Prediction of Daily Fire Occurrence

21/10/2018

I.Introduction

Predicting the occurrence of wildfire incidents is an important component of fire management. Due to the uncertainties in the influencing factors, as well as to random effects in the fire process, such a prediction must necessarily be probabilistic. Past probabilistic models of fire occurrence use meteorologic factors, anthropogenic factors as explanatory variables. The effect of climatic factors is often represented by components of the climate data given by NASA (https://nex.nasa.gov/nex/static/htdocs/site/extra/opennex/) and OPENNEX CLIMATE DATA ACCESS TOOL(http://opennex.planetos.com/).

II.Methodology

1. BN construction: Fire Diagnosis

First you choose the variables. In this case, all are Boolean:

•Tampering is true when the alarm has been tampered with.

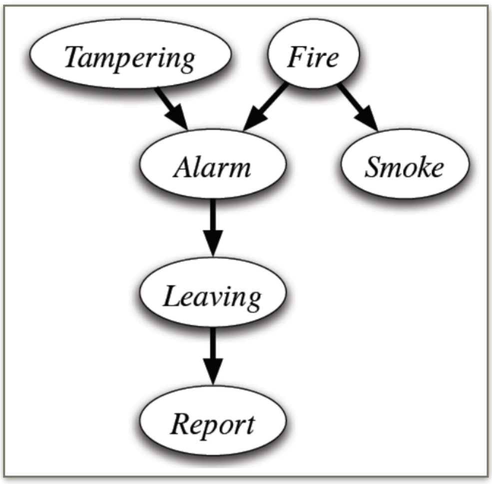
•Fire is true when there is a fire.

•Alarm is true when there is an alarm.

•Smoke is true when there is smoke.

•Leaving is true if there are lots of people leaving the building.

•Report is true if the sensor reports that lots of people are leaving the building.

