

Reducing Wildland Fire Hazard Exploiting Complex Network Theory: a Case Study Analysis

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We discuss a new systematic methodology to mitigate wildland fire hazard by appropriately distributing fuel breaks in space. In particular, motivated by the concept of information flow in complex networks we create a hierarchical allocation of the landscape patches that facilitate the fire propagation based on the Bonacich centrality. Reducing the fuel load in these critical patches results to lower levels of fire hazard. For illustration purposes we apply the proposed strategy to a real case of wildland fire. In particular we focus on the wildland fire that occurred in Spetses Island, Greece in 1990 and burned the one third of the forest. The efficiency of the proposed strategy is compared against the benchmark of random distribution of fuel breaks for a wide range of fuel breaks densities.

1. Introduction

Uncontrolled wildland fires have been the cause of widespread environmental, biota, structural hazards and significant human loss (Albini and Brown, 1996; Heymes et al., 2013; Vincent et al., 2015). According to the Food and Agriculture organization of the United Nations (FAO) an average of 19.8 million hectares of forests were affected by fire annually. During the wildland fire that swept through Victoria, Australia in 2009, caused the death of 173 people (2009 Victorian Bushfires Royal Commission, 2010), while wildland fires in Greece in 2007 fires resulted in 84 dead (Rosenfeld, 2011). On the other hand, it has been also recognized the prescribed fires are essential elements in the renewing process of ecological cycle of forests. For example several species depend on wildfires to improve habitat, and maintain diverse communities (NC Cooperative Extension, 2002; USGS, 2006).

For this reason, the majority of prevention activities make use of fuel reduction which may be obtained with prescribed fires or with mechanical treatment of the vegetation. Prescribed fires are run to benefit natural resources and reduce the risk of unwanted wildfires in the future. Mechanical treatment of fuels means reducing the amount of vegetation which has built up to dangerous levels, or changing the arrangement of these fuels in the environment. Mechanical treatments can benefit ecosystems and people by: i) reducing the probability of catastrophic fires; ii) helping maintain and restore healthy and resilient ecosystems; iii) protecting human communities.

The allocation of fuel breaks (mainly zones without vegetation) has been demonstrated to reduce the fire intensities and increase survival of some forest types. This not only reduces the negative impacts on those forests but the wildfire itself may very well provide benefits in the form of additional fuel management and ecological process (Finney, 2005; Parsons, 2006;).

Spatial patterns of fuel treatments can theoretically alter the propagation rate of large fires (Finney, 2001, 2003). By reducing the overall growth rate of a fire, the probability is reduced that a fire will impact a given site in a given time period as a heading fire. Slower moving fires have reduced intensity and create less negative net value change for some ecosystem resources. In any case the fuel reduction increases the chance that suppression action can intervene in fire growth before reaching certain portions of the landscape.

Land managers and decision makers have been using fire behavior and simulation models as a tool to predict fire potential and identify area with high risk of wildfires. However, the widely used existing simulation models, such as FARSITE (Finney, 1998), NEXUS (Scott, 1999), FFE-FVS (Reinhardt and Crookston, 2003),

BehavePlus (Andrews et al., 2005), and FlamMap (Finney, 2006) use the average attribute values of a forest for predictions without considering spatial variability in fuels and vegetation within a forest.

To overcome these limitations, recent effort has been put into the development of advanced physics-based numerical fire behavior models capable of considering spatial variability of fuels within forest as well as fuel and atmosphere interactions (Penman et al., 2014; Lauret et al., 2014; Platt et al., 2015). The wildland-urban interface fire dynamics simulator (WFDS), an extension of FDS developed by the US Forest Service and NIST (Mell, 2010), is one of the models that simulate fire initiation and propagation as a fine-scale, physics-based process that takes into account size, shape, composition and spatial arrangement of fuel particles.

However, practical applications of the fine-scale fire behavior models have been limited due to the large amount of data and computation time required to represent detailed variability of fuels within a forest and model the time-dependent fine scale fire–fuel and fire–atmosphere interactions.

