Wildland/Urban Interface Fire Susceptibility and Communities at Risk:

A Joint Fire Modeling Project for Butte County, Idaho, Bureau of Land Management, Upper Snake River District GIS and Idaho State University GIS Training and Research Center

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Kerynn Davis

Keith Weber, webekeit@isu.edu

ABSTRACT

Wildland/Urban Interface (WUI) fires and Communities at Risk (CAR) projects are high priorities to federal land management agencies. It is important that the federal government help educate homeowners, firefighters, local officials, and land managers regarding susceptibility to wildland fire. The Bureau of Land Management's (BLM) Upper Snake River District (USRD) Geographic Information Systems (GIS) team and the GIS Training and Research Center (GIS TReC) at Idaho State University (ISU) have created models to predict potential wildfire susceptibility areas for Butte County, Idaho. During this project, models were created of specific individual susceptibility associated with wildfires: topography, fuel load, and the number of structures vulnerable to wildland fire. These models were evaluated together to create a final fire susceptibility model for Butte County, Idaho. This report describes each of the WUI fire susceptibility components and what affect each has on the final fire susceptibility model. The final model is an accurate depiction of the spatial distribution of wildfire susceptibility in Butte County and can be used by regional fire managers to manage wildfire susceptibility.

KEYWORDS

Fire, Wildfire, GIS, Butte County, Idaho, BLM, Fire Regime, Slope, Aspect, Fuel Load

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INTRODUCTION

The Wildland/Urban Interface (WUI) is more than a geographic area. It is anywhere homes and other anthropogenic structures exist among flammable vegetative fuels (Owens and Durland, 2002). Because wildland fire is an essential component of healthy ecosystems, people need to live compatibly with wildland fire (Owens and Durland, 2002). As people move into the Wildland/Urban Interface zones, planners and agencies responsible for fire management and protection are in need of tools to help them assess fire susceptibility and make decisions regarding funding, development, and deployment of suppression resources. One valuable tool used by fire managers is Geographic Information Systems (GIS). GIS allows for spatial analysis of large geographic areas and is easily integrated with remote sensing (satellite imagery). Using both GIS and remote sensing, a Wildland/Urban Interface (WUI) Fire Susceptibility model was created. It is comprised of seven component models that describe various aspects of fire susceptibility. These component models are generally organized as topography, fuel load, and structure density models.

- **Aspect: Sun Position –** takes into account varying fire susceptibility associated with aspect, especially as it relates to desiccation effects.
- **Slope: Rate of Spread** – translates how the steepness of a surface affects the rate of spread of a fire.
- **Slope: Suppression Difficulty** – takes into account how varying slope influences suppression efforts by firefighters and their equipment.
- **Fuel Load: Intensity** – describes how different fuel load classes release heat energy during a fire and thereby affect their environment.
- **Fuel Load: Rate of Spread** – describes how different fuel types spread and affect fire susceptibility.
- **Fuel Load: Vegetation Moisture** – takes into account how different levels of vegetation moisture affect fire susceptibility. It improves the fuel load components by accounting for moist vegetation, which may be abundant but not readily flammable.
- **Structure Vulnerability** – includes the density of man-made structures.

Each of the component models are weighted and summed to produce the Final Fire Susceptibility Model. The Butte County, Idaho WUI fire susceptibility assessment is a continuation of WUI projects that have been completed and validated.

METHODS

GIS Data Sets:

- Digital Elevation Model (DEM) of Butte County
- Landsat 5 TM imagery for Butte County and environs – Imagery used for this project was acquired in June-July, 2009.
- 2009 National Agriculture Imagery Program (NAIP) images for Butte County acquired June, 2009
- Structure density raster layer was based on structures visible in the Butte County 2009 NAIP imagery.

DATA ACQUISITION AND PREPARATION

ELEVATION DATA

The DEM data for Butte County was obtained from Idaho State University (ISU) GIS Center's Spatial Library. Through the use of ArcMap 9.3.1 these data were used to produce the aspect and slope fire susceptibility component models. These models were created using pixels with 30 meter spatial resolution.

LANDSAT IMAGERY

- Landsat 5 TM multi-spectral imagery was used (Path 39, Row 29, acquired July 23, 2009, Path 39, Row 30, acquired July 23, 2009, Path 40, Row 29, acquired June 28, 2009, Path 40, Row 30 acquired July 30, 2009, Path 41, Row 29, acquired July 21, 2009, and Path 41, Row 30, acquired July 21, 2009). The Landsat Imagery was ordered from the USGS, via the EROS Data Center's website.

OTHER DATASETS

The Butte County boundaries and roads datasets were downloaded from the Inside Idaho website. The Butte County boundary was selectively saved as a separate shapefile and re-projected to IDTM-83. The roads dataset was masked to include only the roads within Butte County using the county boundary mentioned above as the mask.

Data Processing:

The WUI fire susceptibility model consists of seven component models that can be categorized as follows:

- Topography
  - Slope
    - *Suppression difficulty*
    - *Rate of spread*
  - Aspect
    - *Sun position*

- Fuel Load
  - *Rate of Spread*
  - *Fire Intensity*
  - *Vegetation Moisture*
- • Structure
  - *Structure Density (structure vulnerability)*

Each component model was treated separately to learn how each affected fire susceptibility. In order to evaluate the fire susceptibility contribution of each component model made, we normalized the value range using a scale from 0 to 1000, where 1000 indicates the highest susceptibility. For each component model (except the Structure Density) we normalized using weightings described in Mattsson *et al*. (2002) and Jansson *et al*. (2002) to complete our analysis. After completing these analyses, we examined the impact each fire model component had on the overall fire susceptibility in Butte County, Idaho.

