaziland, including land cover, elevation, mean annual rainfall and mean annual temperature.

In this paper, we attempt to construct a BN model for wildfire occurrence, which includes the effect of weather, vegetation and humans and deals with the problem of non observable variables. In contrast to Dlamini (2009), our BN model is based on continuous (3hr or 6hr) weather data and can thus serve for prediction purposes. The Fine Fuel Moisture Code of the Canadian Fire Weather Index (Van Wagner 1987) is utilized in the BN to model the effect of weather conditions on the fire occurrence. The model is applied to the Greek Mediterranean island of Rhodes.

2 METHODOLOGY

2.1 *Bayesian Networks*

Bayesian Networks (BN) are directed acyclic graphs and consist of nodes, arcs and probability tables attached to the nodes (Jensen & Nielsen 2007). Each node represents a discrete random variable, i.e. its sample space consists of a finite set of mutually exclusive states. The arcs describe the assumed dependence structure among the random variables, whereby it is common to describe these relations with family terms. In the example BN of Figure 1, $\boldsymbol{X_3}$ is the child of $\boldsymbol{X_1}$ and $\boldsymbol{X_2}$, and $\boldsymbol{X_1}$ and $\boldsymbol{X_2}$ are the parents of $\boldsymbol{X_3}$. Nodes that are not directly connected can be conditionally independent of each other (this depends on the network structure and the available evidence, as described by the d-separation rules, see e.g. Pearl 1988). A conditional probability table (CPT) is attached to each of the nodes, giving the probability of the variable to be in one of its states conditioned on the states of its parents. If we consider a BN with discrete random variables $\mathbf{X} = [\boldsymbol{X_1}, \dots, \boldsymbol{X_n}]$, then the full (joint) probabilistic model of these variables is the joint Probability Mass Function (PMF), $\boldsymbol{p}(\mathbf{x}) = \boldsymbol{p}(\boldsymbol{x_1}, \dots, \boldsymbol{x_n})$, which can be specified with the help of the chain rule:

$$p(\mathbf{x}) = p(x_n|x_{n-1}, \dots, x_1)p(x_{n-1}|x_{n-2}, \dots, x_1) \dots p(x_2|x_1)p(x_1) \quad (1)$$

By making use of the independence assumptions encoded in the graphical structure of the BN, this chain rule reduces to:

$$p(\mathbf{x}) = \prod_{i=1}^{n} p(x_i|pa(x_i)) \quad (2)$$

wherein $pa(x_i)$, are realizations of the parents of X_i. In other words, the joint probability mass function (PMF) of all random variables in the BN is simply the product of the conditional PMFs of each individual random variable given its parents. Therefore, the graphical structure of the BN, together with the conditional PMFs $\Pr(x_i|pa(x_i))$, are sufficient for specifying the full (joint) probabilistic model of $\mathbf{X} = [X_1, \dots, X_n]$.

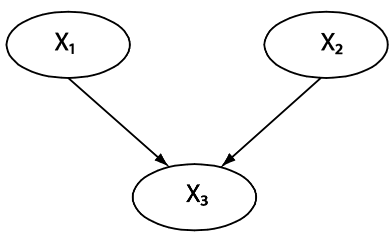

Figure 1: A simple Bayesian Network. X_1 and X_2 are the parents of X_3, and X_3 is the child of X_1 and X_2.

