The Use of Geographic Information Systems for Modeling a Structure's Wildfire Risk: A Study of the Charlotte Fire, Pocatello, Idaho USA

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Abstract

This research focuses on the use of Esri's ArcFuels and Missoula Fire Sciences Laboratory's FlamMap to produce a wildfire exposure analysis on structures affected by the Charlotte Fire. Exposure analysis involves producing both conditional flame length and burn probability, which are combined to determine a structure's wildfire risk. The individual datasets within the model were tested for accuracy and influence on structure loss. A one-tailed t-test was used to test if the means were greater for homes with or without loss for conditional flame length, burn probability, slope, and canopy datasets. A Chi-Square test was performed to test for significant differences within the aspect and surface fuel datasets. The results of these analyses were used to illustrate possible limitations within the wildfire model. The results of this study could be used to improve future exposure analyses, data processing, and mitigation planning by wildfire managers through an improved understanding of the limitations and benefits of the FlamMap wildfire models.

Introduction

The Federal Register defines the Wildland Urban Interface (WUI) as the area where structures and other developments meet or intermingle with undeveloped wildland (United States Department of Agriculture and United States Department of Interior, 2001). The WUI is where wildland fires destroy the most structures when fuels and weather are conducive to fire and where human-caused fire ignitions are the most common (Radeloff, Hammer, Stewart, Fried, Holocomb, and McKeefry, 2005). Ingalsbee (2010) states there are over 44 million homes in the United States in fire-prone WUI areas and the Forest Service predicts a 40% increase of new homes in the WUI by 2030. Research has estimated annual fire suppression costs to be 2 to 4 billion dollars (Ingalsbee, 2010). This illustrates the importance of understanding structures at risk of wildfire for city and county planning to reduce structure loss and overall costs.

Land and resource managers assess wildfire impacts on ecological, social, and economic systems (Scott, Thompson, and Calkin, 2013). These systems are known as highly valued resources and assets (HVRAs). A home or structure is an example of a HVRA and will be the focus of this analysis. Quantifying wildfire risk on HVRAs assists managers with strategic, operational, and tactical decision making for wildfire mitigation (Scott *et al*., 2013).

Wildfire risk to HVRAs, also called exposure analysis, is modeled in GIS by measuring wildfire likelihood and

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intensity (Scott *et al*., 2013). Wildfire likelihood quantifies the probability of wildfire occurrences on HVRAs. Wildfire likelihood depends on a geospatial context across a broad area, whereas wildfire intensity is measured as a discrete point on the landscape or pixel (Scott *et al*., 2013). Wildfire likelihood and intensity are driven by complex interactions between ignitions, fuel, topography, and weather (Scott *et al*., 2013).

Exposure analysis is a critical first step in developing risk mitigation strategies. Nicole Vaillant, a fire ecologist at the Wildland Fire Lesson Learned Center (2013), explained it is critical for wildfire managers to understand limitations within these models when making mitigation decisions due to the complex variables influencing wildfire. Therefore, the Charlotte Fire exposure analysis within this study was used to analyze the effectiveness and limitations of the exposure analysis based upon homes with and without loss as a result of the Charlotte Fire. These results and limitations in turn can help guide effective decision making for future wildfire model building and wildfire mitigation projects to reduce HVRAs loss and overall costs.

The exposure analysis was performed on 120 homes within the Charlotte Fire boundary. The wildfire occurred on June 28, 2012, in Pocatello, Idaho USA and burned 4.2 sq. km or 1029.4 acres. There were 61 homes lost and 59 homes that survived the wildfire (Figure 1). There was no identified cause of the fire, but it was thought to be manmade.

Data

Home and Fire Data

The Charlotte Fire burn perimeter shapefile, created by the Bureau of Land Management, was obtained from the Idaho State University GIS Department. The locations of homes within the burn perimeter were identified by compiling addresses from the Bannock County Online Parcel Viewer. The addresses were geocoded in ArcMap, which placed the home point in close proximity to its actual location. The points were then photo-interpreted directly over the home using pre-fire 2011 National Agriculture Imagery Program (NAIP) one meter imagery.

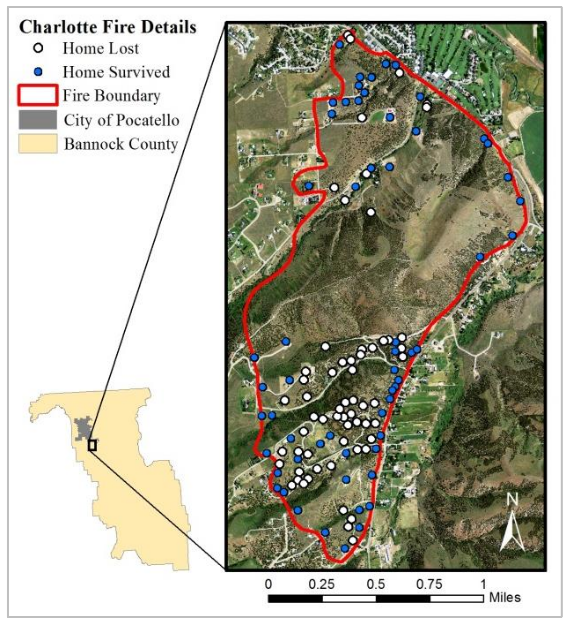

Figure 1. Charlotte Fire location and home details.

