Linking spatio-temporal data to FWI for wildfire probability in Mediterranean

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1. Aim of the Study

Wildfire occurrences in the Mediterranean are mainly caused by humans and favored by fire weather conditions, topography and fuels. The Canadian Fire Weather Index (FWI) is used worldwide to express Fire Danger conditions. This study focuses on the following questions:

- How good does the Canadian Fire Weather Index express weather induced Fire Danger conditions in the Mediterranean in the mesoscale?
- Can human presence/activity be used as an indicator of fire danger?
- How accurately can a Bayesian Network (BN) model including both weather and human influence by high resolution spatio-temporal data estimate fire occurrence probabilities in the Mediterranean?

2. Methods

A **geodatabase** is built to store and manage spatio-temporal data, such as weather conditions, fire records, land cover types, etc (Figure 1). All data are attached to a grid with cell dimensions 1km x 1km, which serves as the spatial reference of the study. The temporal reference is 1 day. The stored data will be used as the observed information to learn the parameters of the BN.

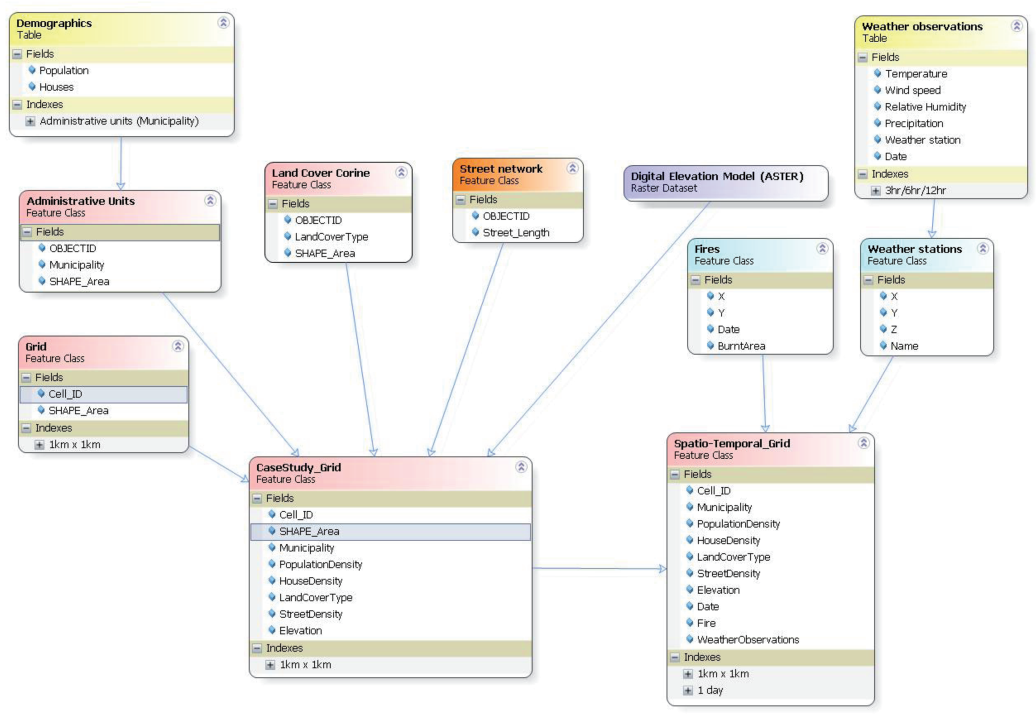
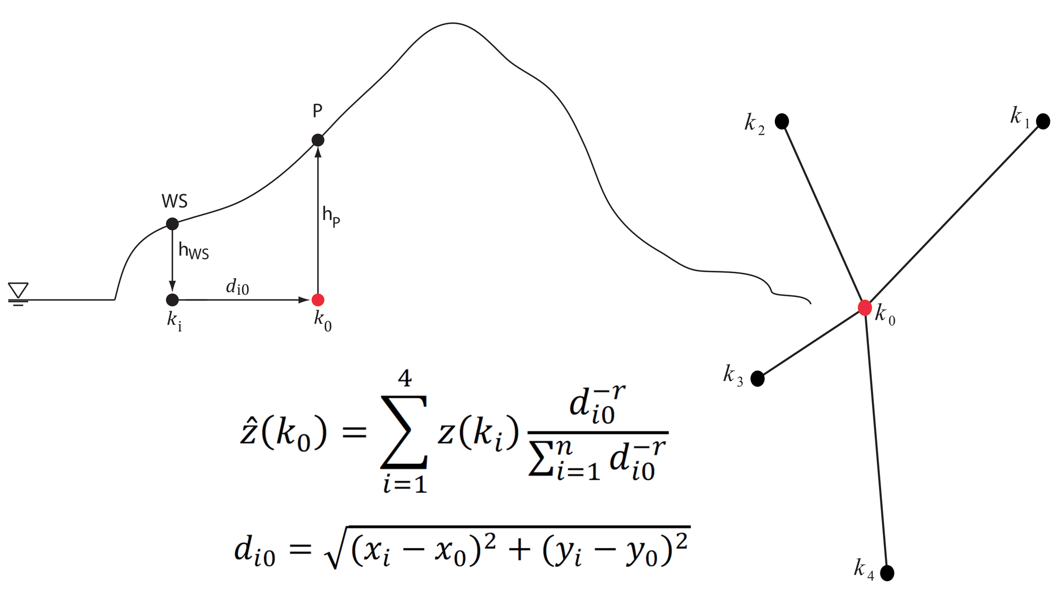


