Statistical Fire Models : Review

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Abstract

Statistical models provide a useful resource that can help us to understand the causes and consequences of fires. They are used to identify and quantify the effects of the most significant fire-related factors and environmental factors. The number of factors listed in the fire statistics is very large and the first task in the analysis is to determine those factors and the factor categories that have a significant effect. The fire-related factor categories that are identified as having the greatest effect are: - The extent and the nature of fire damage, - The area and location of fire origin, - The type of material ignited and the ignition factor, - The fire frequencies. The most significant environmental factors are: - The fire extinguishing measures, - The decontamination processes, - The fire site characteristics, - The meteorological conditions. The purpose of the statistical fire model described in this paper is to present a review of the most important models proposed in literature in the fire domain.

1. Introduction

The focus of empirical modelling of fire in the past has been on the determination of the key characteristics used to describe the behaviour of the fire. The principal use of these models was to estimate the probable dispersion in the wind direction (and the potential danger for the safety of fire fighters) for planning of extinction, much of which has traditionally been performed under the form of back of the envelope calculations to plot on a wall map. Because of this simple need, empirical models of fire spread were always one dimensional models in which the independent variable is expected is the rate of propagation of the front of the head fire in the wind. Rather pragmatic nature of these models, their implementation relatively simple, direct relation with the behaviour of real fires, and perhaps most importantly, their development, mostly by forestry agencies for their own immediate use, were the empirical fire spread models have gained acceptance with the authorities of forest fires in the world and to varying degrees at the base of all operational models of fire behaviour in use today [1].

The objective of this work is not to explain all the models (hypothesis, developments, field of application) in an exhaustive way. The main aim is to give an overview of what exists and to give the basis on which the work made in this paper has been established. We propose a generic categorization of statistical models of fire that is based on the following criteria:

- The probability of ignition and biophysical influences on fire, such as fuel load, moisture content, flammability of the vegetation, and topography
- The spread of fire once it gets established. Effects of fire can then be calculated to form a complete estimation of the risks related to fire;

Effects of fire on people and environment and the response of the system of detection, which influence the time of people's evacuation.

2. Statistical fire modelling

2.1. Fore frequency of ignition models

The frequency of ignition is an important variable in the quantification of risk. The best data available is now becoming quite dated. The result from this kind of probabilistic modelling is very useful in engineering design.

2.1.1 Probability based models for estimation of wildfire risk [2]. Preisler H.K. et al, present model for estimating probabilities of wildfire on a given day and ona1km grid on Federal land. The model was spatially and temporally explicit. Each square-kilometre grid for each day can have a different probability value. The model may also include any number of fire danger and weather variables. The model may also be used to produce maps of predicted probabilities and to estimate

the total number of expected fires, or large fires, in a given region and time period.
Preisler H.K. et al, have found that the model is useful for examining different aspects of fire risk and for assessing the usefulness of various fire danger indices and weather variables.

2.1.2 Risk Assessment: a Forest Fire Example [3]
Brillinger D.R. et al, Developed a risk model for use in estimating the probability of a forest fire taking place at a particular location and time as a function of those and other explanatory variables. The work is implemented for the case of a fine grid of cells and an accompanying large data set. To proceed the data are grouped into small spatio-temporal cells (voxels). They mention that one difficulty needs to be mentioned. The results of this modelling are for runs of all the predictions being carried out at the same time. The reason for this choice is that the computing time required was less than, says, running one prediction at a time.

2.1.3 Statistical Analysis of Extreme Forest fires [4].
To study extreme wildland fire that caused extensive damage to natural resources. A model developed by Ramesh N.I based on a generalised Pareto distribution (generalised extreme value (GEV) distribution) who was used to model data on acres of wildland burnt by extreme fire in the US since 1825, and adapted the point process modelling approach to model the extreme wildfires A semi-parametric smoothing approach is adapted with maximum likelihood method to estimate model parameters. Local likelihood method is used to get smooth parameter estimates of extermal models incorporating trend in time.
The results of the analysis using extreme wildland fire data from US show a significant increase in the occurrence of wildfires in the second half of the last century. The result also suggests a declining trend in the amount of acres burnt due to extreme wildfires.