To assess whether a home was with or without loss, Bannock County Assessor data for monetary loss per address was verified. Sixty-one homes were documented as a total loss. News reports recorded 66 home losses. The additional 5 structures recorded by the news could not be verified and were not included in this study. A structure in this project is considered a home residence and does not include the loss of outbuildings.

LANDFIRE Data

The data required for the exposure analysis were retrieved from LANDFIRE.gov. LANDFIRE data describe surface fuel, canopy fuel, and topography. The data needed to be at a larger scale than the study area to include wildfire risk from the surrounding environment. This allowed fires to burn into and out of the study area. A two mile buffer of the Charlotte Fire perimeter was selected for the data extent as recommended by the ArcFuels tutorial (Western Wildland Environmental Threat Assessment Center, 2014). Eight LANDFIRE raster datasets obtained were elevation, slope, aspect, canopy cover, canopy height, canopy bulk density, canopy base height, and surface fuel. Data resolution was 30 meters. Raster data were projected from NAD 1993 Albers to NAD 1983 UTM Zone 12N to be consistent with the home and burn perimeter data.

Methods

Tools and software required to perform the exposure analysis included ArcFuels to prepare the data for processing, FlamMap, to create the exposure analysis, and lastly statistical analyses through the use of ArcMap, SPSS, and Excel (Figure 2).

ArcFuels and Data Preparation

ArcFuels is a toolbar used within ArcMap that assists with data preparation before wildfire modeling in FlamMap. It additionally converts data into workable formats after FlamMap wildfire modeling. First, the ArcFuels toolbar was used to build the Landscape file (LCP) using the eight LANDFIRE raster datasets. LCPs are binary files containing a compilation of ASCII data, derived from the elevation, slope, aspect, canopy cover, canopy height, canopy base height, canopy bulk density, and surface fuel raster data.

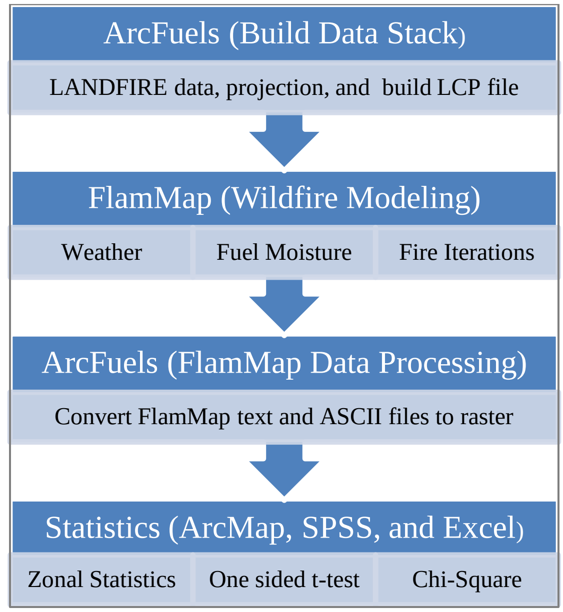

Figure 2. Project methods.

FlamMap Wildfire Modeling

FlamMap is open source software used to model wildfire. It is a conditional wildfire modeling software which means that the environmental conditions can be input to simulate wildfire. These conditions consist of weather, fuel moisture, and fire iterations. Weather data for the time and date of the Charlotte Fire, including wind direction and speed, fuel moisture content, and the quantity of fire iterations were input into FlamMap. These variable conditions along with the LCP file describing topography and vegetation are used to predict wildfire likelihood and intensity within the project area. Outputs created from the FlamMap wildfire model were burn probability (BP), which measures wildfire likelihood, and conditional flame length (CFL), which measures wildfire intensity.

Weather entered into the model was determined by historical weather data.

On July 28th at 2:30 pm at the time of the fire, the wind speed was 10 mph, and the wind direction was WNW, at a 292 Azimuth (Weather Underground, 2014).

The second variable entered into FlamMap was fuel moisture; this included both dead and live fuel moisture. For both categories a very low fuel moisture file was selected. The historical average rainfall for Pocatello, Idaho in June is 0.95 inches (Weather Underground, 2014). In June 2012, Pocatello only received 0.17 inches of rain (Weather Underground, 2014). Additionally, before the fire there were 12 days above the average temperature of 81° (Weather Underground, 2014). Also, the week before the fire the wind was above average, with wind gusts 35 to 40 mph (Weather Underground, 2014). Therefore, the high temperatures, winds, and low precipitation depicted a very dry landscape with low fuel moisture.

Lastly the quantity of random fire iterations was selected. FlamMap fire iterations are fire points randomly placed within the project area. The model predicts how the random fire points will burn based on the weather, fuel moisture, topography, canopy, and surface fuel data. These wildfire simulations create the BP and CFL outputs.