Figure 1. Geodatabase structure for spatio-temporal data

In order to estimate daily weather parameter values in the whole grid, **weather interpolation** is made based on observations from weather stations. Inverse Distance Weighting (Shepard's Method) interpolation method is used for this purpose. Temperature is additionally fitted to the altitude based on the **normal lapse rate** (0.65°C/100m). As shown in Figure 2, temperature values measured in a weather station ($Temp_{WS}$) are firstly projected to the sea level ($Temp_{ki}$), then interpolated to the grid area and then returned to the according elevation, h_P (location P).

$$Temp_{k_i} = Temp_{WS} + 0.0065 \cdot h_{WS}$$



$$\hat{z}(k_0) = \sum_{i=1}^{4} z(k_i) \frac{d_{i0}^{-r}}{\sum_{i=1}^{n} d_{i0}^{-r}}$$

$$d_{i0} = \sqrt{(x_i - x_0)^2 + (y_i - y_0)^2}$$

Figure 2. Interpolation of weather parameters with Inverse Distance Weighting (Shepard's method). Temperature is also influenced by altitude as indicated by normal lapse rate.

Inverse Distance Weighting (Shepard's method) creates estimates ($\hat{z}(k_0)$) by weighting observed values ($z(k_i)$) of nearby locations based only on their distance (d_{i0}) from the interpolation location (k_0). As a result, estimates of daily values of weather parameters (temperature, wind speed, relative humidity, precipitation) are obtained in a 1km² grid resolution.

The **Canadian Fire Weather Index** (FWI) is used in this study to express daily fire danger conditions. FWI provides with its six standard components (three fuel moisture codes and three fire behavior indexes) numeric ratings of relative potential for wildfire. Daily noon (12 o'clock) values of temperature, wind speed and relative humidity, as well as 24hr precipitation values are used as input to calculate the fuel moisture codes and the fire behavior indexes of the Canadian FWI system (Lawson & Armitage 2008). The deterministically calculated daily FWI is a continuous variable in the Bayesian Network.

A **Bayesian Network** model is constructed to estimate wildfire occurrence rates based on temporal and spatial data (Figure 3).