Topographic Sub-Model Components

Creating the Topographic: Slope: Suppression Difficulty Component Model

Using the Butte County DEM as input, a slope grid was calculated using Idrisi. The resultant pixel values equate to the slope of the DEM at that point. The output pixel value unit of the grid was expressed in degrees of slope, the z-factor was 1 and the output cell size was 30 meters. To create the Slope: Suppression Difficulty Component model, the slope model created above was used and applied weightings for Slope: Suppression Difficulty following Mattsson *et al*. (2002) (table B-6 in Appendix B) using Idrisi (Reclassify) as shown in Figure 1.

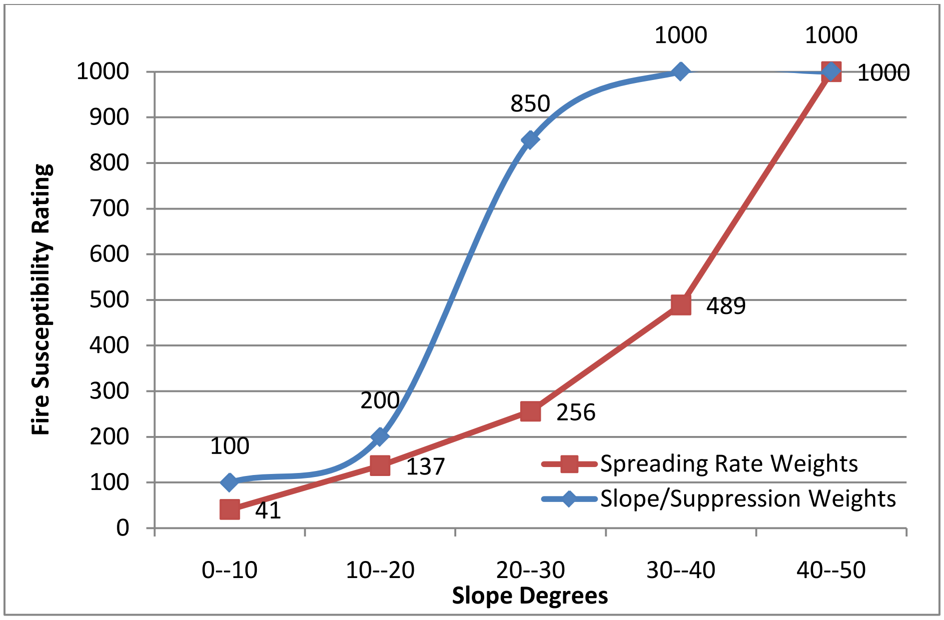

FIGURE 1 - WEIGHTING FOR SLOPE/SUPPRESSION DIFFICULTIES DESCRIBE HOW SUPPRESSION IS IMPACTED BY THE ANGLE OF SLOPE. WEIGHTING FOR SPREADING RATE DESCRIBE HOW SPREADING RATES INCREASE WITH ANGLE OF SLOPE. (MATTSSON ET AL, 2002)

CREATING THE TOPOGRAPHIC: SLOPE: RATE OF SPREAD COMPONENT MODEL

To create the Slope: Rate of Spread sub-model, we reclassified the Slope model based on weightings from Mattsson *et al.* (2002) using Idrisi (Reclassify) (Figure 1). These weightings are shown in table B-5 in Appendix B.

CREATING THE TOPOGRAPHIC: ASPECT SUN POSITION

Aspect indicates the horizontal *direction* of an instantaneous surface face. Using the Butte County DEM as input, an aspect layer was calculated using Idrisi. The resultant pixel values equate to the angular horizontal direction of the DEM surface at that point. Output units were degrees (where 0 is north, 90 is East, etc.) and the output cell size was set to 30 meters.

To create the Aspect: Sun Position component model, we reclassified the aspect layer, following Mattsson *et al.* (2002) (table B-7 in Appendix B) using Idrisi (Reclassify) (Figure 2).

