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Detecting Weak Points of Wildland Fire Spread: A Cellular Automata Model Risk Assessment Simulation Approach

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In this work, we propose a risk-assessment approach based on Cellular Automata (CA) simulations which incorporate both theoretical/ first principles and (semi)empirical fire behavioural models. The proposed approach can deal with spatial heterogeneity in both the fuel and landscape characteristics, can be coupled with Geographical Information Systems (GIS) and can take as input local meteorological data (even in real time). Using the CA model we are able to construct the topographic map of hazard intensity defined in terms of the expected burned area resulting from an ignition in a particular point of the region under surveillance. For our illustrations we used the case of Spetses Island whose a major part of its forest burned in 1990. Using the proposed framework, we revealed the weak points of fire spread risk, i.e. potential ignitions points which result to maximum likelihood of burned area.

1. Introduction

One of the most challenging and important problems in ecology is the design and implementation of efficient wildland fire-prevention and fire-suppression policies in forests (Albini and Brown, 1996). Wildland fires have caused numerous irreversible environmental damages with serious negative ecological and socio-economic implications such as the loss of human lives, flora and fauna bio-diversity and rare-species extinction, habitant fragmentation, floods, loss of timber harvest capability, economic loses etc. There is no doubt that the systematic -in terms of mathematical modelling and analysis – quantification of the fire spread dynamics is of outmost importance toward the risk assessment of a potential outbreak. Factors such as weather/climate conditions (wind field, air humidity and temperature), characteristics of the distributed local fuel (type and structure of the vegetation, moisture and density), landscape/earth characteristics (slope, fragmentation and natural barriers) as well as fire-suppression tactics are key elements toward this effort (Bergeron and Flannigan, 1995). However, due to the inherent complexity of such a phenomenon, deploying at different time and space scales risk assessment is far from simple, yet a most challenging one. Traditionally, wildfire risk assessment is evaluated considering just the fuel content in the area under study. Thus all the factors mentioned above, which interact nonlinearly to determine the dynamics of the spreading of forest wildfires, are not considered in the evaluation of the hazard level. Recently, some studies have considered the adoption of software for the simulation of the wildfire spreading for the construction of hazard map (Carmel et al., 2009; Ager and Finney, 2009; Ager et al., 2010). In Carmel et al. (2009), a high number of simulations have been carried out to compute the burn probability and fire intensity map, changing the weather condition and the ignition point. The simulation approach is used in Ager and Finney (2009) and Ager et al. (2010) to construct risk maps when different strategies of risk reduction are adopted. Clearly, the core of the approach is the adoption of accurate and efficient simulation models. The most known and used fire model is the Rothermel fire model (Rothermel, 1972), which gives the rate and direction of fire spreading as function of the local landscape and weather conditions. Rothermel's equations have subsequently been applied in a variety of approaches which in terms of spatial representation can be categorized in two types (Sullivan, 2009). The first type consists of

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models in the continuum, where it is assumed that the fire-front travels on a continuous (homogeneous) landscape, forming an elliptical pattern. In general such models consist of a system of partial differential equations for which the numerical solution is however computationally demanding (Richards, 1995). The second type, which is simpler and computationally faster, consists of the models where the time - space is properly discretised (Pastor et al. 2003). Depending on the technique used to discretise the space and the time we can further distinguish two approaches: the vector one which is based in the Huygens' wavelet principle (Tymstra et al., 2010; Anderson et al., 1982) and the so called cell-based approaches which are based on Cellular Automata (CA) (von Neumann, 1966) algorithms. In particular in the CA models, the space representing the landscape is divided in cells which evolve discretely in time following a set of rules which connect the state of each cell just to the cells which are in proximity. For their efficiency, Cellular automata have been applied for the forest fire spreading in a variety of studies (Encinas et al., 2007; Karalyllidis and Thanailakis, 1997; Trunfio, 2004; Lopes et al., 2002; Yassemi et al., 2008; Alexandridis et al., 2008, 2011a). Cell-based methods, indeed, can perform the same simulations in a fraction of the run time taken by their vector-based counterpart (Peterson et al., 2008). For this reason, some recent studies (Gregorio et al., 2013) have adopted cell-based methods to build risk maps. Indeed, hazard maps need to perform thousands of simulations which can be run in reasonable time just with very efficient, accurate but simple algorithms .