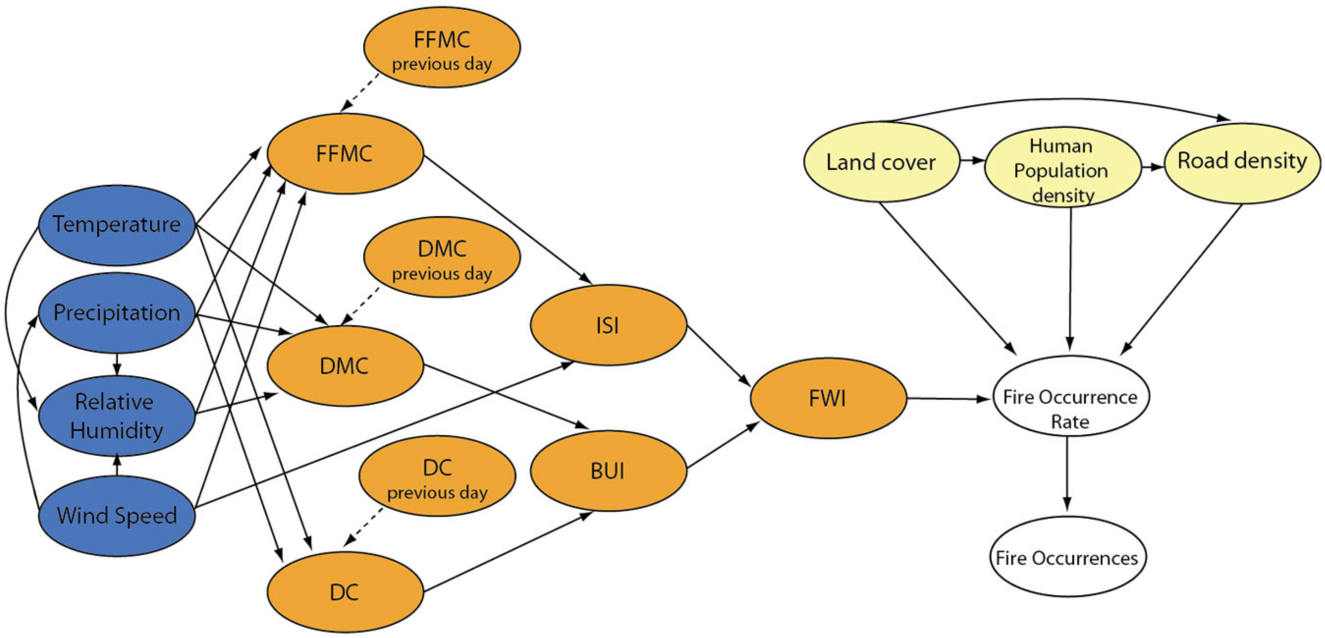


It results the Bayesian network illustrated as the right chart(Fig. 1).

2. Using relevance data

USDA Forest Service provides input observed weather parameters (dry bulb temperature, wind speed, relative humidity and precipitation). And consists of six components: three fuel moisture codes (FFMC: Fine Fuel Moisture Code; DMC: Duff Moisture Code; DC: Drought Code) and three fire behavior indices (ISI: Initial Spread Rate; BUI: Build Up Index; FWI: Fire Weather Index).

We then use probabilistic model for predicting fire occurrence. Fig. 1 summarizes the proposed probabilistic model by means of a Bayesian Network (BN). In the BN, probabilistic dependence among the variables is represented graphically by means of arrows. This makes it convenient not only for graphical communication of the model but also for quantitative probabilistic modeling. For these reasons, BN are increasingly applied for risk assessment of natural hazards. In Fig.1, Blue nodes represent weather conditions; orange nodes are the components of the prediction system; the variables in yellow represent the anthropogenic influence and the vegetation type; the variables in white are the predicted fire occurrence rate



and the actual number.

Fig. 2 Bayesian Network for fire occurrence prediction

The BN in Fig. 1 models daily fire occurrence in a cell of $1km^2$, which is the spatial unit of this study. When using the model for prediction, not all explanatory variables may be known with certainty. As an example, the forecasted weather variables will be uncertain, which can be directly implemented in the BN. The fire occurrence rate λ, which is defined as the mean number of fires per day and km^2 , is estimated from the data. In our forecast model, it is a function of land cover, human population density, road density and FWI. For a given daily fire occurrence rate λ, the number of fires follows a Poisson distribution, assuming independence among fire events for given occurrence rate. The conditional probability of observing n fires given λ is thus: $Pr(N = n \mid \lambda) = \frac{(\lambda\alpha)^n}{n!} exp(-\lambda\alpha)$, where n = 0, 1, 2, …, λ is the mean occurrence rate and α = 1 km^2 is the area of the cell.

The rate λ is related to the explanatory variables x = [x1, …, xk] by means of the link function $log(\lambda) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k = x^T \beta$, where β = [β_0, …, β_k] is the vector of regression coefficients. The mean occurrence rate is then given as $\lambda = exp(x^T\beta) = exp(\beta_0) \cdot exp(\beta_0 x_1) \cdot exp(\beta_2 x_2) \cdots exp(\beta_k x_k)$. Land cover is a categorical variable; therefore, a separate binary variable x_i is defined for each of its categories. This variable takes value 1, if the land cover in this area belongs to this category, and value 0 otherwise.

3. Coupling of BN and NASA GISTEMP database

BN can be coupled with GISTEMP database as illustrated in the Fig. 3. Spatial feature groups, lines and polygons are processed and stored in GISTEMP database. In each cell, a copy of BN represents the fire consequence. And ArcGIS is used for geospatial analysis and mapping.

