RISK OF WILDFIRES WITH KNOWN IGNITION POINTS: CASE OF RESIDENTIAL BUILDINGS

Elmira Kalhor1,2, and Vanessa Valentin1
1 University of New Mexico, USA
2 ekalhor@unm.edu

Abstract: Wildfire is considered the dominant disaster in many regions of the world including the United States, Australia, Canada and parts of Europe. However, unlike other natural disasters, such as flooding, earthquakes and hurricanes, the risk of wildfire to the built environment is not vigorously studied. Most of the research in the wildfire risk management area is limited to the study and management of wildfire within the wildland. On the other hand, there is an increasing progress of housing projects towards the natural lands. The Wildland Urban Interface (WUI) is where the developed and undeveloped areas meet. Because of high vulnerability of the WUIs to wildfires, there is a need to identify, quantify and manage the expected damage of wildfires to the WUIs. This study calculates the risk of wildfires to residential buildings considering a specific ignition point. The model inputs include the spatial distribution of the buildings, an absolute or proxy value for the damage from wildfire, and atmospheric and landscape attributes needed to simulate the fire propagation on a specific land. The model outputs are the distribution of damage at each time interval from the initial ignition and total risk of a fire with a given ignition point.

1 INTRODUCTION

Wildland-Urban Interface (WUI) is where the undeveloped land intermixes or interfaces with man-developed land (Davis 1990). Also called flame zones, these WUI lands are developed areas vulnerable to wildfires. About 90% of the WUIs in the Western United States are classified as high severity fire regimes (Theobald and Romme 2007). However, this sensitivity has not suppressed the progress of housing development projects towards fire prone forest and park lands. WUIs have grown 52 percent in size during three decades from 1970 and are projected to increase by an additional 10 percent until 2030 adding up to over 510,000 square kilometers (Theobald and Romme 2007).

Chuvieco et al. (2010) defines a framework for fire risk assessment as an important component of risk management. In their model, they address the need of including vulnerability in fire risk assessment. The risk of wildfire is the product of fire danger and probability. The authors address ways to calculate and analyze different parameters of the risk assessment model from probability of ignition to a model of propagation prediction to finding tangible and intangible values at stake.

The probability of fuel-ignition on a specific land has been assessed using econometrics tools and neural networks. These approaches have been used for formulating the ignition as a function of the characteristics of the landscape and infrastructures (Romero-Calcerrada et al. 2007; Vasilakos et al. 2009; Chuvieco et al. 2010). Federal agencies in the United States such as the US Forest Service and its
associated labs have also produced the fire danger maps danger rating classes. These maps give
information on the occurrence of fire.

There are different propagation models developed to provide decision support systems for specific forest
management subjects. Chuvieco et al. (2010) assigned a propagation potential to each cell, in a coarse
cell size, based on fuel type, moisture and wind. USDA’s Rocky Mountain Research Lab has developed
the Flammap software (Finney 2006). Flammap uses “Minimum Travel Time” to simulate the propagation
of wildfire. Given the landscape, fuel, wind and ignition point, Flammap is able to return a set of outcomes
including but not limited to the rate of spread, influence grid (number of nodes that succeeded burning from
each cell), fire line intensity, and burn probabilities. However, Flammap does not consider probabilistic
modeling for producing a probabilistic distribution of the expected fire propagation. Randig is the command
line version of Flammap which can be used for random selection of wildfire ignition points and is used for
estimating the efficacy of the treatment options in Oregon, USA (Ager, Vaillant, and Finney 2010).

Another approach that has the capability to do probabilistic modeling of wildfire propagation is known as
Cellular Automata (CA)-based fire propagation model originally proposed by Clarke, Brass, and Riggan
(1994). This model is used to simulate fire propagation and final wildfire perimeter. This model is also a
command line program and gives the user flexibility in terms of choosing between using crisp or random
variables. To model the behavior of wildfire, core concepts of fire propagation are adopted from Rothermel
(1972) and the model is verified by simulating the Lodi Canyon fire of 1986, in California, USA. Due to its
flexibility, simplicity and availability, this model is used in this study to assess the spatial and temporal
distribution of buildings exposure to wildfires.