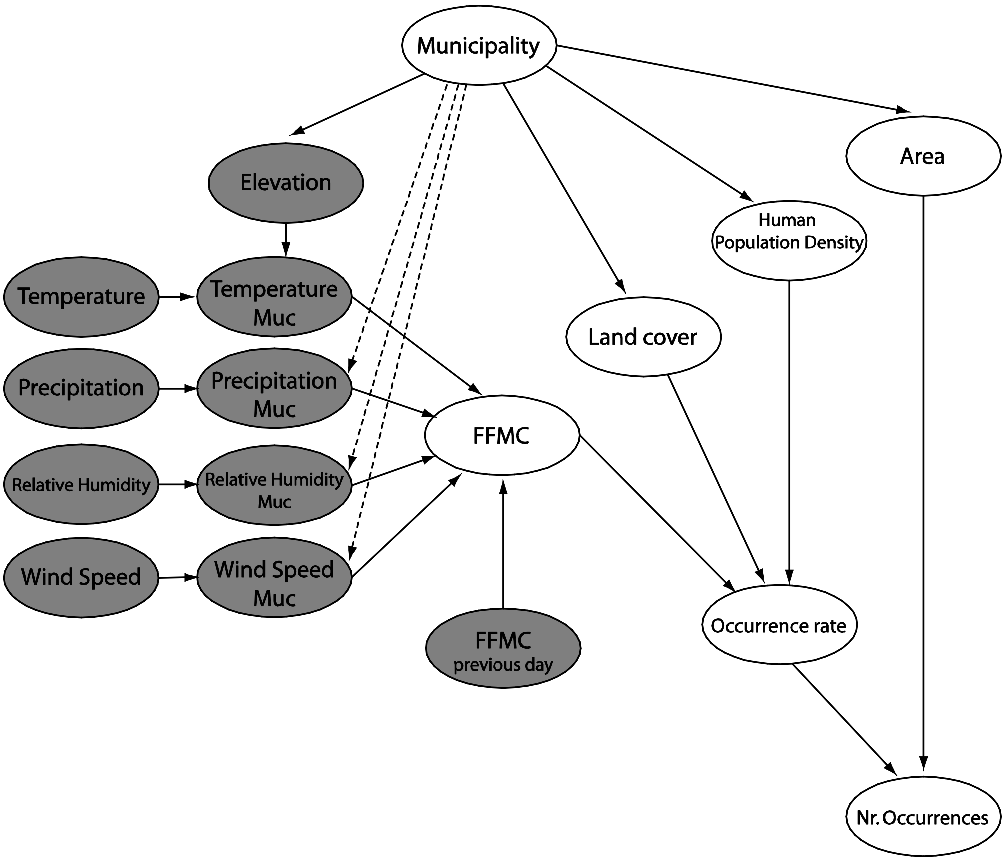

Figure 2: Bayesian Network for fire occurrences.

Although the definition of BN does not require the links to represent causal relations, it should be checked that the implied conditional independence assumptions in the BN correspond to observations of the real world. However, ensuring causality among variables will commonly lead to less complex and more intuitive BN models (Jensen & Nielsen 2007, Straub & Der Kiureghian 2010), and is thus preferable.

2.2 *BN for Fire Ignition*

In this study we construct a BN to estimate wildfire occurrence rates based on temporal and spatial data (Figure 2). Here, the spatial reference of the model is the municipality level (administrative unit), to account for the available data (i.e. fire records that are available only for a municipality without geo-reference). The temporal reference is one day. Therefore, the BN represents the factors influencing wildfire occurrence in a municipality (as specified by the corresponding node) during a particular day.

The nodes of the model represent variables influencing wildfire occurrence. Grey nodes represent the variables used for the calculation of the daily fuel moisture and are treated separately in the parameter estimation, as described in paragraph 3.3. Every node has a number of discrete mutually exclusive states, meaning that continuous random variables (such as Area or Human population density) are discretized.

The nodes Municipality, Area and Human population density are deterministic, and can be determined from spatial and demographic data. Land cover has labeled states that are related to fuel type (e.g. forest, natural grasslands, olive groves, artificial surface, etc.) and the probability of occurrence of each fuel type is taken as the proportion of the area covered within a municipality.

The node FFMC (Fine Fuel Moisture Code) represents the continuous variable fuel moisture. The node is a child of the weather variables (temperature, wind speed, relative humidity and precipitation) and the fuel moisture of the previous day. The daily values of FFMC are calculated deterministically as described in paragraph 3.3.

The node Occurrence rate represents the mean number of wildfire occurrences per day and km². In this model, the rate is a function only of land cover, human population density and FFMC, which includes all weather related variables. The occurrence rate is not observable and is estimated based on historical data.

For given daily rate of occurrence and land area, the number of wildfires during a day can be modeled by a Poisson distribution, assuming independence among fire events for given occurrence rate. The CPT of the number of occurrences N is therefore obtained as,

$$\Pr(N = k|\, \lambda, \alpha) = \frac{(\lambda\alpha)^k}{k!} \exp(-\lambda\alpha)\,, \quad k = 0,1,2,\ldots \tag{3}$$

wherein λ [$\text{day}^{-1}\text{km}^{-2}$] is the occurrence rate and α [km²] is the area.