2.1.4 Statistical Model for Forecasting Monthly Large Wildfire Events in Western United States [5].
One of the strong points of the statistical model is the ability to produce forecasts with specified precision and, as a consequence, the ability to study the accuracy of the outputs when compared with historic data. That is why. Preisler H.K et al develop a statistical model for assessing and mapping the forecasting skills of fire-danger predictors and producing 1-month-ahead wildfire-danger probabilities in the western United States. The method is based on logistic regression techniques with spline functions to accommodate nonlinear relationships between fire-danger predictors and probability of large fire events. Estimates were based on 25 years (1980–2004). The model using the predictors monthly average temperature, and lagged Palmer drought severity index demonstrated significant improvement in forecasting skill over historic frequencies (persistence forecasts) of large fire events.
Preisler H.K et al suggest that the methods useful for assessing the skill of predictor variables in forecasting 1-month-ahead large fire events. PDSI (Palmer Drought Severity Index) values in the previous 12 months together with forecast next-month temperatures were useful indicators for forecasting fire probabilities 1 month ahead.
One important feature of the model is its ability to develop a fire-danger rating system where the manager can tell with confidence what the overall error rate will be. A second feature of the model is the facility with which the limitations of the model with a particular set of predictors may be studied.

2.2. Statistical models of spread and behaviour fire

This review considers the development of some of the models and modelling approaches designed to predict the spread and spatial behaviour of fire events. Such events and their accurate prediction are of great importance to those seeking to understand and manage fire-prone ecosystems. The goal of statistical and empirical models is mainly restricted to the prediction of the rate of spread. They do not use any physical modelling to describe the heat transfer from the burning zone to the unburnt fuel [6].Fire spread and behaviour models may be divided into two broad classes [7]:

- Those concerned with the quantification of fire behaviour through the prediction of parameters such as rate of spread and fire line intensity,
- Those concerned with the prediction of the final shape (or spatial extent) of a fire event.

It is interesting to note that the majority of models that have been developed in recent years have been the result of efforts based on two major models: the canadian McArturs (1966) [8], [9] and the american Rothermel (1972) [10].

2.2.1 The McArthur's model for grassland fires and forest fire. The McArthur's model for grassland fires and forest fire is a good example of an empirical model and the most widely used model. It is purely statistical description of test fires of such spread [11]. The model has been developed and tested in dry regions of south eastern Australia, using a database of over 5000 uncontrolled fires and 500 intensively studied prescribed burns. It has been developed to the point of operational usage [8], [12].

2.2.2 The Rothermel wildland fire spread model [10]. Rothermel created the most widespread and practical mathematical model to date; The Rothermel wildland fire spread model (Rothermel, 1972) is sometimes referred as a semi-empirical model to emphasise its hybrid physical and empirical nature. A surface fire, the type of fire the Rothermel model was developed for, spreads through a layer of contiguous fuel extending from the ground up to approximately 2 metres. This definition differentiates a surface fire from one moving through the tree canopies (crown fires) or one burning through organic soil material (ground fire). Although this model uses the principle of conservation of energy to derive an equation for the rate of spread, no distinction is made between the different modes of heat transfer. The propagating flux ξ, which is used to extract an equation for the rate of spread, is determined empirically [13], [14].

The Rothermel model groups input parameters into four main categories: Fuel type, fuel moisture, topography, and weather. One simplifying assumption regarding the fuels is that for a small area and short time periods, the fuels are taken to be homogeneous [13], [14].

The fuel parameter groups include fuel particle properties such as fuel loading, fuel moisture content, and surface-area-to-volume ratio. The remaining topography and wind groups account for the slope, aspect, relative humidity, wind speed, etc. The burning layer, composed of the conglomerate of fuel parameters, is referred to as the fuel bed or fuel model [13], [14]. The output variables are the rate of spread, the direction of maximum spread, and the effective wind speed. Other quantities such as fire line intensity, heat release per unit area, and flame length can also be derived [13].

There are some of the most widely used models that are based on parts of the model Rothermel, modifying it for more or less specific terms lake [15]: Canadian Forest Service (CFS) - Acceleration (1991), McAlpine and Wakimoto (1991), CALM Spinifex (1991), Canadian Forest Fire Behaviour Prediction (CFBP)(1992), Button (1995), CALM Mallee (1997), CSIRO Grass (1997), Heath (1998), PortShrub (2001), CALM Jarrah I (1999), CALM Jarrah II (1999), Gorse (2002), PortPinas (2002), Maquis (2003).