According to Nicole Vaillant (2014), when determining the amount of fire iterations, the goal is to give each raster cell an equal chance of burning. This can be analyzed by running many fire models until the mean change becomes close as the quantity of fires increases. Therefore 5 models were run with an increase of 500 fires for each model. The fire iterations ranged from 500 to 2500 fires. The lowest mean change occurred between 1500 and 2000 fires with a mean change of 0.00027 burn probability (Table 1). Therefore, the model with 2000 iterated fires was selected for the exposure analyses.

Table 1. Fire iteration mean change comparison.

Fire Iterations	Mean Change	Min	Max
500 to 1000	0.00051	-0.041	0.042
1000 to1500	0.0037	-0.023	0.027
1500 to 2000	0.00027	-0.034	0.028
2000 to 2500	-0.004	-0.051	0.022

ArcFuels and FlamMap Data Processing

The weather, fuel moisture, fire iterations, and LCP file were processed using the FlamMap wildfire model. This model produced both CFL and BP outputs which were needed for structure exposure analysis. CFL and BP were built as text and ASCII files within FlamMap. The ArcFuels tool was utilized to convert the CFL and BP ASCII data into shapefiles, and then into raster format for further statistical analyses in ArcMap.

Statistical Methods

Statistical means of CFL and BP were tested between homes with and without loss using ArcMap Zonal Statistics as a Table tool. Statistical analyses were also performed on each topography, canopy, and surface fuel dataset used to produce CFL and BP outputs. These tests showed whether there were significant mean differences in the datasets between homes with and without loss. The one-tailed t-test was used to test the mean differences for CFL, BP, slope, and canopy datasets. The Chi-Square statistic was used to test for significant mean differences in the aspect and surface fuel datasets (Figure 2).

Data Improvements for Calculating CFL and BP means

Urban class within the surface fuel dataset created issues when calculating the CFL and BP mean values. Urban class is non-burnable and sets the value of CFL and BP to zero. The urban class resulted in burnable values of zero for 20 of the 120 homes if the home point shapefile was used to gather BP and CFL values. Therefore a 45.7 meter buffer was used to gather mean BP and CFL values around each home and not the home point shapefile. The 45.7 meter buffer is currently used by the United States Forest Service to determine a structure's exposure to wildfire (Vaillant, 2014). According to Scott *et al*. (2013), including a buffer around HVRAs more accurately estimates the structures exposure to wildfire. The buffer increases the sample size for estimating wildfire risk from the structure's surrounding environment and does not bias the overall wildfire risk (Scott *et al*., 2013).

Researchers additionally discussed the negative impact of the urban class, especially when it defines linear elements such as roads and riparian environments. These urban elements are misrepresented because of the scale of the raster data (Scott *et al*., 2013). The roads in the Charlotte Fire study area measured 8-10 meters wide from the NAIP imagery. Therefore the 30 meter LANDFIRE pixel data amplified the impact of non-burnable roads. Due to the close vicinity between roads and homes, this decreased the CFL and BP means due to the zero burnable values of the urban class. According to fire ecologist Nicole Vaillant (2014), current Forest Service wildfire models use FSVeg raster land data where each cell has a probability of burning. The Charlotte Fire study area was composed of private and not federal land, so the FSVeg data with burnable values could not be used.

Roads were the primary component of the urban class in the Charlotte Fire study area. The urban class from the surface fuel data was masked out before calculating BP and CFL mean data. This decreased the impact from the zero values in the non-burnable urban class.

Statistics Model to Collect Mean Data

Lastly, ArcGIS ModelBuilder was used to produce the mean data gathered from the 45.7 meter home buffer. An Iterate Feature Selection tool was used within the model so that each home buffer was passed individually through the Zonal Statistics Table tool. Without the iterator, overlapping polygons would miscalculate the area due to intersecting buffers. The iterate tool created an individual table for each home's mean data. Individual tables produced were then merged into one table to analyze the mean values.

Exposure Analysis

An exposure analysis which measures a structure's risk to wildfire is determined by combining CFL and BP. In the following sections, CFL and BP are defined, and the statistical results of the one-tailed t-test and scatter plot are discussed.

Burn Probability

Burn probability (BP) is the probability of a pixel burning given one random ignition on the landscape. The following equation was used to calculate BP with FlamMap:

BP = # of times a pixel burns / # of fires iterated

Therefore with 2000 fires iterated, if the burn probability equals 0.01, then the pixel on the landscape was projected to burn 20 times out of 2000 fires ran in the model. The wildfire model showed a greater BP in the middle to south range of the Charlotte Fire and it lessened towards the north fire boundary (Figure 3). The north boundary of the Charlotte Fire ran along the Bannock Highway. Across the highway was classified as an urban environment because there is a golf course and dense residential area. This resulted in a low BP. The narrow low burn probabilities that string throughout the Charlotte Fire and appear dark green are a result of the roads that are classified as a part of the urban layer within the surface fuel data (Figure 3). These are the areas that were masked out of the mean data to calculate the exposure analysis statistics.