2.3 *Fine Fuel Moisture Code (FFMC)*

The Canadian Forest Fire Weather Index (FWI) is one of the most widely used indexes for the evaluation of fire risk in relation to weather conditions (Lawson & Armitage 2008). Having as input easily observable weather parameters, FWI provides with its six standard components (three fuel moisture codes and three fire behavior indexes) numeric ratings of relative potential for wildfire. One constituent of the FWI is the Fine Fuel Moisture Code (FFMC), which provides a numeric rating of the daily moisture content of litter and other cured fine fuels, and which is used in the BN to express the influence of daily weather changes on the flammability of the fuels.

The FFMC acts as an indicator of the relative ease of ignition and flammability of fine fuels and is calculated through a moisture balance. FFMC rating is on a scale of 0 to 100. Higher values represent lower moisture contents and hence greater flammability. Any value above 70 is considered high and any value above 90 is considered extreme. The four weather variables needed to calculate FFMC are dry-bulb temperature, relative humidity, wind speed and precipitation. The first three are recorded at noon and the precipitation value is the 24 h total rainfall from noon to noon [in mm].

Rainfall leads to a decrease in FFMC, while temperature, together with relative humidity and wind speed, affect the rate at which the FFMC increases due to drying. Relative humidity also affects the equilibrium moisture content, which is the lowest moisture content that a fuel will reach for a given combination of weather conditions.

2.4 *Parameter Estimation*

It is possible to learn both the structure and the parameters of a BN with historical data and expert knowledge (Jensen & Nielsen 2007). Here, we consider the structure of the BN known (Figure 2), i.e. it is based on our knowledge of the process, and the learning process reduces to the task of estimating the parameters of the conditional probability distributions.

The random variable “Occurrence rate” in the BN of Figure 2 is a hidden variable, also called latent variable (Russell & Norvig 2003). Although hidden variables are not observable, they are included in the model because they allow reducing the number of parameters required to specify a BN. The Expectation-Maximization (EM) algorithm is used to solve the problem of learning the conditional probability distributions of the hidden variables. The algorithm involves two steps that are performed iteratively, namely the computation of expected values of hidden variables (E-step) and the maximization of the parameter likelihood, using the expected values as if they were observed values (M-step).

In case of a BN let **x** denote the observed values, **Z** the hidden variables, and $\boldsymbol{\theta}$ the parameters of the model. Then the ith iteration of the EM algorithm is (Russell & Norvig 2003):

$$\boldsymbol{\theta}^{(i)} = \text{argmax}_{\boldsymbol{\theta}} \sum_{\mathbf{z}} p\left(\mathbf{z}\middle|\mathbf{x}, \boldsymbol{\theta}^{(i-1)}\right) \ln L(\boldsymbol{\theta}|\mathbf{x}, \mathbf{z}) \tag{4}$$

$L(\boldsymbol{\theta}|\mathbf{x}, \mathbf{z})$ is the likelihood of $\boldsymbol{\theta}$ for given observations **x** and **z**. The summation operation in Eq. (4) corresponds to the E-step, the maximization operation to the M-step.

3 CASE STUDY

3.1 *Rhodes*

The Greek Mediterranean island of Rhodes has been chosen as a case study area, because it represents quite adequately the climate and the mixed land uses of fire-prone Mediterranean regions. The island is located in the south eastern part of the Aegean Sea, its area is 1409 km² and in 2001 the number of permanent residents was 115.334 (Hellenic Statistical Authority). On the administrative level, the island is divided into 43 municipalities. The inner part of the island is mountainous with the highest elevation at 1215 m. The climate of Rhodes is a dry summer subtropical climate (Mediterranean) with wet winter and long dry summer periods and an annual mean temperature of around 22 °C. The natural vegetation consists of evergreen shrubs, genista, pine forests and mixed forests with cypresses. The main agricultural activities on the island are the cultivation of olives and vines. Wildfires are common on Rhodes; wildfires occurring in September 2008 led to a burned area of 122 km², according to recordings of the Greek Fire Service.

3.2 *Data Sources*

Both spatial and temporal explicit data are used in this study. The elevation of the island has been taken from the Advanced Spaceborne Thermal Emission and Reflection radiometer (ASTER) Global Digital Elevation Model (GDEM). ASTER GDEM is a project of the Ministry METI of Japan and NASA. The spatial resolution is 15 meters in the horizontal plane. Pre-production estimated accuracies were 20m for vertical data and 30m for horizontal data at 95% confidence. Three GeoTIFF data sets cover the whole area of the island (ASTGTM_N35EO27, _N36EO27, _N35EO28).