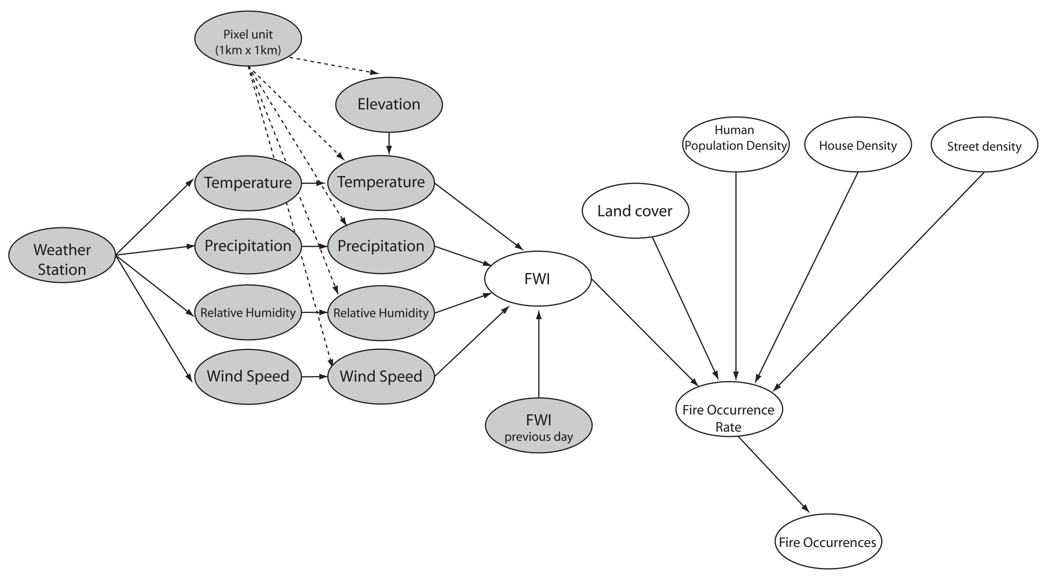


Figure 3. Bayesian Network model for wildfire occurrences. The parameters of the model are learned with spatio-temporal data.

In this study the BN expresses the effect of weather conditions, land cover and human presence on the rate of wildfire occurrences (Papakosta & Straub 2011). The white nodes in Figure 3 represent random variables and the arcs represent the relationships between the nodes. A conditional probability table (CPT) is attached to each node. Grey nodes represent the variables used for the calculation of the daily FWI and are treated separately in the parameter estimation.

The node Fire Occurrence Rate represents the mean number of fire occurrences per day and km². The occurrence rate is not observable and is estimated with historical data. Fire Occurrences is a random variable that can be modeled by the Poisson distribution for given rate of occurrence. The probability mass function of this variable used to calculate the CPT of the variable is given as:

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

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

The Expectation-Maximization algorithm is used for the **parameter estimation** of the model (estimation of parameters of the conditional probability distributions), 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, u the hidden variables, and θ the parameters of the model. Then the ith iteration of the EM algorithm is (Russell & Norvig 2003):

$$\theta^{(i)} = \operatorname{argmax}_{\theta} \sum_{\mathrm{u}} p\left(\mathrm{u} \middle| \mathrm{x}, \theta^{(i-1)}\right) \ln L(\theta|\mathrm{x},\mathrm{u})$$

$L(\theta|\mathrm{x},\mathrm{u})$ is the likelihood of θ for given observations x and u. The summation operation corresponds to the E-step, the maximization operation to the M-step.

3. Case Study

Cyprus was chosen as a case study area, since it represents sufficiently both the climate conditions and the land use and vegetation types of Mediterranean areas. Both spatial and temporal explicit data are used in this study. Weather data from 5 weather stations for the period 2006-2010 were used for this study (Figure 4).