Other listed empirical models are not as popular. They are based on parts of the model Rothermel, modifying it for more or less specific terms.

2.2. Statistical models of fire detection

Fire detection systems are among the most important components in surveillance systems used to monitor buildings and the environment. As part of an early warning mechanism, it is preferable that the system has the capacity to report the earliest stage of a fire.

2.3.1 Mapping fuels and fire regimes using remote sensing, ecosystem simulation, and gradient modelling [16]. Rollins M.G. et al proposed an integrated approach for mapping fuels and fire regimes using extensive field sampling, remote sensing, ecosystem simulation, and biophysical gradient modelling to create predictive landscape maps of fuels and fire regimes. They developed a hierarchical approach to stratifying field sampling to ensure that samples represented variability in a wide variety of ecosystem processes. Using general linear models, discriminant analysis, classification and regression trees, and logistic regression, they created maps of fuel load, fuel model, fire interval, and fire severity based on spatial predictive variables and response variables measured in the field. Independently evaluated accuracies ranged from 51 to 80%. The approach of Rollins M.G. et al is easily adaptable to mapping potential future conditions under a range of possible management actions or climate scenarios.

The resulting maps provide fine-grained, broad-scale information to spatially assess both ecosystem integrity and the hazards and risks of wildland fire when making decisions about how best to restore forests of the western United States to within historical ranges and variability.

2.3.2 Fire detection using statistical color model in video sequences [17]. Celik T. et al have developed a real-time fire-detector, which combines color information with registered background scene. Color information of fire is determined by the statistical measurement of the sample images containing fire. Simple adaptive background information of the scene is modeled using three Gaussian distributions, where each of them is used to model the pixel values of the colored information in each color channel. The foreground objects detected are combined with color statistics and output is analyzed in consecutive frames for fire detection. The system detects the fire as soon as it is started, except in the explosive conditions, in which generally smoke is seen before the fire is started.

The proposed algorithm can be extended to incorporate the smoke in the video sequences, which may be used as faster fire alarm detection in such special conditions.

2.3.3 Forest fire detection based on Gaussian field analysis [18]. Lafarge F. et al presented an automatic classification method based on Gaussian field theory which allows forest fire detection from TIR (Infra Rouge Thermique) images. They preceded model the image as a realization of a Gaussian field. The fire areas, which have high intensity and are supposed to be a minority, are considered as foreign elements of that field, and determine by a statistical analysis a set of probabilities which characterizes the degree of belonging to the Gaussian field of a small area of the image. So, Lafarge F. et al estimate the probability that the considered area is a potential fire.

The proposed method is especially adapted to the extraction of anomalies specied by intensity peaks in remote sensing data. The idea consists in modeling the image as a realization of a Gaussian field and determining a degree of belonging of the peaks to the field with respect to both radiometric and spatial characteristics.

The results only depend on α (where α is the limit probability, a confidence coefficient on the result which acts as a"P-value". In practice, α is close to 102. This decision law mainly relies on the probability PH (i.e. on the radiometric characteristic of the cluster) which acts as a confidence coefficient. Both detection rate and false alarm rate provide convincing values. Interesting information, related to the evolution of the fires, can also be obtained through the estimation of fire propagation direction.

2.3.4 Automatic fire detection system using CCD camera and Bayesian Network Nam [19]. Cheong K.H et al developed a new vision-based fire detection algorithm using an adaptive background subtraction model with a Bayesian inference to verify real fire pixels. This work used a three-level Bayesian Network that contains intermediate nodes, and uses four probability density functions for evidence at each node. The probability density functions for each node are modelled using the skewness of the color red and three high frequency components obtained from a wavelet transform.

The proposed system was successfully applied to various fire-detection tasks in real-world environments and effectively distinguished fire from fire colored moving objects. Experimental results showed that the proposed approach was more robust to noise, such as smoke, and subtle differences between consecutive frames when compared with other methods. However, reducing false alarms and the missed fire regions remain as ongoing challenges for successful fire detection in a real-life environment.