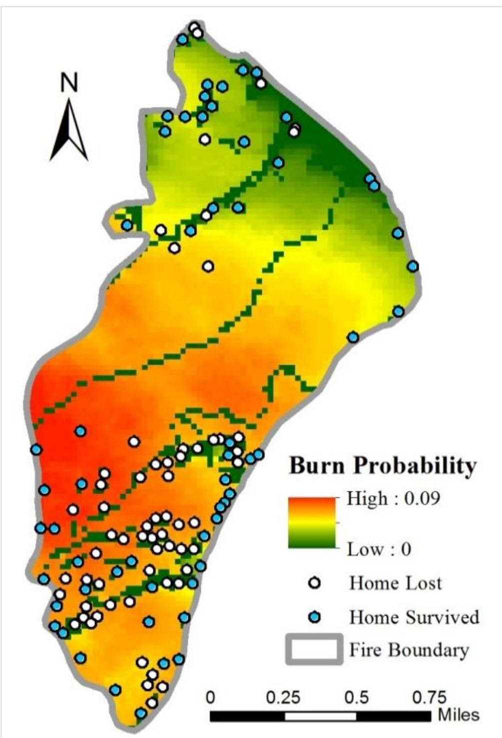

Figure 3. Burn probability detail of burn area.

Overall there were more homes lost as BP increased (Table 2). A one-tailed t-test was performed to test if the mean values for BP were significantly greater for homes with loss than homes without loss. BP was significant (p = 0.013).

The homes were clustered in two areas of the Charlotte Fire (Figure 4). There were 37% more homes lost in the southern boundary of the fire and 82% fewer homes were lost in the northern boundary (Table 3).

Table 2. BP value percent difference between homes with and without loss.

BP Value	Loss	No Loss	Difference
0 - .025	13	12	8%
.026 - .050	15	19	24%
.050 - .075	28	24	15%
.076 - 1	5	4	22%

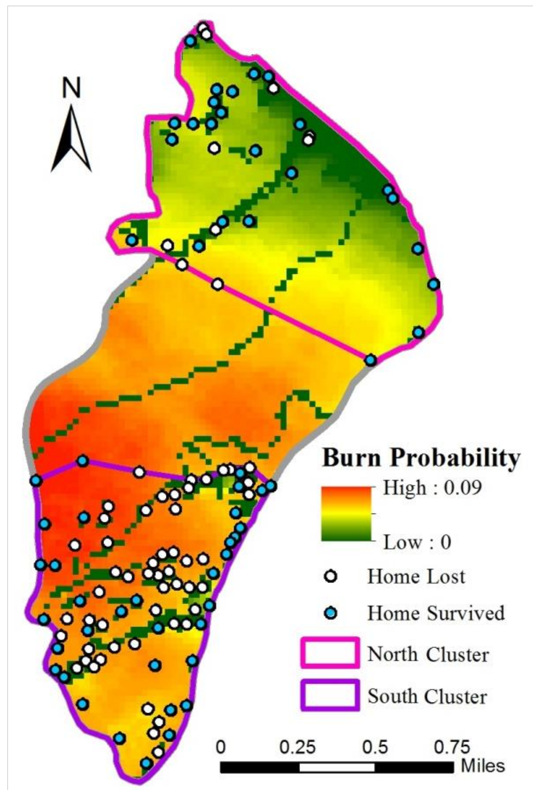

Figure 4. Home north and south clusters.

Table 3. Home quantities and percent difference between homes with and without loss, grouped into clustered areas.

	North Cluster	South Cluster
Loss	10	51
No Loss	24	35
Difference	82%	37%

Conditional Flame Length

The Conditional Flame Length (CFL) is a measure of conditional wildfire intensity. Fire Intensity Levels (FILs) are used to create the CFL. FIL is a measure of fire behavior and base flame length at a point on the landscape. There are 6 intensity levels which increase in 2 foot increments for each level (Table 4). A Flame Length Probability (FLP) gridded text file contains information about the burn probability and FILs for each x and y coordinate. The ArcFuels tool bar was used to convert the FlamMap FLP text file into a point shapefile, and then into raster format. For further analysis of CFL means, the ArcMap Zonal Statistics Table tool was utilized. The following equation was used to calculate CFL within FlamMap:

$$\mathbf{CFL = \sum (BP_i/BP)\,(F_i)}$$

Where:
BP_i is the probability of a fire at the i^{th} flame length category, BP is the burn probability, and F_i is the flame length midpoint of the i^{th} FIL category.

Table 4. Fire intensity level descriptions.

Fire Intensity Level	Flame Length Range (in feet)
1	0 - 2
2	2 - 4
3	4 - 6
4	6 - 8
5	8 - 12
6	12 +

Results of the CFL mean data showed similar quantities of homes with and without loss in each of the CFL ranges (Table 5). Highest CFL ranges were located within the center of the Charlotte Fire boundary (Figure 5). A one-tailed t-test was performed to test if the mean CFL values were significantly greater for homes with loss than homes without loss. CLF was not statistically significant (p = 0.087). T-test results illustrate the BP mean difference was greater for homes with loss than homes without loss, whereas the CFL mean difference was not significantly greater for homes with loss.

Table 5. CFL differences between homes with and without loss.