The probability that the fire can ignite a structure has received little attention in the literature. The fire
attributes and the building materials and configuration can have an effect on this probability. Cohen (1995)
proposed the Structural Ignition Assessment Model (SIAM) which links the flames and heat from wildfires
and external materials used in buildings to assess if a building will be ignited by specific heat from a fire or
not. In his research, the author performed laboratory tests to define the ignitability of each component of
the house.

Associated with wildfire, there are a variety of vulnerabilities in the WUIs from social to environmental, to
economical, to the built environment. According to Cutter et al. (2008), along with the immediate and
factual damage caused by the event, the vulnerability of the subject or the system should be accounted
for in the calculation of the impact of the disaster. Vulnerability is a complex context (Cutter et al. 2008),
however, exposure is a definitive element of the vulnerability (Hufschmidt 2011). Hollenstein (2005)
defines exposure as an index of the spatio-temporal distribution of the elements at risk.

The elements at risk in this study are residential houses. In order to show the distribution of exposure to
danger, an exact or proxy indicator should be adopted. Using historical records, Cohen (1990) assumes
that once ignited, structures will be completely destroyed. One can justify this assumption since during a
fire, suppression activities will be more likely diverted towards protecting un-burnt houses or assets; while
for burning houses, the efforts will be spent on saving lives. However, in order for fire to ignite a building,
the characteristics of the exposed materials play an important role in the probability of ignition of the
house (Cohen and Saveland 1997).

In this study, structures ignition is formulated as a binary variable assuming that if a building falls inside
the spatial burning cells of the fire, it will be ignited and totally destructed, and therefore, the expected
damage of the house is its total estimated value. An ongoing study by the authors is the use of
econometrics in order to formulate ignition probability as a function of the structural and neighborhood
characteristics, which will help future research to represent ignitability of structures in probabilistic form.
Since the analysis is in the form of raster data (some converted to matrixes), a point is a virtual
representation of a cell on the ground with an arbitrary resolution.


2 RISK AND VULNERABILITY ASSESSMENT MODEL

Wildfire is a complex phenomenon that is dependent on a variety of factors. The location of the ignition cell, the topography of the landscape, the fuel availability, the fuel moisture and the wind and atmospheric conditions, among others, affect the propagation scheme of a wildfire. In ecological assessments, the magnitude of wildfires is measured in terms of the amount of energy (in Kilowatts) released during different phases of the propagation of the fire; and sometimes the flame length is used as a proxy measure for this energy release (Keeley 2009).

As a danger, wildfire has a compound probability of occurrence. This probability is, at the coarse level, composed of the probability of ignition of a specific cell and the probability that the fire will propagate from that given cell and reach to the location of interest. Last, but not least, is the probability that the fire can damage an asset. Following Chuvieco et al. (2010), the risk of wildfire that has started on a given cell on the landscape \((x_i, y_j)\) to the location of a vulnerable asset of interest in the study area (denoted by \((i', j')\)) is shown in equation [1]:

\[ R_{ij}^{(x,y,t)} = P_{propagation}^{(x,y,t)} \times P_{burn}^{(i',j')} \times V_{ij} \]

Where, \(R_{ij}^{(x,y,t)}\) is the risk of damage to an asset located on cell \((i, j)\) from a fire initiated on the cell \((x, y)\) of the study area, after \(t\) time. \(P_{propagation}^{(x,y,t)}\) is the probability that the fire ignited on point \((x, y)\) will reach to point \((i, j)\) after \(t\) time periods and \(P_{burn}^{(i',j')}\) is the probability that point or asset located at \((i', j')\) will start burning if the fire reaches to that point. \(V_{ij}\) is the value of the asset in danger located on point \((i, j)\).

As previously mentioned, an assumption made in this study is that the building that has been reached by a fire has been completely harmed. This assumption eliminates the need for detailed damage assessment while providing an upper bound for the calculation of damage.