In this work we propose a computational approach introduced in (Russo et al., 2005a), where the landscape is represented as a (lattice) network whose links reflect the fire spread probabilities (Alexandridis et al., 2008; 2011a). The model may incorporate detailed GIS, landscape and meteorological data (Alexandridis et al., 2008; 2011a; 2011b; Russo et al. 2013, 2015a,b). For the definition of the spatial distribution of fuel breaks, the group of nodes through which the fire spreads faster are found. To this aim, the network centralities are computed and the nodes with the bigger centralities are removed from the network. Finally, as an example we apply the proposed strategy to a real case of wildland fire that occurred in Spetses Island, Greece in 1990 and burned the one third of the forest.

2. Methodology

The proposed approach provides a systematic methodology for the spatial distribution of fuel breaks including the heterogeneity of landscapes and meteorological data. The approach consists of three steps (Russo et al., 2015a): (i) the landscape is represented as a (lattice) network whose links reflect fire spread probabilities, (ii) the network centralities are computed, and, (iii) the nodes with the bigger centralities (i.e. the nodes through which the information flows faster within the network) are removed from the network. A detailed Cellular Automata (CA) simulator (Alexandridis et al., 2008, 2011b) is utilized for the first step, while, for the second step, the Bonacich centrality is used (Bonacich and Lloyd, 2001). Hence, the spatial distribution of fuel breaks is reduced to the problem of finding a partition of network nodes that when removed the flow information (i.e. the fire propagation) goes slower.

2.1 The Cellular Automata model

The CA model (Alexandridis et al., 2008, 2011b) assumes that, at each time step t , each (i, j) cell has one of the following discrete states: State $(i,j,t)=1$: a cell is without burning fuel (city, rural areas); State $(i,j,t)=2$: a cell is burning; State $(i,j,t)=3$: a cell has been burned.

The model evolves according to the following rules:

Rule 1: IF state $(i, j, t) = 1$ THEN state $(i, j, t+1) = 1$, which implies that a cell with no fuel cannot be burned;

Rule 2: IF state $(i, j, t) = 2$ THEN state $(i, j, t+1) = 3$, which implies that burning cells are burned at the next time step;

Rule 3: IF state $(i, j, t) = 3$ THEN state $(i, j, t+1) = 3$, which implies that burned cells do not reignite;

Rule 4: IF state $(i, j, t) = 2$ THEN state $(i\pm 1, j\pm 1, t+1) = 2$ with a probability p_b , which implies that the fire is propagated to the neighbour cells with probability p_b defined as follows:

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

where p_0 is a nominal probability of fire spread under no wind condition, flat terrain and certain density and type of vegetation, that is calculated from experimental data; p_{den} is related to density of the vegetation, p_{veg} to the type of the vegetation, p_w to the wind field (speed and direction), p_s to the local slope. The effect of wind, is modeled as follows:

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

where c_1 , c_2 are constants 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 is given by:

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

where E_1 and E_2 are the altitude of the two cells and l is the length of the square side, while for diagonal cells

$$\theta_s = \tan^{-1}\left(\frac{E_1 - E_2}{l\sqrt{2}}\right) \quad (4)$$

The above model can integrate GIS, meteorological data as well as vegetation characteristics including flammability.

2.2 The reconstruction of the network and computation of centralities

The landscape is represented by a network of interconnected patches, $G(V, E)$, where $V = \{v_k\}, k = 1, 2, \dots, N$ is the set of vertices corresponding to the N total cells and E is the set of elements $e_{v_k v_l}$ which are the links between neighbor cells $\{v_k, v_l\}$. The weights of links are $e_{v_i \rightarrow v_j} = p_b$, where p_b are the probabilities computed with the CA simulator.