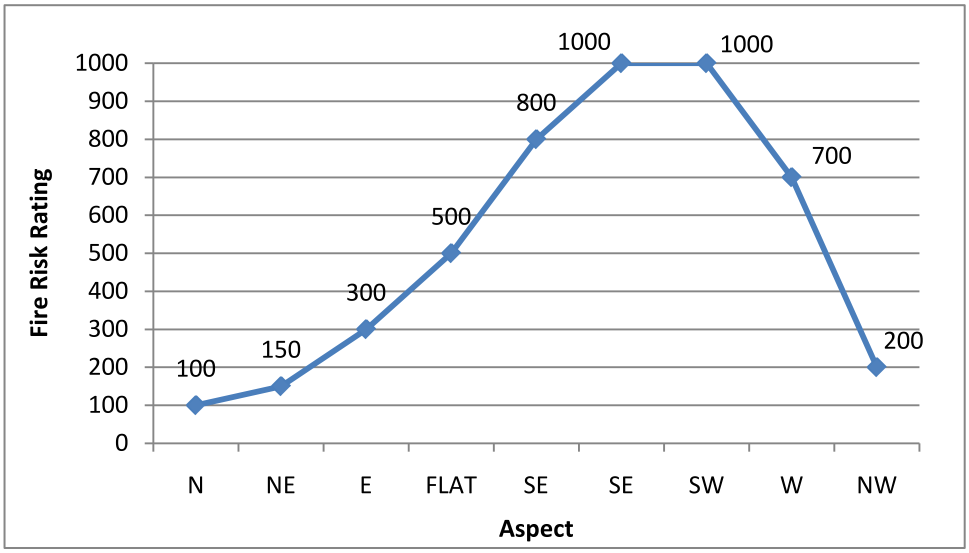

FIGURE 2. WEIGHTINGS FOR ASPECT/SUN POSITION DESCRIBE HOW THE SUN DESICCATES THE GROUND AT DIFFERENT ASPECTS (MATTSSON ET AL, 2002).

Fuel Load Sub-model Components:

Creating the Fuel Load Fire Susceptibility Components

The fuel load fire susceptibility components were derived from fuel load estimates and a Normalized Difference Vegetation Index (NDVI) layer calculated from Landsat 5 TM satellite imagery. The proportion of photosynthetically active vegetation found within each 30 x30m pixel was estimated using NDVI. NDVI uses band 3 (visible red) and band 4 (near infrared) from imagery that has been corrected for atmospheric effects. This pre-cursor correction is accomplished using Idrisi's ATMOS tool and original Landsat imagery with pixel DN values given in raw or radiance format. NDVI is then calculated using Idrisi's VegIndex tool. The resulting NDVI has an interval of -1 to +1, where -1 is no vegetation and +1 is pure photo-synthetically active vegetation. The following equation was used to create the NDVI layer:

$$NDVI = \frac{Band\,4 - Band\,3}{Band\,4 + Band\,3}$$

Equation 1. *Equation for calculating NDVI.*

The PCA (Principal Components Analysis) was created using Idrisi (Image Processing → Transformations → PCA). This produced 4 components. PCA components 1, 2, and 3 were used in subsequent analysis and classification.

Classification Tree Analysis (CTA) of Landsat imagery was conducted using Idrisi to estimate fuel load in Butte County. To estimate fuel load, we used 322 fuel load estimates taken throughout the three Landsat scenes. These estimates (ground truth sites) were the result of field sampling during the late summer of 2009. The full sample points dataset was subset so that 50% of the samples within each fuel load class (1-4; table 1) were selected. One of the sub-samples were used as training sites within the Idrisi CTA tool (n = 161) and the other sub-sample (n = 161) was used for independent validation. Each 30 x 30m pixel of the Landsat imagery was was classified into a fuel load layer using four fuel load classes (Table 1).

TABLE 1 - FUEL LOAD CLASSES

Fuel Load Class	Description
1	0 tons/acre (No vegetation)
2	<2 tons/acre (Grassland with some Sagebrush)
3	2-6 tons/acre (Low and Typical Sagebrush)
4	>6 tons/acre (Forest)

The CTA procedure used all atmospherically corrected Landsat imagery bands (bands 1-5, and band 7), the NDVI layer, an MSAVI2 layer, and three topographic layers (elevation, slope, and aspect). We validated the predictions of the model using techniques described in the next section “Fuel Load Model Validation”.

Fuel Load Model Validation

The fuel load model was validated using the following methodology. A standard error matrix where each predicted (modeled) class was compared against the measured (field) class at all sample point locations (n = 161). A Kappa statistic was also calculated to serve as an indicator of how much better or worse our classification performed compared to a purely random classification.

Fuel Load/Vegetation Moisture

The Fuel Load/Vegetation Moisture component incorporates the fuel load model and NDVI layer. The fuel load layer (described above) was reclassified (to values 0, 1, 4, and 6) using Idrisi (Reclassify) as described in Table B-1 (Appendix B).

A vegetation moisture layer was created through reclassification of the NDVI grid using Idrisi (Reclassify) to delineate wet vegetation (NDVI > 0.60), dry vegetation (NDVI = 0.15 to 0.60), and no vegetation (NDVI < 0.15) also described in Table B-1 of Appendix B.

The Fuel Load/Vegetation Moisture layer was created by multiplying the fuel class values with the vegetation moisture class values using Idrisi's Image Calculator tool and then reclassified as described in Table B-2 of Appendix B (Figure 3).

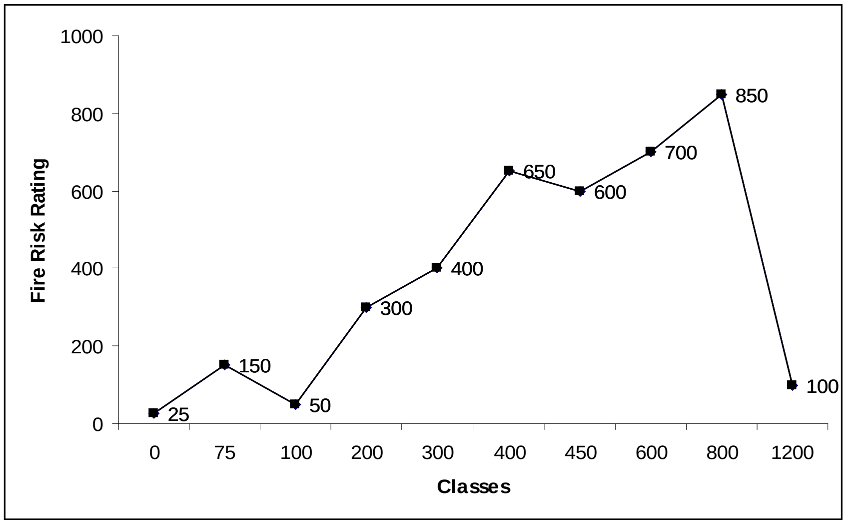

FIGURE 3 - WEIGHTINGS FOR FUEL LOAD/ VEGETATION MOISTURE (JANSSON ET AL, 2002).