CFL Value	Loss	No Loss	Difference
0 - 2	14	10	33%
2.1 - 4	22	24	9%
4.1 - 6	21	24	13%
6.1 - 8	4	1	120%

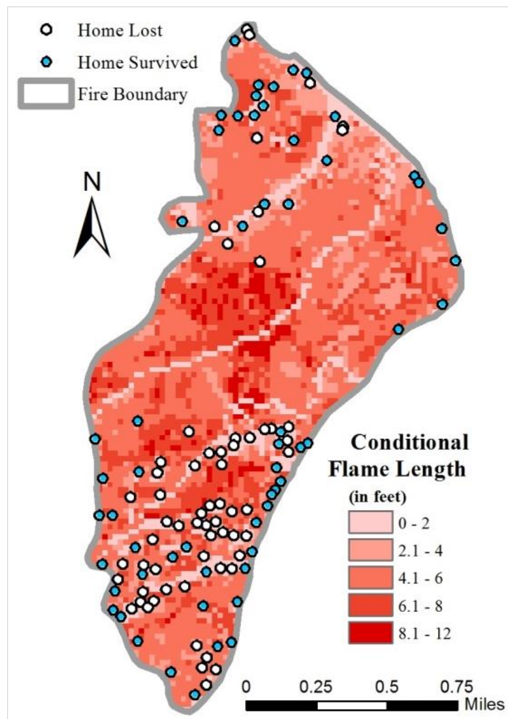

Figure 5. Conditional flame length of the Charlotte Fire area.

Exposure Analysis Scatter Plot

Scott *et al.* (2013) expressed an exposure analysis is an assessment of wildfire hazard-likelihood (BP) and intensity (CFL) where HVRAs are located. Combining these fire modeling outputs with HVRA locations is a critical step in developing wildfire risk mitigation strategies (Scott *et al.*, 2013). Scatter plots are a way to visualize an exposure analysis for individual HVRAs (WWETAC, 2014). Therefore, a scatter plot was used to visualize exposure risk to structures, using CFL along the y-axis and BP along the x-axis (Figure 6). The scatter plot illustrates the CFL and BP means are similar in range, but greater for homes with loss.

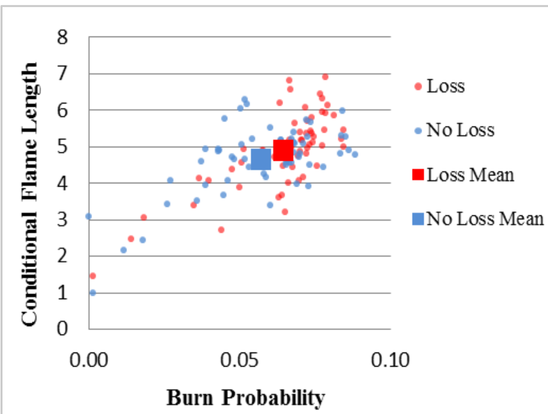

Figure 6. Scatter plot showing the results of each home's exposure to wildfire by its mean conditional flame length and burn probability.

Individual Datasets Analyzed

The exposure analysis was formed from 8 raster datasets including information on topography, surface, and canopy fuels. The 45.7 m home buffer was also used to calculate the mean statistics of each input dataset. A one-tailed t-test was used to test for significant differences in the slope and canopy characteristics. The Chi-Square test was used to analyze the categorical data within the aspect and surface fuel datasets.

Topography Data Analyses

Topography influences the likelihood and spread of wildfire. Slope means were gathered for each of the 120 homes affected by the Charlotte Fire. These were then tested for statistical significance between homes with and without loss.

Slope

Percent of slope influences fire behavior. The National Wildland Fire Behavior Group (NWFBG, 2008) state fires burn more rapidly uphill than downhill. This is because fuels above the fire are brought into closer contact with upward moving flames (NWFBG, 2008). Steep slopes also present the problem of burning material rolling down-hill and igniting fuel below the main fire (NWFBG, 2008). Fires on flatter slopes are more influenced by fuels and wind (NWFBG, 2008).

Results from the one-tailed t-test showed that slope was statistically greater for homes with loss than without loss (p = 0.028). The slope mean of homes with loss was 10.5%, while homes without loss had a mean of 9.6%. Overall, there were more homes with loss as slope increased (Figure 7).

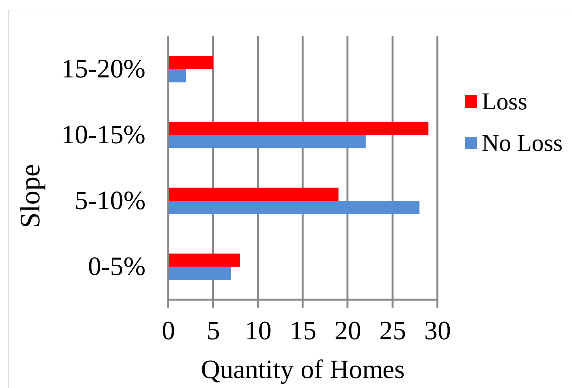

Figure 7. Quantity of homes and slope. Illustrating there were more homes with loss with increased slope.