In the context of fire risk assessment, we have designed a computational approach to build hazard maps on the basis of a cellular automata model. Our CA model has been shown to be robust and efficient in predicting the fire spreading behaviour in several cases (Alexandridis et al., 2008, 2011a, 2011b; Russo et al., 2013). Here, we propose an approach for the risk assessment which is based on the developed CA model. As a test case, we computed the hazard map for the Spetses Island, the forest of which was almost completely burned in 1990.

2. The cellular automata model

A two dimensional grid was used to discretize the landscape into square cells with each cell representing a patch of land. Each arbitrary (i, j) cell can have one of the following discrete states at each time step t:
State(i,j,t)=1: This represent a no-fuel mode (city, rural areas with no vegetation)
State(i,j,t)=2: Cells that contains no-burning fuel.
State(i,j,t)=3: Burning cells.
State(i,j,t)=4: Burned cells.

The model evolves according to the following rules:
Rule 1: IF state(i, j, t) = 1 THEN state(i, j, t+1) = 1; No-fuel states do not change state
Rule 2: IF state(i, j, t) = 3 THEN state(i, j, t+1) = 4; Burning cells are be burned down at the next time step.
Rule 3: IF state(i, j, t) = 4 THEN state(i, j, t+1) = 4; burned regions do not reignite.
Rule 4: IF state(i, j, t) = 3 THEN state(i±1, j±1, t+1) = 3 with a probability p_{burn} fire is propagated to the neighbour cells.
The probability depends on parameters such as (type and density of vegetation, weather conditions, slopes of landscapes e.t.c.)
Hence, the probability p_{burn} is defined as:

$$p_{burn} = p_0\left(1+p_{veg}\right)\left(1+p_{den}\right)p_w p_s \qquad (1)$$

p_0 is a nominal probability of fire spread under no wind, flat terrain and certain density and type of vegetation and it is calculated from experimental data. p_{den} is a factor associated to density of the vegetation, p_{veg} is a factor associated to the type of the vegetation, p_w is related to the wind field (speed and direction), p_s is relevant to the local slope.
For the effect of wind field, the associated factor was defined by:

$$p_w = \boldsymbol{exp}\left(c_1 V\right)f_t \ , \quad f_t = \boldsymbol{exp}\left(V c_2\left(\cos(\theta)-1\right)\right) \qquad (2)$$

c_1, c_2 are constants to be determined and θ is the angle between the direction of the fire propagation and the direction of the wind. The factor related to the slope-effect reads:

$$p_s = \boldsymbol{exp}(a\theta_s),\ \theta_s = \boldsymbol{tan}^{-1}\left(\frac{E_1 - E_2}{l}\right) \tag{3}$$

where E1 and E2 are the altitude of the two cells and l is the length of the square side, for diagonal cells:

$$\theta_s = \boldsymbol{tan}^{-1}\left(\frac{E_1 - E_2}{l\sqrt{2}}\right).$$

As the model is stochastic, it should be expected that simulations starting from the same initial condition will produce similar albeit different patterns. The CA model can be used to compute the map of hazard risk intensity defined as the expected burned area when the fire starts from a particular area (single cell or group of cells) of the region under surveillance.
Here the hazard intensity is defined as:

$$R = \frac{1}{N}\sum_{i=1}^{N}\frac{N_b(i)}{N_{nb}(i)} \tag{4}$$

N denotes the number of simulations for a given initial condition, N_b denotes the number of burned cells and N_{nb} denotes the total number of not-burned cells within the area of interest. The above index can be interpreted as the maximum likelihood ratio of burned area.