FUEL LOAD: RATE OF SPREAD COMPONENT MODEL

The fuel load-derived Rate of Spread component model was created by a reclassification of the fuel load layer, following Mattsson et al. (2002) (Table B-3 in Appendix B), using Idrisi (Reclassify) (Figure 4).

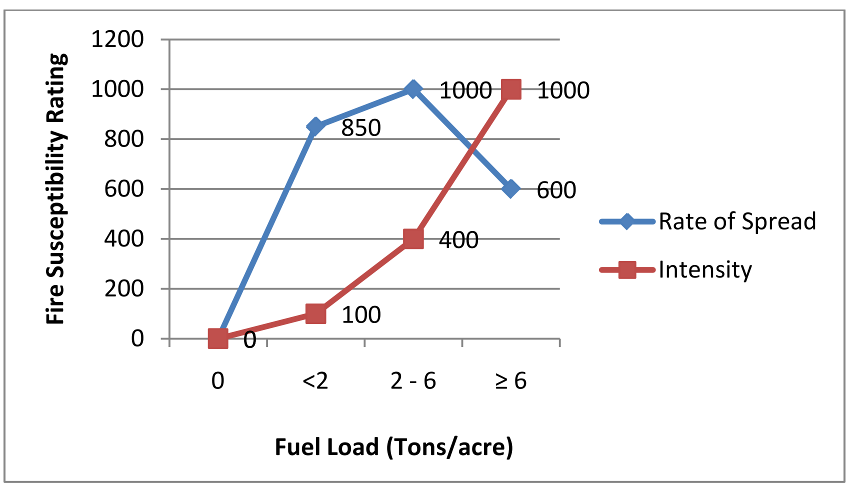

FIGURE 4 - WEIGHTINGS FOR FUEL LOAD/RATE OF SPREAD AND FUEL LOAD/INTENSITY (MATTSSON ET AL, 2002).

Fuel load: Fire Intensity Component Model

The fire intensity component model was derived by a reclassification of the fuel load layer, using values following Mattsson *et al*. (2002) (Table B-4 in Appendix B) (Figure 4).

Structure Sub-Model Components:

Structure Vulnerability Component Model

To create the Structure Vulnerability sub-model we used 2009 NAIP aerial imagery for Butte County. The imagery was systematically searched and each building or structure that was visible within the imagery was digitized as a point feature within ESRI's ArcGIS. A point density raster layer was then derived from this dataset. To make this component model consistent with the other sub-models, the range of pixel values was stretched to a range of 0 – 1000 with the areas having the highest structure density being given a fire susceptibility rating of 1000.

WUI Fire Susceptibility Model

After completing the above analyses, we examined the impact each fire model component had on overall fire susceptibility for Butte County, Idaho. The final fire susceptibility model was determined as a weighted average using Idrisi macro modeler and the 7 component models. The weight of each component is given in Table 2. The weights, like the curves used for each fire susceptibility component model were determined through expert knowledge of regional fire managers.

TABLE 2 - COMPONENTS AND WEIGHTS OF THE FINAL FIRE SUSCEPTIBILITY MODEL

Component	Description	Percentage
Aspect	Sun position	5%
Slope	Rate of Spread	17%
Slope	Suppression Difficulties	11%
Fuel load	Vegetation Moisture	11%
Fuel load	Rate of Spread	17%
Fuel load	Fire Intensity	17%
Structures	Structure Vulnerability	22%

RESULTS:

Table 3 shows the results of the fuel load validation analysis. The overall Kappa statistic was determined to be 0.71 indicating that the classification was approximately 71% better than chance. The NDVI layer used with the fuel load model to produce the vegetation moisture sub-model is shown in Figure 5.

TABLE 3- ERROR MATRIX FOR THE FUEL LOAD MODEL.

		Field Measurement (tons/acres)					
		0	**<2**	**2-6**	**>6**	**Total**	**User Accuracy**
	0	36	0	4	2	**42**	86%
Modeled Fuel	**<2**	1	27	3	0	**31**	87%
(tons/acre)	**2-6**	2	13	19	5	**39**	49%
	>6	1	0	4	44	**49**	90%
	Total	**40**	**40**	**30**	**51**	**161**	**Overall Accuracy**
	Producer's Accuracy	90%	67%	63%	86%		**78%**