To obtain information on land cover, the 2000 version of Corine Land Cover (CLC) is utilized (European Environment Agency). CLC provides consistent localized geographical information on the land cover of the 12 Member States of the European Community in a scale of 1:100.000. The CLC is the result of the combination of information from different sources, including satellite images, aerial photographs, topographic maps, thematic land cover maps and ground truth surveys (the minimum unit mapping was set at 25 ha (0.25 km²)) and is classified in 44 types. Out of these, only 25 are present on the island.

A thematic map with the administrative boarders of municipalities of the island, provided by Agroland SA, is utilized. Demographic data on the population of each municipality in 2001 was obtained from the Hellenic Statistical Authority.

Historical data on the occurrences of fires during the period 2000-2009 were obtained by the statistical department of the Greek Fire Service. The data offered information on the date of fire occurrence and the municipality that it occurred.

The spatial data are edited and processed with ArcGIS 9.3. Data related to the mean elevation, land cover classes and area are then extracted for each of the 43 municipalities.

3.3 *Determining the model*

For the calculation of FFMC, weather data on temperature, relative humidity, wind speed and precipitation for the years 2000-2009 were obtained from the German Weather Service. The measurements were made at the Greek official weather station at the airport of Rhodes (36°24' N, 28°05' E, 11m). Temperature, relative humidity and wind speed are recorded in 3-hour intervals. The daily values at noon are extracted and used as an input for the FFMC calculations. In the case of missing values of relative humidity and wind speed at noon, values from the previous measurement at 09:00 are utilized. In the case of a missing temperature value, the recorded value of the previous day at noon is taken. Since there is only one official weather station on the island, the weather variables at other locations are inferred from the data obtained at this station. For temperature, the value in each municipality is estimated based on the normal lapse rate of temperature of 0.65°C/100m (Gabler et al. 2008). Consequently the temperature for each municipality at noon T_{muc} is,

$$T_{muc} = T_{ws} - 0.0065 * \bar{h}_{muc} \tag{5}$$

where T_{ws} is the measured temperature at the weather station at noon and $\bar{h}_{muc}$ is the mean elevation of the municipality. For all other weather variables, the values in the municipalities are taken as the value recorded at the weather station. The calculation of the FFMC at each municipality is based on the formulation given in Van Wagner & Pickett (1985).

The parameters of the BN are determined through the EM algorithm. The numerical implementation is carried out with the Hugin software. In total 109.994 records, corresponding to daily values for 7 years (2000; 2004–2009), each for 43 municipalities, are used for parameter estimation.

3.4 *Results*

The main result of the parameter estimation is the PMF of the occurrence rate conditional on the FFMC, the land cover and the human population density. To show the influence of each of these three factors individually, we evaluate the BN by fixing only the corresponding factor. Because the factors are not d-separated in the BN (they are connected through the common node municipality), they are statistically dependent. Therefore, this approach slightly overestimates the influence of the individual factors. By also fixing the remaining factors, this effect was investigated and found to be small. The advantage of fixing only one factor at a time is that the results are then averaged over the remaining factors and are thus more representative, since they are effectively based on a larger number of underlying data.

Figure 3 shows the mean occurrence rate for different ranges of human population density. The occurrence rate increases with increasing values of human population density.

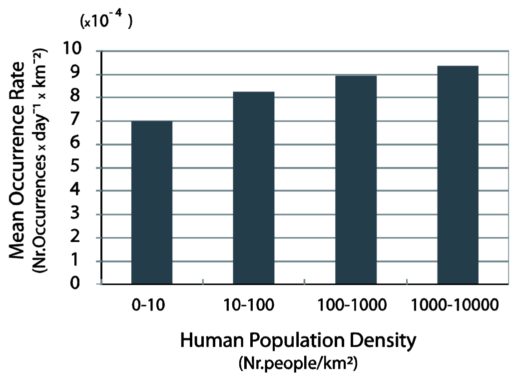

Figure 3: Mean fire occurrence rate and human population density.