3. Results: The Risk-Map for the Island of Spetses

For illustration purposes we employed the proposed approach for the case of Spetses Island. The states of the altitude, vegetation density and type were taken and processed from digital geographical data. Here, we used the Arc GIS 9.2 by ESRI. Using the GIS system we created a shape-file coding the type and the density of the island's vegetation. This file was created by the digitalization of photomaps. Then we created a shape-file coding the altitude data, based on a digital model of the ground configuration of the Island. Based on these digital files, a vector data file was built, containing the values of all the aforementioned variables of interest, overlaid on the grid. The side of the square grid was selected to be equal to five meters giving a crisp representation of the area. Hence the total number of cells for the area of interest was 1400x1000. Matlab was our simulation environment. Fig. 1a illustrates the map of the altitude. The type and the density of vegetation are divided into discrete states: 1 is for agricultural areas, 2 is for shrubs and 3 is for pine trees, for the type, and, 1 is for sparse vegetation, 2 for medium, and, 3, for dense vegetation. Figure 1b shows the vegetation density map of the island (having three types of vegetation, namely haleppo-pine trees, shrubs and agricultural areas). For our illustrations, the meteorological conditions were considered constant with a north wind direction of approximately 5 Beaufort. The values of the parameters are taken to be the same as the ones reported in (Alexandridis et al. 2008, 2011a) (see table 1).

Table 1: Parameter values for the CA model

Parameter	Value	Category	Density	p_{den}	Category	Type	p_{veg}
p_o	0.58	1	Sparse	-0.4	1	Agricultural	-0.3
a	0.078	2	Normal	0	2	Shrubs	0
c_1	0.045	3	Dense	0.3	3	Pines	0.4
c_2	0.131						

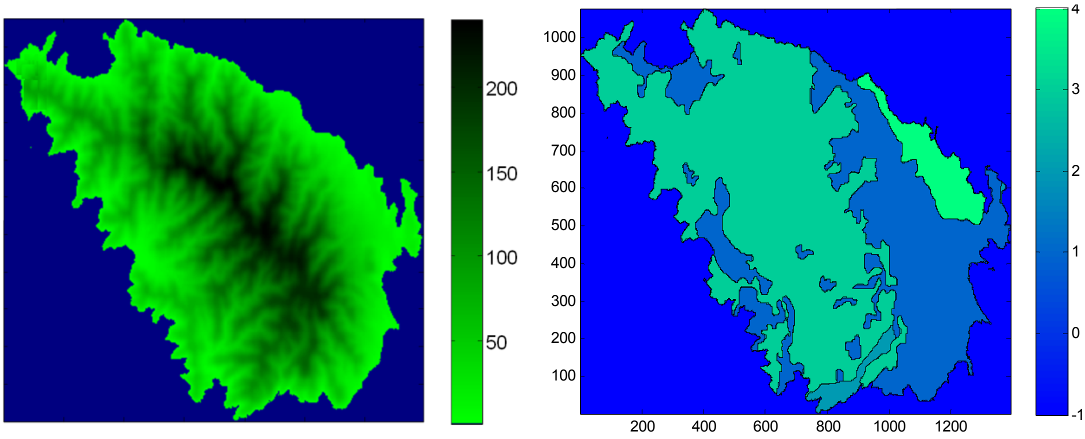

Figure 1: Map of the Island of Spetses (left) altitude, (right) density of vegetation is divided into discrete states: 1 is for sparse vegetation, 2 for medium, 3 for dense vegetation, and, 4 for areas without vegetation (here representing the city of Spetses). The total number of cells in the grid is 1400x1100.