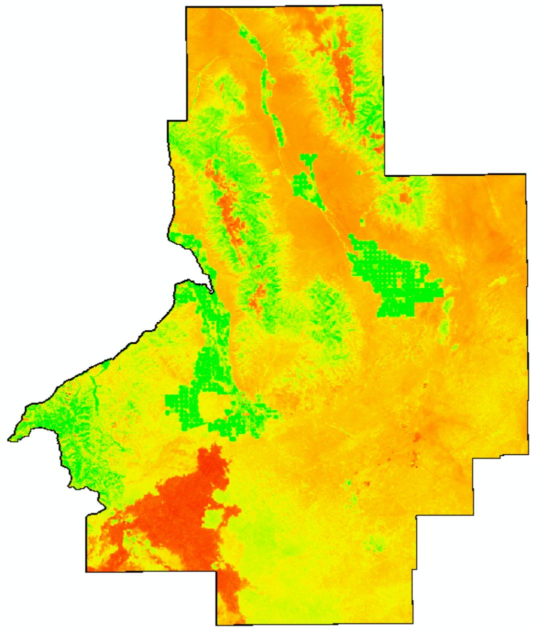

FIGURE 5 - THE NDVI INTERVAL RANGES FROM -1 TO +1 AND DESCRIBES AREAS PREDICTED TO HAVE NO VEGETATION (-1) TO AREAS OF HIGHLY PHOTOSYNTHETICALLY ACTIVE VEGETATION (+1).

The three component models derived from the fuel load model are shown in figures 6, 7, and 8. Figure 6 is the vegetation moisture component model where irrigated and riparian areas contain the lowest susceptibility values even though they may have relatively high fuel loads, while grasses and shrubs throughout Butte County contain the highest values. These high susceptibility areas are due to the low moisture content associated with sagebrush steppe rangelands that can dominate some areas. The effect of fuel load on a fire's rate of spread is shown in figure 7. Some areas with relatively high fuel loads contain lower susceptibility values, whereas grasses and shrubs contain higher rate of spread values. These high susceptibility areas are due to the high concentration of 2-6 tons/acre fuels which can carry fires quickly due to the frequent presence of cheatgrass or other fine fuel understories. Finally, figure 8 is a fire-intensity model. Coniferous forests in the highlands comprise the highest susceptibility and the most intense wildfires.

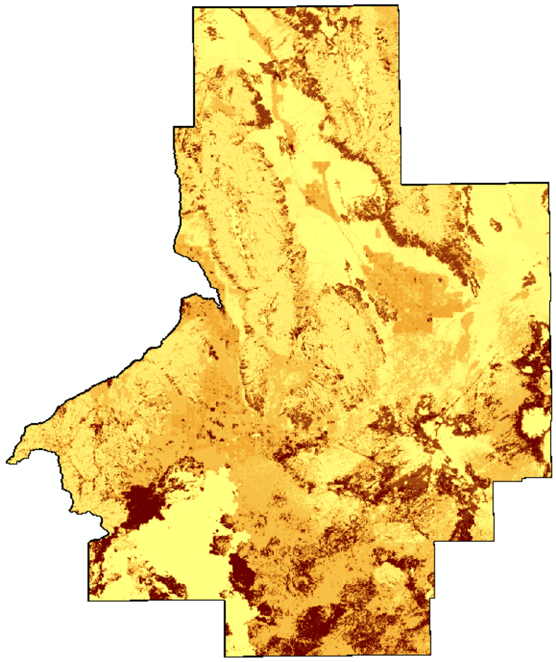

FIGURE 6 – FUEL LOAD - VEGETATION MOISTURE (darker colors indicate higher susceptibility)

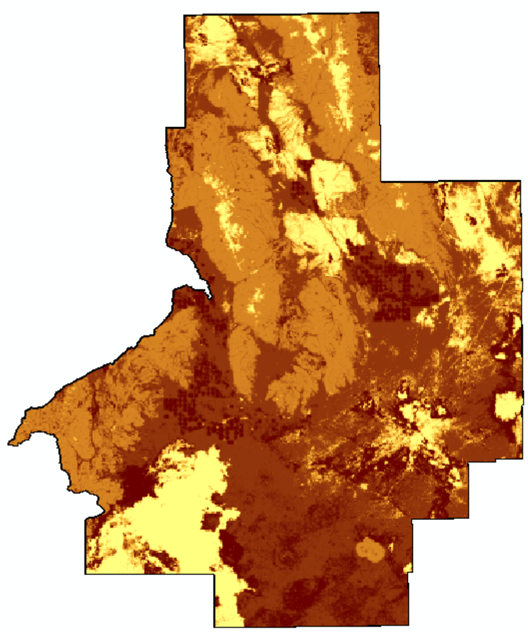

FIGURE 7-EFFECT OF FUEL LOAD ON FIRE'S SPREAD RATE (darker colors indicate higher susceptibility)

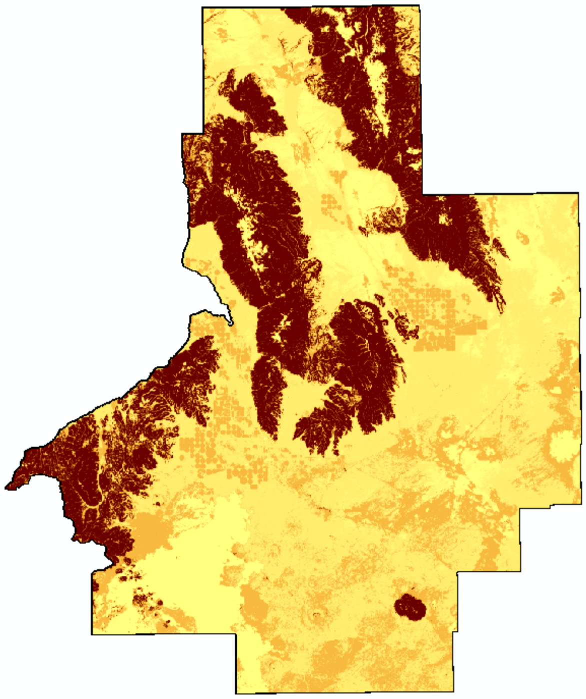

FIGURE 8 - FUEL LOAD/FIRE INTENSITY (darker colors indicate higher susceptibility)