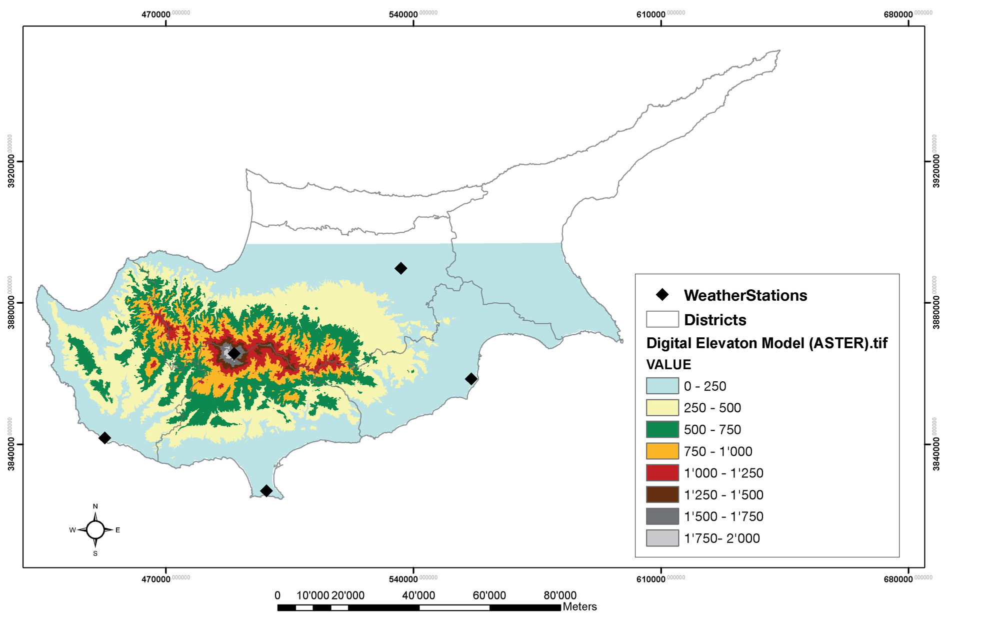


Figure 4. Digital Elevation Model (DEM ASTER) and 5 Weather Stations on Cyprus case study

4. Results

The weather interpolation and the FWI calculation for the period 2006-2010 in the 1km x 1km grid results to daily maps (Figure 5). A comparison of FWI values and fire incidents proves that FWI expresses adequately weather induced Fire Danger conditions in a Mediterranean area in the mesoscale. Still, due to prolonged dry Mediterranean summer periods, FWI reaches extreme high values and remains high during summer months.

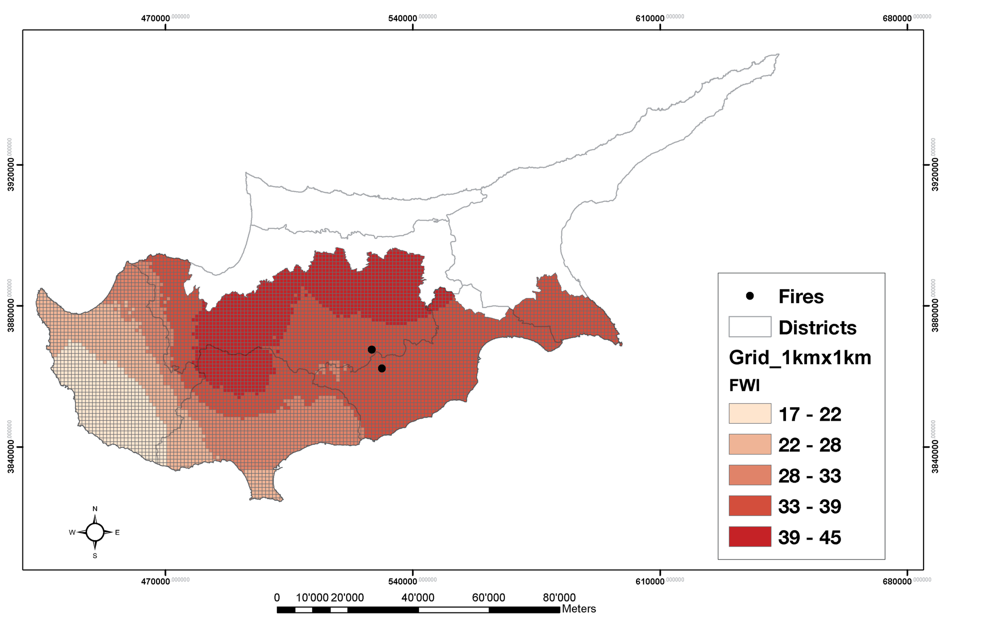


Figure 5. FWI values and fire incidents on one day on Cyprus case study (23.05.2006)