A slight influence of the land cover on the mean occurrence rate is observable (Figure 4). The agricultural areas (arable land, permanent crops of vineyards and olive groves, heterogeneous agricultural areas) have higher mean occurrence rates than the natural/semi natural areas (forests, scrub/herbaceous vegetation and natural grasslands, open spaces with little or no vegetation). In heterogeneous agricultural areas, where complex cultivation patterns and settlements are mixed, the occurrence rate is the highest among all land covers.

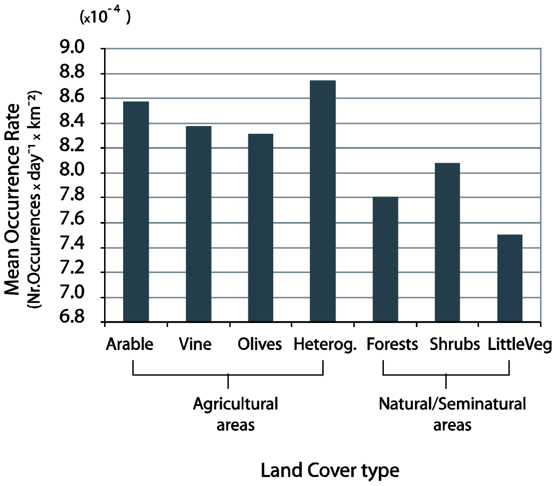

Figure 4: Mean fire occurrence rate and land cover type.

FFMC is found to have only slight influence on the occurrence rate, which is estimated as 8.35×10^{-4} [Nr.Occurrences x day^{-1} x km^{-2}] for FFMC values in the range of 0 – 40 and 8.59×10^{-4} [Nr.Occurrences x day^{-1} x km^{-2}] for FFMC values in the range of 95 – 100. To facilitate interpretation of this result, Figure 5 shows calculated FFMC values for year 2000, together with daily precipitation and the observed number of fires. The FFMC values are generally high, and the only large changes occur during and after rainfall events.

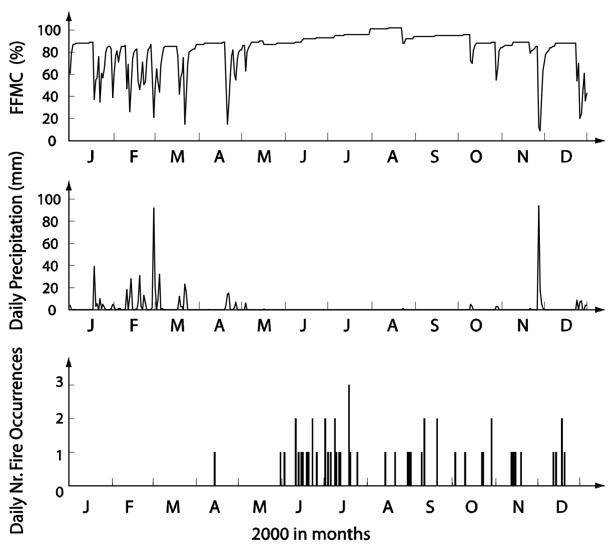

Figure 5: FFMC values at a representative municipality, together with observed precipitation at the weather station and total number of wildfire occurrences on the island for year 2000.

Figure 6 shows histograms of FFMC values calculated for days with zero, one or two recorded wildfires. These three conditional histograms and the corresponding conditional means and standard deviations exhibit similar trends, which supports the findings from the BN.

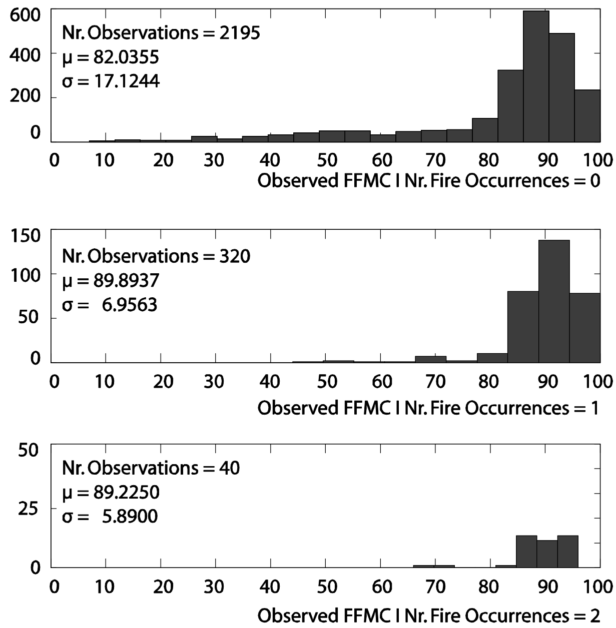

Figure 6: Histograms of FFMC for a representative municipality, conditional on the recorded number of fires occurring on the island.