Equation [1] represents the spatiotemporal distribution of risk of a wildfire initiated at cell \((x, y)\). The cumulative risk from the fire can be calculated as shown in equation [2].

\[ R_{ij}^{(x,y)} = \sum_i \sum_j P_{propagation}^{(x,y,t)} \times P_{burn}^{(i',j')} \times V_{ij} \]

\(P_{propagation}^{(x,y,t)}\) is calculable through fire simulation. As previously mentioned, the propagation simulator used in this study is the CA based model proposed by Clarke, Brass, and Riggen (1994). At each time interval, the fire front will grow on the structure of the existing fire status resulting in a process oriented model. The growth of fire is defined as the movement of firelets\(^1\) from a burning point to a virgin (un-burnt) point. When modeling fire propagation, firelets are sent out of the existing burning cells (cells). The generation and direction of firelets is a function of the wind magnitude and direction, topography attributes (slope and aspect), availability of fuel on the destination cell, temperature and moisture. Except for slope and aspect, other attributes are of stochastic nature. As a result, the decision of fire front moving from each cell is modeled as a random process through a Monte Carlo simulation.

At the beginning of each simulation, the slope, aspect, and fuel layers (with unique cell size and projections) are input to the model along with a wind array representing climate of the study area. Wind array specifies the range of possible winds direction and magnitudes. A cell is selected as the place where the hypothetical fire will start. Eight immediate surrounding cells are weighted based on their slope and the direction of wind. These weights are associated with the probability that the firelets from the ignition cell will choose the cell as the destination. Using a roulette wheel-like selection procedure, firelets destination(s) will be selected. Once a new cell is selected as the destination of a firelet, it is treated as the original ignition cell. Random controllers restrict the number of propagations within each time interval.

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\(^1\) Firelet is the term used by Clarke et al. (1994) to show the mobile elements of fire.
Next interval starts with current burning cells as the ignition points. The fuel load of burning cells is decreased by 1 at the end of each time interval. The termination criterion is reaching to the time limit.

For a specific ignition point, the simulation will be run for a number of iterations to incorporate the randomness of the atmospheric conditions. During each simulation, a binary value \( \mathbf{1}_{(i,j)}^{\text{iteration},t} \) is calculated for each cell to identify if the fire has propagated to that cell up to a specific time interval \( t \):

\[
\mathbf{1}_{(i,j)}^{\text{iteration},t} = \begin{cases} 1 & \text{if the simulated fire reaches to point } (i,j) \\ 0 & \text{otherwise} \end{cases}
\]

The probability of propagation \( P_{(ij)}^{\text{propagation},(xy),\text{time}=t} \) is then calculated as given in equation [4].

\[
P_{(ij)}^{\text{propagation},(xy),\text{time}=t} = \frac{\sum_{\text{iteration}=1}^{n} \mathbf{1}_{(i,j)}^{\text{iteration},t}}{n}
\]

where \( n \) is the total number of iterations (simulations).

As previously mentioned, another assumption made in this study is that if the fire can find a way to ignite the cell on which the building is located, then the building will get ignited. The probability of structural ignition is therefore calculated using equation [5]:

\[
P_{(ij)}^{\text{burn}} = \begin{cases} 1 & P_{(ij)}^{\text{propagation},(xy),\text{time}=t} > 0 \\ 0 & \text{otherwise} \end{cases}
\]

The value of the expected damage is the total price of the building. The structures layer is overlaid on the time-dependent fire status layer in order to find the structures that are burnt according to simulation results (Figure 1).

![Figure 1: Overlaying structures layer and the fire status layer for calculating the value of the exposed asset](image)

The total risk from a fire ignited on point \( \mathbf{1} \) is calculated using equation [2].
3 STUDY AREA AND DATA COLLECTION

The focus of this study is Los Alamos Census Designated Place (CDP) which is a town in Los Alamos County in the Northern New Mexico. The total population of the city in 2010 was 12,019 with median age of 43.5. There are 5,289 households residing in the city and 5863 houses. Among the unoccupied houses (i.e. 574 units), 221 are seasonal and recreational houses. According to US Census data, 3662 houses are owner-occupied and most of the remainder are rented. Median and mean income of the population are $106,016 and $116,563 respectively. Los Alamos is located within parts of Santa Fe National Forest, and it is also close to Bandelier National Monument.