In this study, extreme high values of FWI did not lead to higher occurrence rates than high values of FWI. Human activity expressed by land cover (e.g. olive groves) indicates a higher fire occurrence rate. The distribution of the mean fire occurrence rate [Nr. Fires/(day · km²)], conditional on the assumed influencing factors is shown in Figure 6, giving evidence on the influence of human presence and human activity on fire occurrences.

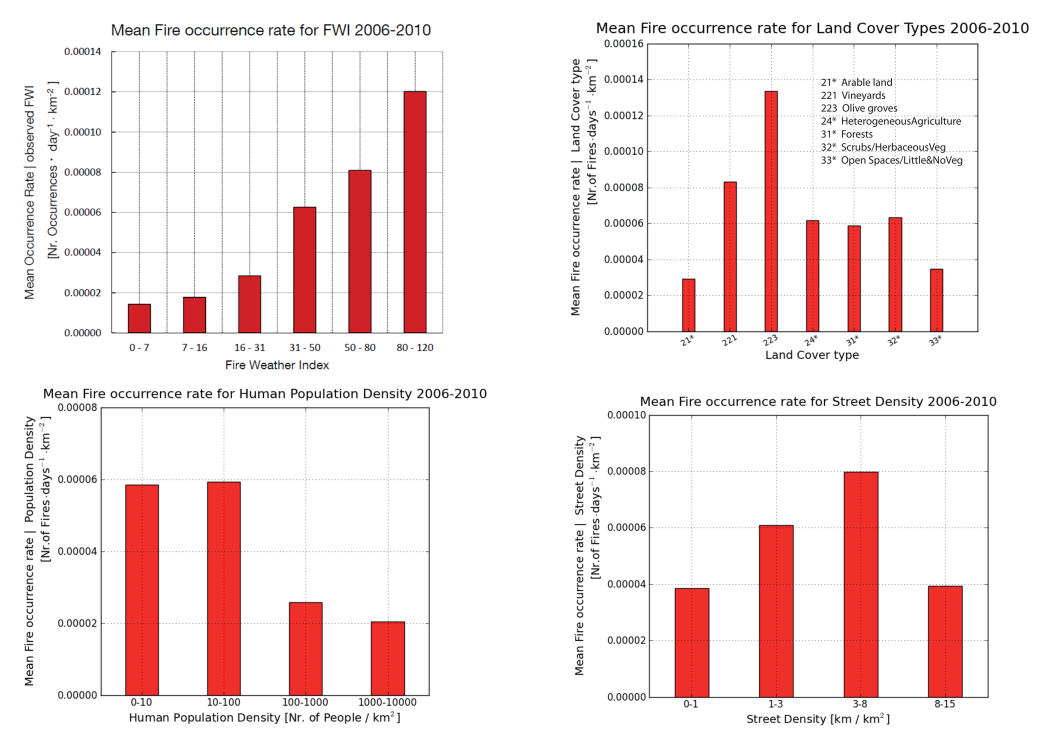


Figure 6. Mean Occurrence Rate [Nr. Fires/(day · km²)] versus fire occurrence influencing factors

5. Conclusions

Higher values of FWI indicate higher fire occurrence rates. Nevertheless, FWI alone is not suficient to predict fire occurrences. Areas with higher population density and dense street network have less fire danger potential. Areas covered with olive groves proved to have the highest mean fire occurrence rate among the other Corine Land Cover classes.

References

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