Aspect Analysis

Slope aspect affects slope exposure to the sun. South and southwest slopes are more exposed to sunlight and generally have lighter and sparser fuels, higher temperatures, lower humidity, and lower fuel moisture (NWFBG, 2008). Therefore, according to the NWFBG (2008), in wildfire analysis southern slopes are considered to be of higher risk to wildfire than northern slopes and are most critical in terms of start and spread of wildland fires (NWFBG, 2008). North facing slopes have more shade which causes heavier fuels, lower temperatures, higher humidity, and higher fuel moistures (NWFBG, 2008). As a result, the NWFBG (2008) expresses north facing aspects will have less fire activity than a south facing slope.

The LANDFIRE aspect raster is divided into 8 different aspect ranges (Figure 8). Each range indicates which direction a raster cell's slope faces. To assess whether aspect may impact home loss, a Chi-Square test was performed. For a Chi-Square test there needed to be more than 5 expected homes in each category. There were fewer than 5 homes in 4 of the 8 aspect ranges. Therefore the homes were grouped into only northern or southern aspects. Northern aspects were ranges greater than 270° or less than 90°. Southern aspects were between 90° and 270°. In northern aspects there were 24 homes without loss and 13 with loss. In southern aspects there were 35 homes without loss and 48 with loss (Figure 9). The test only compared two classes, as a result the Yates correction for continuity was applied. The calculated critical value of the Chi-Square test was 4.406, which is greater than the 3.841 critical value at a 5% significance level for 1 degree of freedom. Therefore, test results illustrated that northern and southern aspects were not significantly different between homes with and without loss.

Fuel Data Analyses

The LANDFIRE fuel data describes the composition and characteristics of canopy and surface fuel (Wildland Fire Science, 2010). Each canopy characteristic was statistically analyzed using the one-tailed t- test assuming there was greater fire risk with an increase in canopy fuel. The four canopy datasets included canopy cover, canopy height, canopy base height, and canopy bulk density. Canopy data were present for areas with existing vegetation types that are forest and woodland (Wildland Fire Science, 2010).

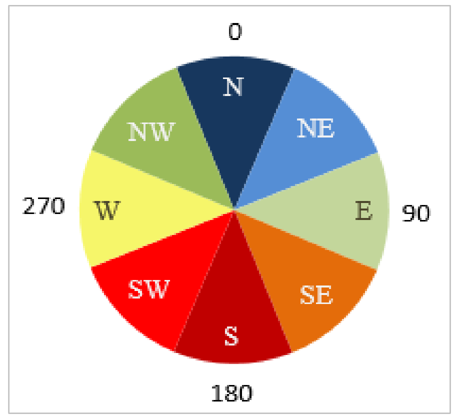

Figure 8. Hot to cool aspects are represented by a color gradient from red to blue.

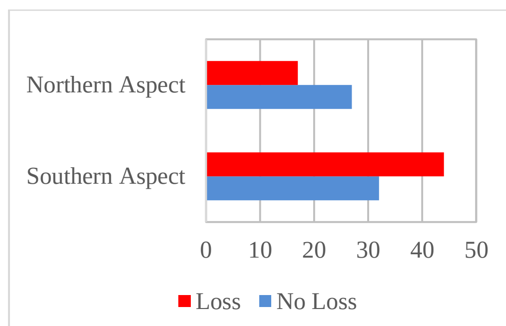

Figure 9. Illustrates a greater quantity of homes with loss that resided in southern aspects.

The Chi-Square test was used to analyze the categorical surface fuel data. Any areas without canopy characteristics are considered surface fuel areas which are covered as burnable biomass within the fuel model data (Wildland Fire Science, 2010). The Wildland Fire Science (2010) expressed for areas with young or short conifers the burnable biomass is represented as shrub type within the surface fuel model.

Canopy Fuel Analyses

In fire behavior fuel models, canopy characteristics are used to compute shading, wind reduction factors, spotting distances, crown fuel volume, spread characteristics of crown fires and incorporate the effects of ladder fuels for transitions from a surface to crown fire (Wildland Fire Science, 2010).

When the canopy raster dataset was compared to 1 meter NAIP imagery, the canopy coverage appeared to be largely underrepresented (Figure 10). Vegetated areas that were not covered by canopy raster data were represented within the surface fuel dataset to predict wildfire.

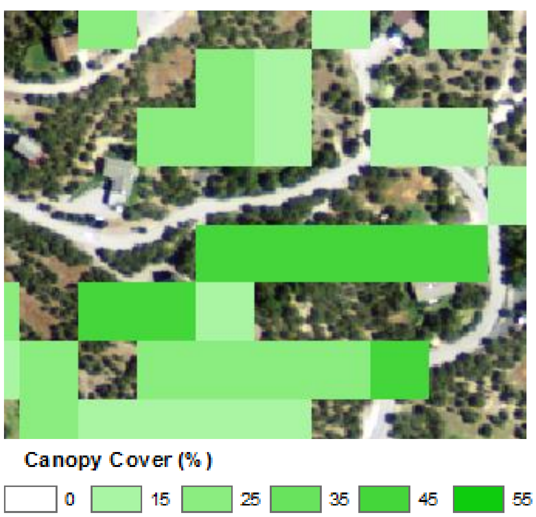

Figure 10. Dense juniper canopy as seen in the NAIP imagery is underrepresented in the LANDFIRE canopy data.