In 2000, Los Alamos witnessed one of the greatest fires in the history of the United States. The Cerro Grande fire was initiated as a prescribed burn in the Bandelier National Monument when, due to adverse atmospheric conditions, the fire went out of control (Figure 2). The town was evacuated for a week and about 300 houses were burnt in the aftermath of this fire. The damage to the entire county was estimated to be about $1 million (PW Coopers 2001), almost all in the Northern part of the city (Los Alamos CDP).

Figure 2: Cerro Grande fire perimeter (Using Monitoring Trends in Burn Severity (MTBS) Project data)

A real estate investigation on physical and non-physical damage was done by Price Waterhouse Coopers consultants (2001). Aside from houses that were burnt during wildfires, 3 - 11 % value diminution was observed in un-damaged houses due to wildfire. A survey analysis contracted to a third party by Los Alamos county showed that 54% of owners of the damaged buildings decided to re-built their buildings in the same place, confirming the results by McGee, Mc Farlane, and Varghese (2009) that the experience of wildfire does not change the risk perception of the community. Interestingly enough, 35% of those who were re-building their homes on the same location said that they planned to build a similar structure (Price Waterhouse Coopers (2001)).

Case study data used for this study include topography data, fuel data, structures layer and value of the assets. Topography data (elevation, slope and aspect) are collected from the online database of the United States Geological Survey (USGS). Fuel data incorporated into fire propagation model is the Canopy Bulk Density (CBD) that is available through LandFire Project’s data set (Rollins and Frame 2006). Canopy bulk density is mass per volume (kg/m³) of canopy fuel and is the property of a stand of trees rather than a single tree (in which case, it will be referred to as crown fuel)(Scott and Reinhardt 2001).

Amongst other types of fuel, buildings are highly exposed to fire in dense canopy and shrub fire (Menakis, Cohen, and Bradshaw 2000). On the other hand, when the wind magnitude and direction are in support, the embers from canopy fires can find their way to the roof system where they can ignite the structures.
Sometimes, through the ladder fuels\(^2\) surface fire can get elevated to the canopy fire (Scott and Reinhardt 2001). However, modeling the transition of surface fire to crown fire has a lot of complexities and reduces the efficiency of the analysis in the context of damage to the built environment.

The structures layer used for this study is limited to the single family housings in Los Alamos. The value for each house is the assessed value of the year 2013 provided by the Los Alamos County assessor’s office. The diminution of un-burnt house values after a fire is not seen in the damage assessments and only physical exposure to fire is accounted for.

4 SIMULATION RESULTS

The fuel and structures distribution is shown in Figure 3. The selected ignition point is close to the houses that were previously burnt due to the Cerro Grande fire; however, the fuel data are from year 2012. The study area is simulated in 505 rows by 272 columns. Each cell is 17m by 17 m in size (56 ft by 56 ft). The selection of the cells size is based on the finest resolution among the input raster files. Although it was possible to change the resolution in order to increase the accuracy of the model, longer run-times discourage pursuing higher accuracies. The result of the propagation model for a single iteration of the simulation is shown in Figure 4.

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\(^2\) Ladder fuel is the fuels that will form the channel through which fire escalates from surface to crown or canopy of trees. (Menning and Stephens 2007)
Figure 4: Fire propagation simulation results. Shades of green represent the fuel content of the cells similar to Figure 3. Yellow point is the source of fire. The brown color is the result of color mix between fire cells (orange) and landscape fuel (green) and does not show the intensity of fire.

The results of the model for a specific ignition point are shown in Table 1. The outcomes are narrowed down to represent cells that have been affected during simulations and received a value greater than zero.