Figures 9-11 illustrate the component models generated using the Butte County DEM. Figure 9 assesses the susceptibility of fires spreading quickly due to steep slopes. The steep slopes in Butte County are at the northern and western corners of the county. Next is the suppression difficulty model (Figure 10). Steeper slopes pose increasingly greater problems to fire fighters attempting to access fires in order to suppress them. Figure 9 and 10 appear to be identical where the locations of high suppression difficulty and high rate of spread are the same. Figure 11 is the Aspect: Sun Position component model. South and southwest aspects contain the highest fire susceptibility, due to the intense sunlight and prevailing wind exposure. North and east facing slopes, which are sheltered from intense sunlight and prevailing winds through much of the day, contain the lowest fire susceptibility.

Figure 12 is the Structure Density model built by heads-up digitizing all visible structures within the NAIP 2009 imagery. The highest structure density coincides with areas of highest urbanization.

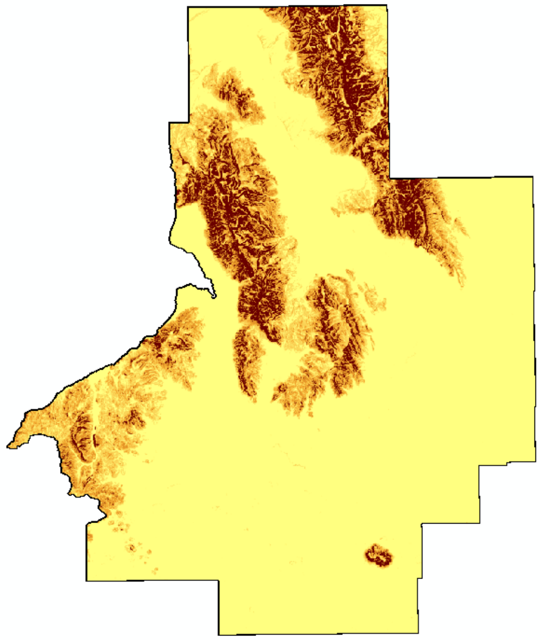

Figure 9 - Slope / Rate of spread (darker colors indicate higher susceptibility)

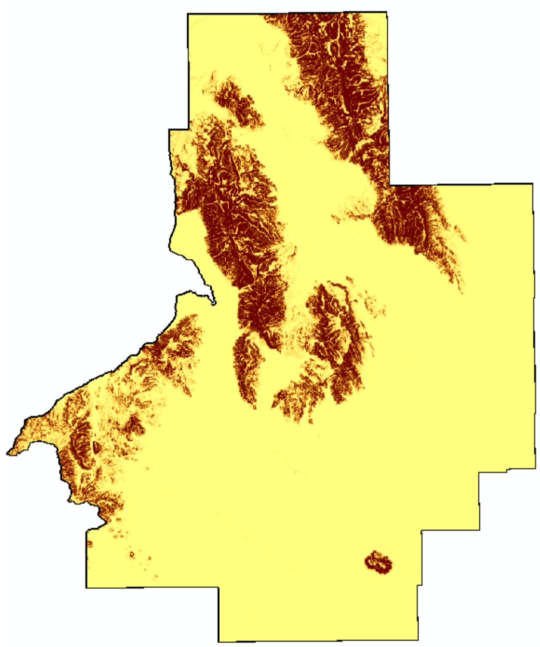

Figure 10 - The slope/Suppression Difficulty model. This model expresses how different slope angles affect (darker colors indicate higher susceptibility)

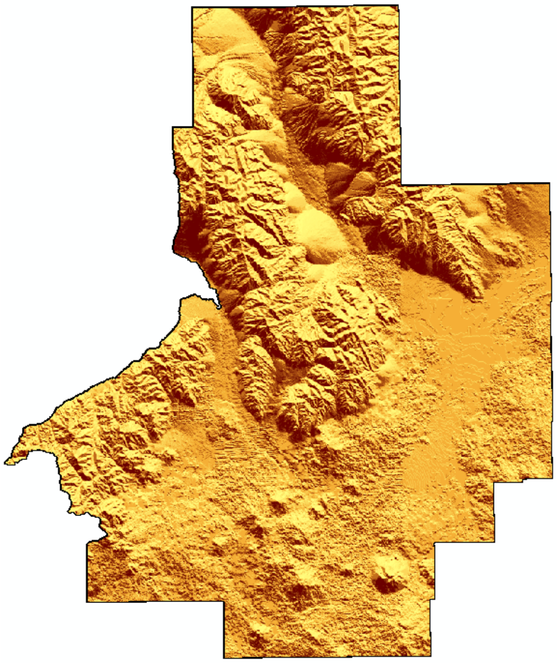

Figure 11 - The Aspect: Sun Position. This model expresses how different aspects affect fire susceptibility. (darker colors indicate higher susceptibility)