2.3.5 Vision Based Fire Detection [20]. A vision based fire detection algorithm based on spectral, spatial and temporal properties of fires has been proposed by Liu C.B et al. The spectral model is represented in terms of the color probability density of fire pixels. The spatial model captures the spatial structure within a fire region. The shape of a fire region is represented in terms of the spatial frequency content of the region contour using its Fourier coefficients. The temporal changes in these coefficients are used as the temporal signatures of the fire region. Specifically, an autoregressive model of the Fourier coefficient series is used. Experiments with a large number of scenes show that the method is capable of detecting fire reliably.

Their Experiments showed that algorithm detects fire with high accuracy, both in single images as well as in image sequences. This approach extends beyond fire detection. They concluded that, the stochastic model that they use to represent the dynamics of fire region can be applied to many other stochastic visual phenomena.

2.3.6 Stochastic time series analysis of pulsating buoyant pool fires [21. Biswas et al., 2007 developed a time series model that captures the puffing effect to simulate the fluctuating scalar (temperature and species) fields of buoyant pool fires. It was jugged time series analyses of fluctuating radiation measurements are very useful from the perspective of fire detection and control, they are also useful in determining appropriate time scales of resolution for time dependent simulations of fires and flame radiation.

2.4. Statistical models of human response and evacuation

2.4.1 Stochastic modelling for occupant safety in a building fire [22]. Hasofer A.M and Odigie D.O presented a stochastic model for the interaction between the spread of untenable conditions and occupant egress. Safety is measured by the expected number of deaths. The building is represented by a network for modelling fire spread and by another network for modelling occupant egress. A major innovation is the introduction of the concept of discrete hazard function.

Hasofer A.M and Odigie concluded that hazard functions can be used to model stochastically the time element for the spread of untenable conditions caused by the fire and for the various components of the response time of occupants. It was also showed that the paths of spread of untenable conditions as well as egress paths can be modelled by using a network representation of the significant locations and routes in the building. Also they suggested that the use of stochastic modelling enables us to quantify with some precision the uncertainty in the outcome of a fire model, given the uncertainties in the inputs.

2.4.2 Statistical modelling of the effect of alcohol and sound intensity on response to fire alarms [23].
Hasofer et al proposed a model used to analyse the results of an experiment to compare the response time of sleeping subjects to three different auditory stimuli. The sound intensity increased steadily with time and the young adult subjects (seven males and seven females) were tested when sober and with blood alcohol levels of 0.05 and 0.08. The analysis revealed that alcohol had a very significant effect in slowing down the response of all subjects. It also revealed that females responded faster than males at all alcohol levels. The great advantage of using the stochastic model is that it permits the estimation of the probability that the response time will exceed high values that may put the sleeping occupant at a severe risk of death or injury in a fire.

The main conclusions of this work were: The response time by a sleeping subject to fire cues of increasing intensity may be modelled as a random walk with a decreasing upper boundary (threshold) and a fixed recognition probability.

3. Conclusion

Major advances in the statistical modelling of fire have been achieved in recent years. These models can predict with good accuracy many fire parameters. As a result, current research into statistical fire models is focusing on the forest fire. This review considers the development of some of the models and modelling approaches designed to predict the ignition, spread, behavior and, detection of fire and other events. Such events and their accurate prediction are of great importance to those seeking to understand and manage fire-prone ecosystems.

It can be seen that the accurate predictive modelling of fire presents a number of problems, both conceptual and practical:

- It has been recognized that such models have shortcomings when used outside the systems in which they were developed, parameterized and validated;
- Current research into fire behaviour models is focusing on the development of rigorous physical models based on the fundamental chemical and physical processes which comprise fire spread;
- The development and use of such models are limited through a lack of knowledge of some of these key processes and difficulties involved with their parameterization.

And the biggest challenge that must be mentioned is the fact that most are motivated statistical modeling oriented forest fire. For this reason, and given that the industrial accident may be caused enormous damage that affect environmental and economic side, we propose in the future to extend the statistical model that takes into consideration the behavior of industrial systems and predict the effects of industrial fires, such as the thermal effect (T), the concentration of pollutants ...

4. References

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