Table 1: Assessed risks (time units are 10 minutes)

<table>
<thead>
<tr>
<th>Source (x,y)</th>
<th>Burnt cell (t,j)</th>
<th>( V_{ij} ) (USD)</th>
<th>( R_{ij} ) (USD)</th>
<th>( RISK(t,j) ) (USD)</th>
<th>( RISK(t) ) (USD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(125,3)</td>
<td></td>
<td>458,410</td>
<td>.8</td>
<td>.8</td>
<td>366,728</td>
</tr>
<tr>
<td>(116,3)</td>
<td></td>
<td>359,890</td>
<td>1</td>
<td>1</td>
<td>359,890</td>
</tr>
<tr>
<td>(113,3)</td>
<td></td>
<td>391,940</td>
<td>.0</td>
<td>.1</td>
<td>0</td>
</tr>
<tr>
<td>(117,3)</td>
<td></td>
<td>294,000</td>
<td>.0</td>
<td>.1</td>
<td>0</td>
</tr>
<tr>
<td>(120,29)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(120,25)</td>
<td>(116,3)</td>
<td>359,890</td>
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<td>359,890</td>
</tr>
</tbody>
</table>

The average value of a single family housing in the study area is 190,004 USD. With the purpose of demonstrating the proposed methodology, two separate points, which were 68 meters apart, were selected as ignition points. One source (129,29) is very close to the structures and unsurprisingly represents higher risk to the built environment under consideration: residential buildings. It is noteworthy that during all of the simulation runs, the fire initiated from the source (120,25) reached the cell (120,129) and ignited that cell. In other words, the vulnerability values to sources of fire on the wildland are not independent from one another. The relationship between the risk resulted from different sources is proposed in equation [6].

\[
RISK(t)_{xy} = RISK(t)_{xy} + RISK(t - t')_{xy,y}
\]
where $t$ is the time when source $(x', y')$ is ignited during propagation of fire from source $(x, y)$.

The results from Table 1 can be used to assess the time value of suppression activities in order to provide cost-benefit analysis of suppression cost and time. For example, in the case of the fire source $(120, 29)$, there is 685,940 USD difference in the risk value between $t = 10$ and $t = 20$, which justifies any suppression activities costing less than this amount. However, the vulnerability value will be less than 100,000 USD after $t = 20$ favoring the less cost suppression effort. Another notion is the difference between the total risk values for the sources. The total risk from source $(120, 29)$ at each time interval is at least twice the risk from source $(120, 25)$ and suppressing fire from reaching point $(120, 29)$ is worth at least 366,728 USD. However, it is important to note that the value of the vulnerability in this study only reflects the residential houses as the value-in-danger and the results of risk assessment for different types of assets may not confirm the suppression cost trade-off described.

5 CONCLUSION AND FUTURE WORK

In this study, a risk model is proposed. A wildfire event is identified by the ignition point. The probability component of risk is composed of the probability of the propagation of fire from the specified ignition point to the location of the asset of interest multiplied by the probability of ignition of the asset when exposed to fire. Using a fire propagation simulator and landscape input including fire fuel and structures setting, the assessment of spatio-temporal distribution of the vulnerability was made possible. Results from this research can be used for assessment of treatment efforts and the evaluation of trade-offs between treatment and suppression costs, for raising social awareness about the effects of the risk mitigation activities and for studying policy and management implications in WUIs.

This study can support decision-making process for various managers. Identifying high risk ignition points on the forested lands helps the public land managers to prioritize their treatment effort accordingly, reduce the risk of wildfire and better protect assets. Furthermore, in case of a fire, firefighting efforts can be better invested on areas with higher risk. Last, but not least, zoning and housing departments can limit the progression of the built environment in order to cooperate with public land managers and to secure more assets or to increase the flexibility and efficiency of firefighting activities in the case of occurrence of a wildfire.

Potential future additions to the model will be the calculation of the probability of ignition on the wildland using regression analysis along with the calculation of the probability of ignition of the asset of interest using an expert-system. These additions enable the researchers to calculate the risk of wildfire initiated on any point on the wild landscape. The vulnerability that is accounted for is only the physical damage from wildfire. However, in the aftermath of most of the fires, un-burnt houses also undergo a value diminution which can be added to the total vulnerability. Ongoing research from the authors is addressing this issue.

One remaining noticeable remark is that although the social perception is that the occurrence of fire will reduce the risk, the simulation results showed that there are still vulnerabilities in the burn scar of Cerro Grande fire. Forested lands will restore the previous fuel stock and the fuel build-up coupled with the harmful atmospheric conditions exacerbated by climate change will reintroduce the risk.

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