4 DISCUSSION

Many authors have suggested that a majority of fires occurring in Southern Europe are due to accident/negligence or arson and thus strongly influenced by the presence of humans (Leone et al. 2009). This is supported by the results in Figure 3, which show that the population density has a distinct influence on the occurrence rate of wildfire. A somewhat weaker dependence of the wildfire occurrence rate on the land cover is also observed (Figure 4), which seems to indicate that agricultural activities lead to an increased occurrence rate.

The results show that for the investigated area, FFMC is only a weak indicator for the rate of wildfire occurrence. This might be explained by the fact that FFMC was developed for the climate and vegetation specific to Canada. In Rhodes, precipitation events are rare from May to September (Figure 5). As a result, the FFMC remains high (>80%) during this period, in which most of the wildfires occur. However, it is also observed from Figure 5 that the meteorological conditions have a clear effect on the occurrence of fires. The model must therefore be improved by utilizing more expressive meteorological indicators. One option is to utilize the entire Canadian Fire Weather Index, which also includes a numeric rating of the moisture content of deeper organic layers. Alternatively, other fuel moisture indexes might prove to be more representative for the South European climate and vegetation.

Once an improved description of meteorological conditions is established, the proposed Bayesian Network model, since it is based on daily weather data, can serve for prediction purposes and early warning. In addition, it can be continuously updated with new observations of weather conditions and wildfire occurrences, leading to an improved model in the future. Future work towards these goals include the validation of the model and linking a GIS to the model for better visualization of the results to support the management of wildfire prevention measures.

5 CONCLUSIONS

A Bayesian Network for wildfire occurrences is constructed and its parameters are learned based on temporal and spatial data. The model includes the effect of weather, vegetation and humans on the wildfire occurrences and deals with non-observable variables. In the investigated Mediterranean area, it is found that human population density has a distinct influence on the occurrence rate. Land cover is also found to influence, if only slightly, the occurrence of fires. The employed fuel moisture index, which in the model represents the influence of meteorological conditions, is shown to be only a weak indicator for the rate of wildfire occurrence. Future work is needed to identify improved meteorological indicators.

6 REFERENCES

Bayraktarli, Y. Y.; Ulfkjaer, J.; Yazgan, U.; Faber, M. H. (2005): On the Application of Bayesian Probabilistic Networks for Earthquake Risk Management. *Safety and Reliability of Engineering* (Proc. ICOSSAR 05, Rome), Augusti et al. (eds) Millpress.

Bensi, M. T. (2010): *A Bayesian Network Methodology for Infrastructure Seismic Risk Assessment and Decision Support.* PhD-thesis. University of Berkeley, California, USA

Blaser, L.; Ohrnberger, M.; Riggelsen, C.; Scherbaum, F. (2009): Bayesian Belief Network for Tsunami Warning Decision Support. In: Sossai, C.; Chemello G. (eds): *ECSQARU 2009*. Springer, pp. 757–786.

Camia, A.; Amatulli, G. (2009): Weather Factors and Fire Danger in the Mediterranean. In: Chuvieco, E. (Hg.): *Earth Observation of Wildland Fires in Mediterranean Ecosystems*. Springer, pp. 71–82.

Chou, Y. H.; Chase, R. A. (1993): Mapping Probability of Fire Occurrence in San Jacinto Mountains, California, USA. In: *Environmental Management*, Vol. 17(1), pp. 129–140.

Chuvieco, E.; Aguado, I.; Dimitrakopoulos, A.P. (2004): Conversion of fuel moisture content values to ignition potential for integrated fire danger assessment. *Canadian Journal of Forest Research*, Vol.34, pp. 2284–2293.

Dlamini, W. M. (2009): A Bayesian belief network analysis of factors influencing wildfire occurrence in Swaziland. In: *Environmental Modeling & Software*, pp. 1–10.