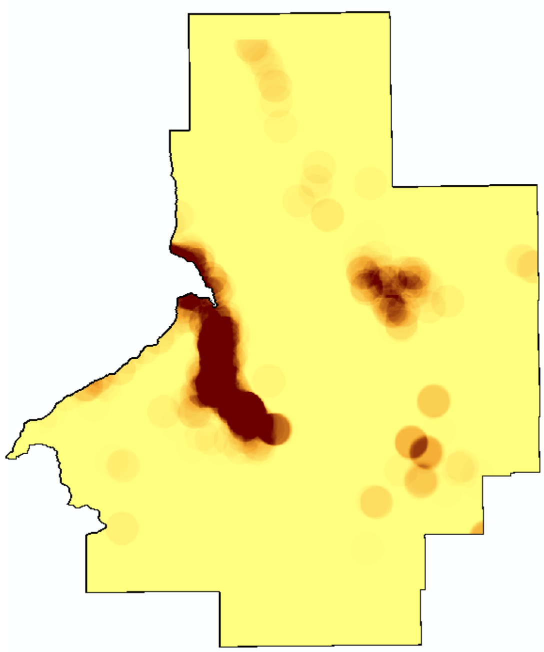

Figure 12 - The Structure Vulnerability model. This model expresses areas that are high susceptibility due to structure density. (darker colors indicate higher susceptibility)

The Final Fire Susceptibility Model for Butte County is generated with map algebra that includes the seven component layers using the weighting values shown in Table 2. The resulting model is shown in Figure 13.

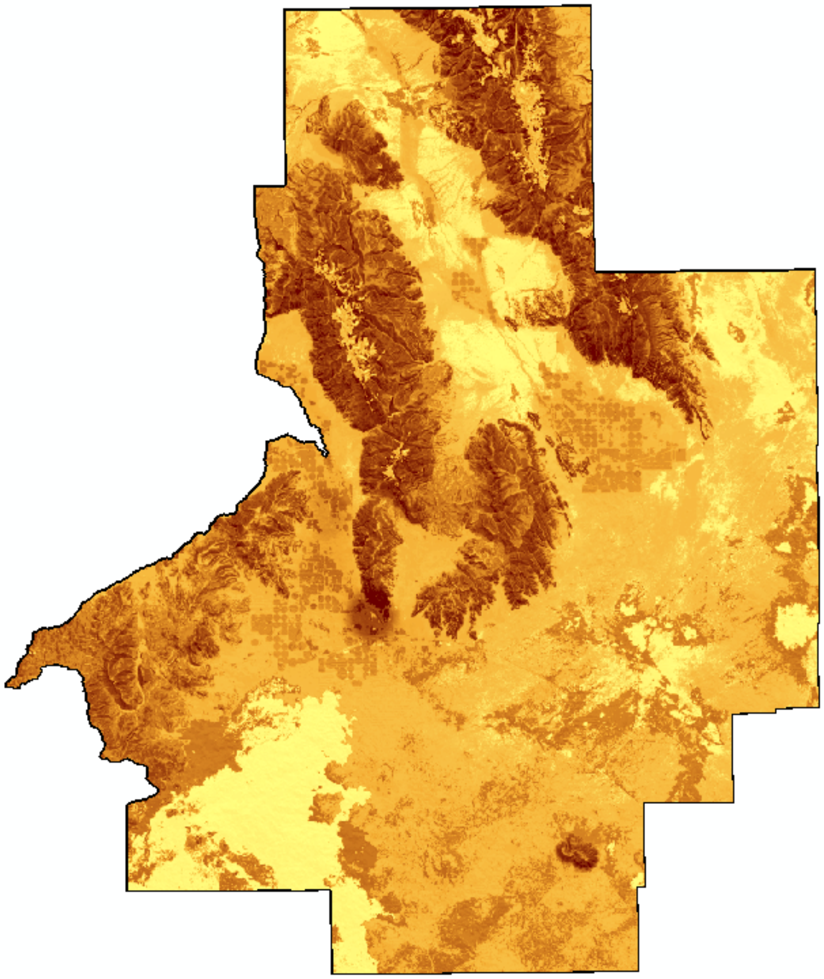

Figure 13 - The Final Fire Susceptibility Model for Butte County, Idaho (darker colors indicate higher susceptibility)

FIRE REGIME CONDITION CLASS

The Fire Regime Condition Class (FRCC) model is used to produce an alternative fire susceptibility model. There are 3 condition classes used in this study. The 3 condition classes are used with 5 fire regimes (Figure 14). The 5 fire regimes are essentially fuels models based upon the historic fire return interval at given area. The condition classes indicate what condition the area is in relative to its historic fire regime as it relates to fire return interval. (*Conran*, personal communication).

The 5 fire regimes are broken out based on a vegetation community's historic fire return interval and historic fire severity (stand-replacing or not). The fire regimes resemble fuel models because fire frequency and severity directly affect fuel loading. An FRCC of 3 can also indicate a fire regime that is non-standard due to too much fire (too many acres burned) which may be the result of cheatgrass invasions. The sagebrush-steppe of the Snake River Plain is a good example of a vegetation community that has had a dramatically increased fire return interval compared to the historic fire interval due to a continuous bed of cheatgrass (*Heide*, personal communication).