Canopy Cover

Canopy cover (CC) describes percent cover of tree canopy in a stand (Wildland Fire Science, 2010). The values of canopy cover are class midpoints of a range, as shown below:

0 = Non-forested vegetation
15 = Forest cover 10% <= and < 20%
25 = Forest cover 20% <= and < 30%
35 = Forest cover 30% <= and < 40%
45 = Forest cover 40% <= and < 50%
55 = Forest cover 50% <= and < 60%
65 = Forest cover 60% <= and < 70%
75 = Forest cover 70% <= and < 80%
85 = Forest cover 80% <= and < 90%
95 = Forest cover 90% <= and <= 100%

The one-tailed t-test results indicated that canopy cover was greater between homes with loss versus homes without loss ($p = 0.033$). The mean difference was 2.06. Homes with loss had a CC mean of 7.7%, and homes without loss had a CC mean of 5.64%.

Canopy Height

Canopy height (CH) describes the average height of the top of the canopy for a stand (Wildland Fire Science, 2010). The units are in meters. Actual CH values were multiplied by 10 for fire modeling purposes. CH classes are represented as midpoints of a range:

0 = Non-forested vegetation (0)
2.5 = 0 < CH < 5 meters (25)
7.5 = 5 <= CH < 10 meters (75)
17.5 = 10 <= CH < 25 meters (175)
37.5 = 25 <= CH < 50 meters (375)
50.0 = CH >= 50 meters (500)

One-tailed t-test results indicated canopy height was statistically greater for homes with loss versus homes without loss ($p = 0.013$). Final mean results were represented in actual and not weighted CH values. The mean difference was 1.86 m. Homes with loss had a mean CH of 4.87 m, and homes without loss had a mean CH of 3.01 m.

Canopy Bulk Density

Canopy bulk density (CBD) is defined as the mass of available canopy fuel per unit canopy volume that would burn in a crown fire (Wildland Fire Science, 2010). CBD data values:

0 - 0.44 kg m-3 (0 - 44)
0.45 = all values > 0.45 kg m-3 (45)

Not all species were used for computing plot-level CBD (Wildland Fire Science, 2010). For example, all Acer and Populus spp. were excluded from the canopy fuel profile as these and other broadleaved species are considered relatively inflammable and therefore unavailable (Wildland Fire Science, 2010). Some stands dominated by broadleaf species, which typically do not permit initiation of crown fire (e.g. Populus spp.), are coded with a CBD of 0.01 kg m-3 (Wildland Fire Science, 2010). Only 1.3% of the Charlotte Fire area was estimated to be broadleaf species. Since crown fire is rarely observed in most hardwood stands, the lowest CBD value possible was used to prevent false simulation of crown fire in these areas (Wildland Fire Science, 2010).

One-tailed t-test results indicated CBD was not statistically greater for homes with loss versus homes without loss ($p = 0.299$). Final mean results were represented as actual and not weighted CBD values. The mean difference was 0.0028 kg m-3. Homes with loss had a CBD mean of 0.033 kg m-3, while homes without loss had a CBD mean of 0.030 kg m-3.

Canopy Base Height

Canopy base height (CBH) describes the lowest point in a stand where there is sufficient available fuel (=> 0.25 in dia.) to propagate fire vertically through the canopy (Wildland Fire Science, 2010). Specifically, CBH is defined as the lowest point at which the canopy bulk density is >= 0.012 kg m-3 (Wildland Fire Science, 2010). CBH supplies information used in fire behavior models to determine the point at which a surface fire will transition to a crown fire (Wildland Fire Science, 2010). CBH data values:

0 – 9.9 meters (0 - 99)
>= 10 meters or broadleaf trees (100)

The one-tailed t-test results indicated that CBH was not statistically greater for homes with loss versus homes without loss ($p = 0.472$). The mean difference was 0.01 m. Homes with loss had a CBH mean of 0.62 m, and homes without loss had a CBH mean of 0.61 m.

Surface Fuel Analysis

The surface fuel data represents distinct distributions of fuel loadings found among surface fuel components (live and dead), size classes, and fuel types (Wildland Fire Science, 2010). The fuel models are described by the most common fire carrying fuel type (grass, brush, timber litter, or slash), loading and surface area-to-volume ratio by size class and component, fuel bed depth, and moisture of extinction (Wildland Fire Science, 2010).

Total area of each surface fuel category was analyzed between homes with and without loss. Sixty-nine percent of the Charlotte Fire boundary was classified as FBFM2. Wildland Fire Science (2010) describes FBFM2 as “burns fine, herbaceous fuels, stand is curing or dead, may produce fire brands on oak or pine stands.” The FBFM2 class also had the most coverage within the

45.7m home buffer (Figure 11). The remaining 31% of the project area contained fuel classes FBFM1, FBFM5, FBFM8, FBFM9, Urban, and Agriculture.