As said before, the spatial distribution of fuel breaks is reduced to the problem of finding a partition of network nodes that when removed the flow information goes slower. Therefore, for the determination of these nodes the centrality for each node is computed. Here, we used the Bonacich centrality (Bonacich and Lloyd, 2001) which for node k is defined as the k -th component of:

$$\mathbf{x} = \left(\mathbf{I} - \frac{\beta}{\lambda_{max}} \mathbf{A} \right)^{-1} \mathbf{e}, \quad (5)$$

where \mathbf{e} is a vector of ones and λ_{max} is the largest eigenvalue of \mathbf{A} . For $\beta = 0$, the above expression reduces to the degree centrality, while for $\beta = 1$ it reduces to the standard Eigencentrality. Thus a high value of betweenness centrality implies that the corresponding cell is connected with other cells by relatively shorts paths and so is central to the information flow (and therefore the fire spread) in the network.

2.3 Hazard Assessment

The hazard intensity R , with respect to the density of fuel breaks d_f , is defined as follows:

$$R(d_f) = \frac{1}{N_r} \sum_{i=1}^{N_r} \frac{N_b(i)}{N_v} \quad (6)$$

$$d_f = \frac{N_e}{N_v} \quad (7)$$

where d_f is the ratio of the number of fuel breaks N_e and the total number of nodes that contain flammable vegetation N_v , while N_r is the number of simulations for a given initial condition and N_b denotes the total number of burned nodes.

3. Simulation Results

For our analysis we took as paradigm the case of the wildland fire that occurred in Spetses in August, 1990. The fire ignited near the middle of the island's forest and was quickly spread to the south by moderate to strong north winds. The fire was extinguished around 11 hours later, after having burned down a forest area of 8 km^2 , almost one third of the total area of the island. Figure 1a shows a map of Spetses island with the actual burned area and the corresponding scaling of the density of vegetation (1 is for sparse and 3 is for dense vegetation; 0 is for agricultural areas and 4 is for city). Figure 1b shows a typical simulation using the CA

model. The CA simulator approximates adequately the fire spread both in time and space: the wildfire burned an area of about 590 ha in 11 hours; the CA simulator resulted to a 540 ha burned area (almost equivalent to the actual burned area) in 11.3 hours (Alexandridis et al., 2008).

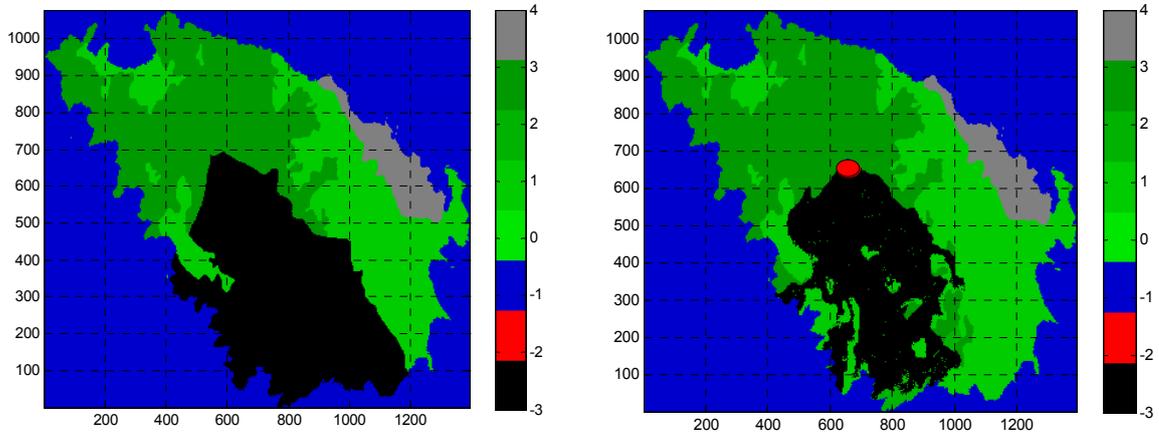


Figure 1. (a) A map of Spetses island with vegetation scaling (0-3) and the actual burned area (black). 0 is for agricultural areas, 1 for sparse density of vegetation, 3 for dense density of vegetation, and 4 is for city, (b) A typical simulation using the CA model. The ignition point is marked by the red ellipse.