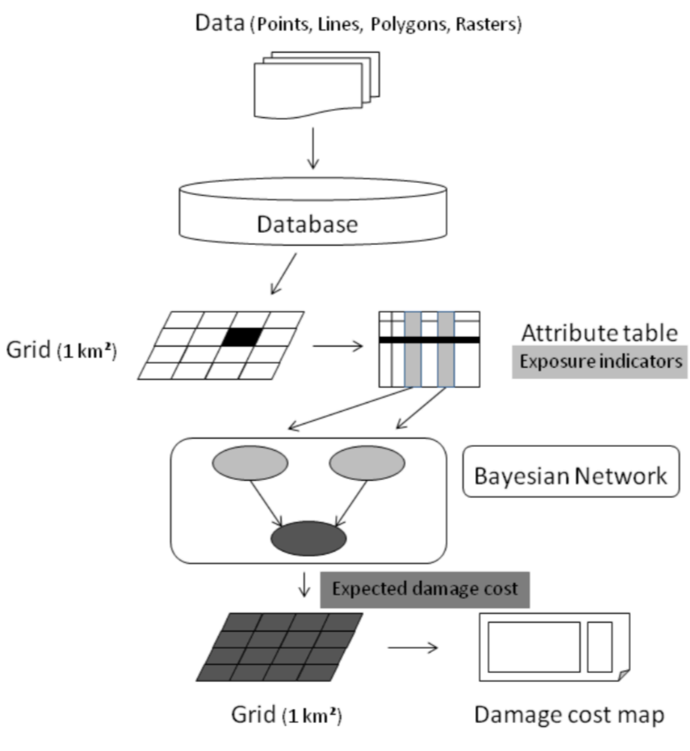


Fig. 3 Coupling with BN and GISTEMP

III. Numerical investigations

1. Study area: California

We employ data from CA, which is selected due to its representative Mediterranean climate (short cool winters and long hot and dry summers, Köppen: Csa/Csb), vegetation and fire history and data availability. The study area used in the analysis are indicated in Fig. 4. The natural areas on the island are mainly covered by coniferous forest.

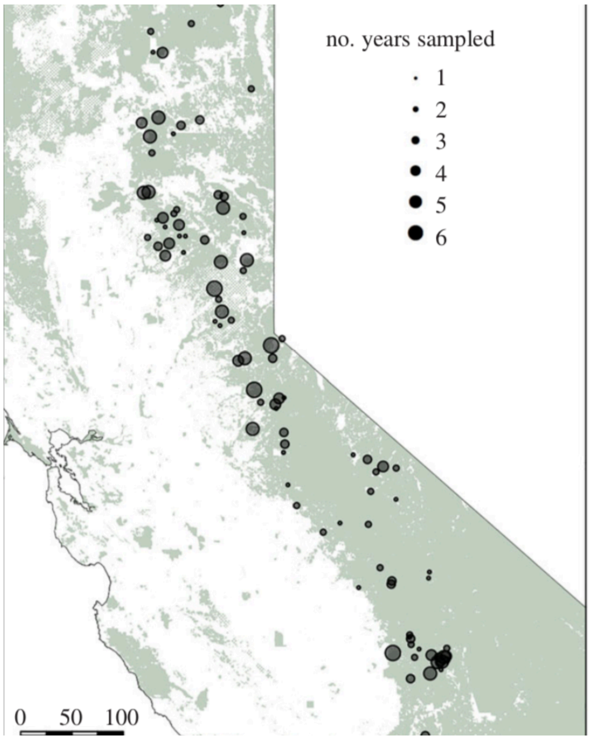


Fig. 4 Map of study areas in California

2. Then we use our forecast model using data given by NASA to forecast fire occurrence, and detail can be seen in the https://github.com/zyning/nasa-spaceapp-2018.

IV. Conclusion

This study is a step towards an improved prediction of fire occurrence for fire management purposes. The selected probabilistic modeling approach provides a quantitative metric of the ability of different explanatory variables to predict daily fire occurrence. As we found in this study, the NASA database for meteorologic is a good indicator for fire danger in the. Since the included fire events are those that initiated a threat and suppression efforts had to be undertaken, the proposed model is potentially more relevant for fire management planning.

Due to the randomness of fire occurrence, there is a limitation to any prediction. Consider the predicted fire occurrence rate at locations and days where fires occurred: the rates predicted with the best models are approximately double the average rate of fires in the study area. Therefore, while the developed models are able to identify days and locations with higher fire risks, this predictions can support the planning of preventive and mitigating measures.