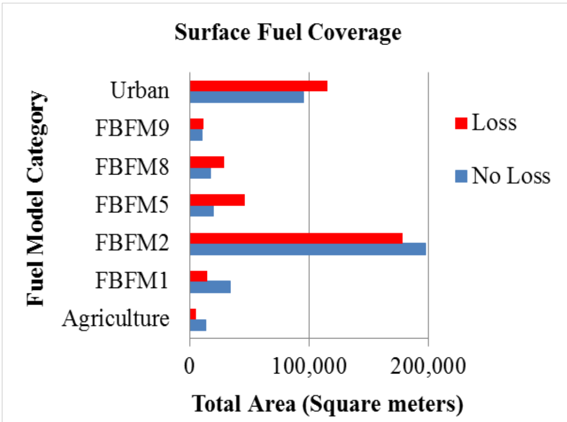

Figure 11. Surface fuel coverage within 45.7 m of homes with and without loss.

Homes with loss had 81% greater coverage for the surface fuel class FBFM5 and 51% greater coverage for FBFM8 (Table 6). FBFM5 represents low intensity fires, young, green shrubs with little dead material; fuels consist of litter from the understory. FBFM8 represents slow, ground burning fires, closed canopy stands with short needle conifers or hardwoods, litter consist mainly of needles and leaves, with little undergrowth, occasional flares with concentrated fuels.

Homes without loss had 87% more coverage in Agriculture and 80% more in FBFM1 (Table 6). FBFM1 represents surface fires that burn fine herbaceous fuels, cured and curing fuels, little shrub or timber present, primarily grasslands and savanna.

A Chi-Square test was performed in Microsoft Excel. Each surface fuel class intersecting a structure's 45.7 m buffer was summed using a pivot table in Excel. The Chi-Square function in Excel compared and computed the actual surface fuel model class counts per homes with and without loss to the calculated expected values of those counts. The test revealed there was not a significant difference between the fuel model categories of homes with or without loss (p = 0.10); however, the p value was close to 0.05, illustrating that the differences in surface fuel classes were close to being statistically significant. This was due to the high differences amongst agriculture, FBFM1, FBFM5, and FBFM8 fuel classes. However, there were not strong differences in FBFM2, FBFM9, and urban fuel classes (Table 6).

Table 6. Surface fuel coverage differences for homes with and without loss.

Fuel Model Class	Homes with Loss Area (Sq m)	Homes without Loss Area (Sq m)	Difference
Agriculture	5,209.8	13,150.8	86 %
FBFM1	14,480.8	33,853.9	80 %
FBFM2	178,011.2	197,033.0	10 %
FBFM5	46,063.0	19,502.0	81 %
FBFM8	28,765.6	17,101.9	51 %
FBFM9	11,255.5	10,261.3	9 %
Urban	115,409.2	95,192.8	19 %

Conclusion/Discussion

In summary, the one-tailed t-test illustrated that within the wildfire model, burn probability, slope, canopy cover, and canopy height were found to have greater means for homes with loss than without loss. These results supported the hypothesis that these wildfire characteristics did increase wildfire risk within the model as expected.

The one-tailed t-test illustrated conditional flame length, canopy bulk density, and canopy bulk height did not have statistically greater means for homes with loss than without loss. However, the canopy raster dataset underrepresented the actual juniper canopy present in the project area. As a result, the canopy fuel means were low for structures within the project area. Canopy fuel loading allows crown fires to spread faster according to Vaillant (2014), so it was assumed these variables would also increase wildfire risk to structures. The Chi-Square tests for surface fuel and aspect datasets revealed there were no significant differences within these classes between homes with and without loss. However, test results were close to being statistically significant. This could be seen in larger differences between four of the seven surface fuel classes and 31% more homes lost within southern aspects.

The model revealed issues in calculating wildfire risk to structures due to the urban layer and its zero burn probability. The amplified effect of the urban layer and linear elements such as roads was changed by buffering the home point file and masking the urban class when calculating the mean values of BP and CFL. The urban class strongly affected areas around roads and the north area of the fire boundary. There were 10 homes with loss in the north cluster of the Charlotte Fire, yet this area had low BP and CFL.

There are many variables influencing a structure's risk of wildfire as seen in the FlamMap model. Understanding limitations and complexity of wildfire modeling is important for GIS researchers and land and resource managers for constructive land management and city planning efforts to decrease the loss of structures at risk of wildfire. Exposure analysis models are often used to propose areas for defensible space programs or to make new development decisions. Defensible space is used to minimize a structure's risk to wildfire through creating distance between flammable fuels and the structure. This is achieved through vegetation removal, thinning, the use of non-flammable construction materials, and the location of stacked fire wood and propane.

As seen in the Charlotte Fire exposure analysis, areas close to urban environments are still at risk of wildfire and should be included within wildfire mitigation programs even though the model predicted low BP and CFL. In addition to understanding model limitations, future improvements in the scale of the data should lead to more accurate wildfire models and as a result, improve strategic and tactical planning to reduce structure loss and overall costs.

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