FAO (Food and Agricultural Organization of the United Nations) (2001): *Global Forest Fire Assessment 1990-2000*. Forestry department; Forest resources. (Assessment Programme, Working paper 55). Available online: http://www.fao.org/DOCREP/006/AD653E/AD653E00.HTM

Flannigan, M. D.; Amiro B. D.; Logan K. A.; Stocks B. J.; Wotton B. M. (2005): Forest fires and climate change in the 21st Century. *Mitigation and Adaptation Strategies for Global Change*, Jg. 11, pp. 847–859.

Gabler, R. E.; Petersen, J. F.; Trapasso, L. M. (2008): *Physical Geography*. Brooks Cole Pub Co, Belmont, USA.

Grêt-Regamey, A.; Straub, D. (2006): Spatially explicit avalanche risk assessment linking Bayesian networks to a GIS. *Natural hazards and Earth System Sciences*, Vol. 6, pp. 911–926.

Jensen, F. V.; Nielsen, T. D. (2007): *Bayesian Networks and Decision Graphs*. Springer, NY, USA.

Joint Research Center (IES) (2006): *Forest Fires in Europe 2006*. JRC Scientific and Technical Reports, Report No7. European Commission, JRC-IES, Land Management and Natural Hazards Unit, Ispra. Italy. Available online: http://effis.jrc.ec.europa.eu/reports/fire-reports.

Kuehn, N. M.; Riggelsen, C.; Scherbaum, F. (in press): *Modeling the joint probability of earthquake, site, and ground-motion parameters using Bayesian Networks*. Bulletin of the Seismological Society of America.

Lawson, B. D.; Armitage, O. B. (2008): *Weather Guide for the Canadian Forest Fire Danger Rating System.* Natural Resources Canada, Canadian Forest Service, Northern Forestry Centre. Edmonton, Alberta, Canada. Available online: http://fire.ak.blm.gov/content/weather/2008%20CFFDRS%20Weather%20Guide.pdf.

Leone, Vittorio; Lovreglio, Raffaella; Martín, M. Pilar; Martínez, Jesús; Vilar Lara (2009): Human Factors of Fire Occurrence in the Mediterranean. In: Chuvieco, E. (ed.): *Earth Observation of Wildland Fires in the Mediterranean Ecosystems*: Springer, pp. 149–170.

Munich RE (2010): *Natural catastrophes 2009*. Analyses, assessments, positions. Munich, Germany. (Topics GEO). Available online: http://www.munichre.com.

Pearl, J. (1988): *Probabilistic Reasoning in Intelligent Systems*. Morgan Kaufmann Publishers, San Mateo, California.

Preisler, H. K.; Brillinger, D. R.; Burgan, R. E.; Benoit, J. W. (2004): Probability based models for estimation of wildfire risk. *International Journal of Wildland Fire*, (13), pp. 133–142.

Russell, S.; Norvig, P. (2003): *Artificial Intelligence. A Modern Approach*. Prentice Hall Series in Artificial Intelligence, Prentice Hall.

Straub, D. (2005): Natural hazards risk assessment using Bayesian networks. *Safety and Reliability of Engineering* (Proc. ICOSSAR 05, Rome), Augusti et al. (eds) Millpress, pp. 2535–2542.

Straub, D.; Der Kiureghian, A. (2010): Bayesian Network Enhanced with Structural Reliability Methods: Methodology. *Journal of Engineering Mechanics*, Vol. 136(10), pp. 1248–1258.

Van Wagner, C. E. (1987): *Development and structure of the Canadian Forest Fire Weather Index System*. Forestry Technical Report 35. Canadian Forestry Service. Ottawa, Ontario, Canada. Available online: http://warehouse.pfc.forestry.ca/HQ/19927.pdf.

Van Wagner, C. E.; Pickett, T. L. (1985): *Equations and FORTRAN Program for the Canadian Forest Fire Weather Index System*. Forestry Technical Report 33. Canadian Forestry Service, Government of Canada. Ottawa, Ontario, Canada. Available online: http://nsl.cs.surrey.sfu.ca/projects/wsn/FWIequations.pdf.

Wotton, B. M.; Martell, D. L. (2005): A lightning fire occurrence model for Ontario. *Canadian Journal of Forest Research*, Vol.35, pp. 1381–1401.

Wotton, B. M.; Martell, D. L.; Logan K. A. (2003): Climate change and people-caused forest fire occurrence in Ontario. *Climatic Change*, Vol.60, pp. 275–295.