Figure 2 shows the diagram of the hazard intensity, $R(d_f)$ as obtained using the proposed approach with $\beta = 0.5$ and by averaging $N_r = 50$ simulation runs all starting from the ignition point of the real fire incident. Maximum values of the burned area are also illustrated with bars. The results obtained with the random distribution tactic are also shown for comparison purposes. All differences were found to be statistically significant under the t-test criterion with a threshold set at $\alpha = 0.1$.

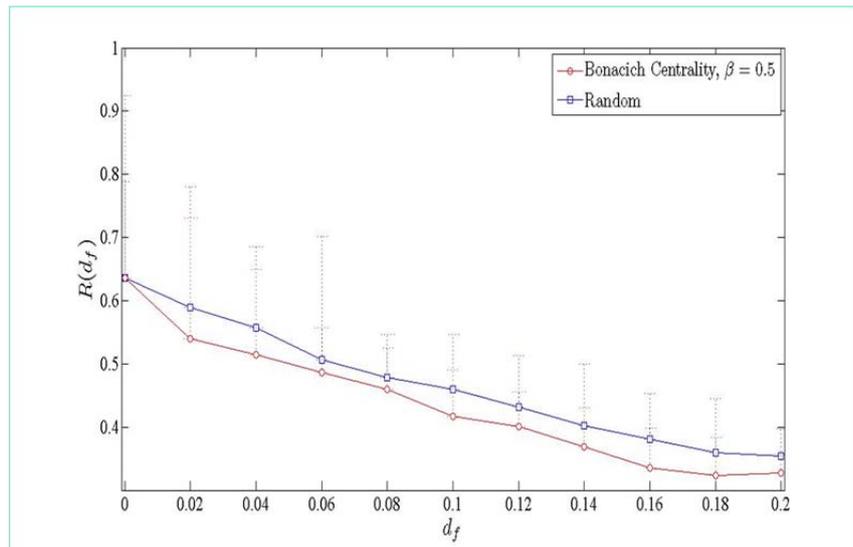


Figure 2. Fire hazard, $R(d_f)$ over $N_r=50$ runs. Circles correspond to the fire hazard resulting when distributing the firebreaks with the proposed approach (Bonacich centrality with $\beta=0.5$). Squares correspond to the fire hazard obtained using random distribution of fire breaks. Maximum values of the burned area are also illustrated with bars.

The random distribution tactic has been applied in previous theoretical studies, which have shown that a random or compartmented distribution of fuel breaks reduce the spread rate of the fire. While the contrary, regular patterns like parallel stripes work affectively just when the direction of fire propagation is perpendicular to the stripes (Russo et al. 2014).

Simulations results in Figure 2 show that the proposed approach for the distribution of fuel breaks results in statistically significant lower hazards than that obtained by the random distribution tactic.

4. Conclusions

The majority of activities for forest fire prevention make use of fuel reduction which may be obtained with prescribed fires or with mechanical treatment of the vegetation. The allocation of fuel breaks to reduce the fire intensities and propagation velocity is then crucial for the forest fire management. Towards this aim we propose the adoption of a new methodology introduced in (Russo et al., 2005a). The approach is based on the complex network theory and a detailed CA modelling, and use the concept of centrality criterion, for the evaluation of information flow through complex networks. Moreover, the CA model can consider spatial heterogeneity in both fuel and landscape characteristics and can take as input local meteorological data. The ability of the CA simulator to adequately approximate the fire spread both in time and space has been shown by comparison with wildland fire that occurred in Spetses Island, Greece in 1990. The efficiency of the approach was compared against the typical random tactic of fuel. Simulations results showed that the proposed approach results in statistically significant lower hazards.

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