Figure 2a shows the resulting risk-hazard map for a part of the Island (a map of the type of the vegetation is also given in Fig.2b as a reference). The number of simulations for each initial condition was set to N=10. The risk-map reveals that the resulting pattern is by no means trivial. As it can been seen, outbreaks starting from nearby spatial initial conditions can differ significantly. For demonstration, in Figure 3a,b we depict the final burned areas with a fire starting at nearby locations.

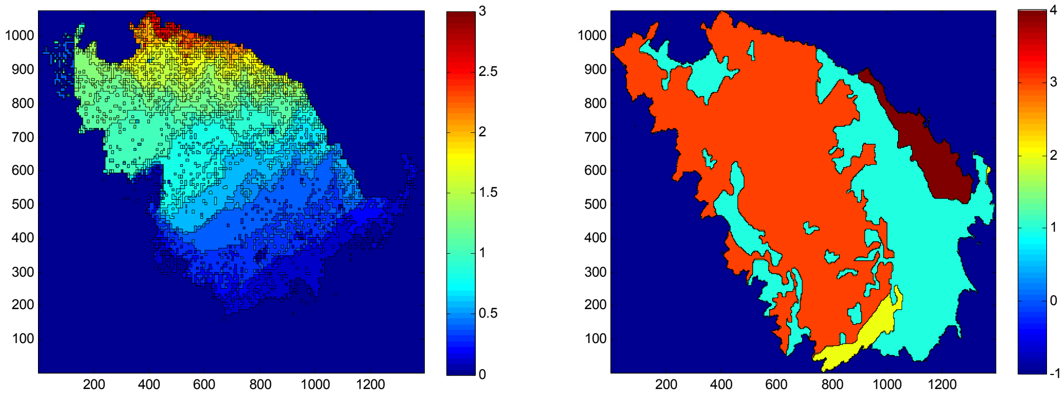

Figure 2: (left) The risk-hazard map for a part of Spetses Island; (right) Map of the type of the vegetation.

4. Conclusions

We propose an approach based on a CA model for the risk assessment of forest wildfires. The model proposed in our previous studies (Alexandridis et al., 2008, 2011) is used to compute the risk of damage for different initial conditions. These studies have shown that the developed CA model is efficient and robust, hence it can be used as tool for the risk assessment. These calculations are then, used to construct a risk map. In particular, given the number of simulations for a given initial condition, the number of burned cells and the total number of not-burned cells within the area of interest, the risk index can be interpreted as the maximum likelihood ration of burned area. Here, we constructed the hazard map of the Spetses Island whose a major part of its forest burned in 1990. The results showed that very close ignition points can lead to significantly different results in terms of the expected burned area and thus the risk intensity.

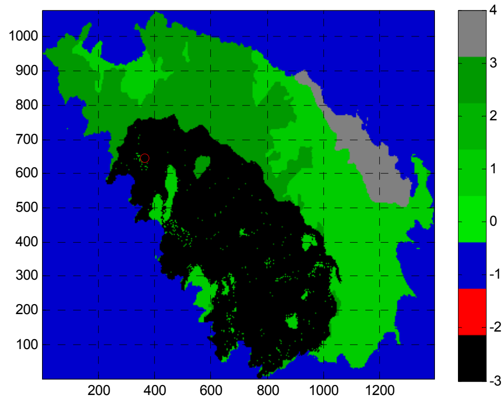

Figure 3: Burned areas resulting from fires starting from nearby spatial locations (marked with circles), yet resulting to significantly different risk intensities.

Future work will be focused on the assessment of risk when considering also tactical fire suppression operations as these are deployed from water-dropping helicopters and air tankers. The proposed approach will be also used for the construction of risk maps for regions in which the risk was calculated with other approaches. Another direction of research that could facilitate the hazard-assessment of forest fires could be also the efficient design of zones that would reduce a potential spread. This could be achieved by bridging the proposed CA model with heuristic optimization techniques (Arca et al., 2013) such as simulating annealing and ant-colony optimization techniques.

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