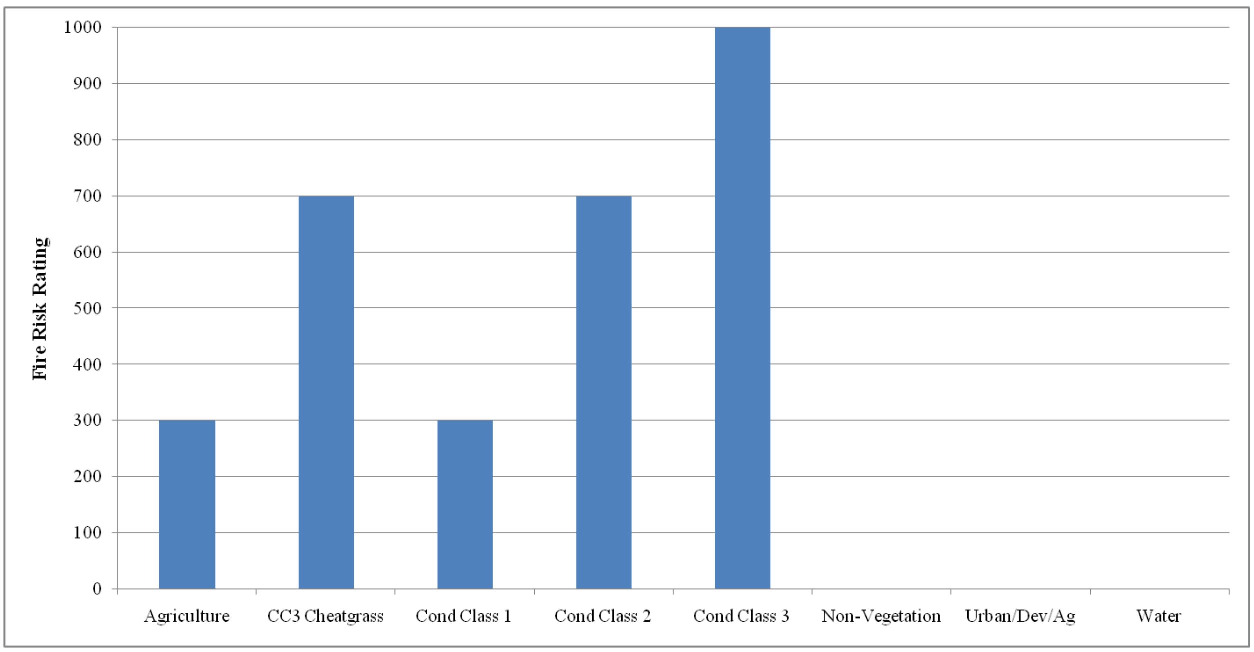

FIGURE 14 - FIRE SUSCEPTIBILITY RATINGS OF THE FIRE REGIME CLASSES.

In preparation for using the FRCC data provided by the BLM in an alternate Fire Susceptibility Model, each category was weighted from 0– 1000 (Figure 14). A FRCC sub-model was then constructed (Figure 15) as a component in the FRCC-based final WUI Fire Susceptibility Model. The Alternate Fire Susceptibility Model was created by substituting the FRCC sub-model in place of Fuel Load: Fire Intensity. The sub-model components and weights comprising the Alternate Fire Susceptibility model were multiplied by the weighting shown in table 4. The resulting values were then added to produce the Alternative FRCC Fire Susceptibility Model (Figure 16). A comparison of the two final models is illustrated in Figure 17 which depicts the difference (using standard deviations from the mean values) between the standard and FRCC models.

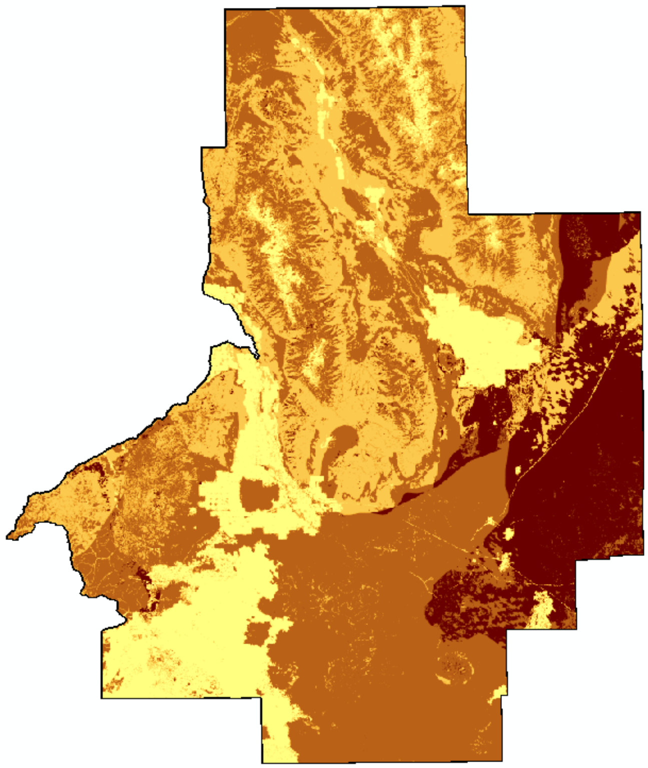

FIGURE 15 - THE FIRE REGIME CONDITION CLASS (FRCC) IS AN ALTERNATE FIRE SUSCEPTIBILITY MODEL.
(darker colors indicate higher susceptibility)

TABLE 4 - SUB MODEL COMPONENTS OF THE FIRE REGIME CONDITION CLASS ALTERNATE FIRE SUSCEPTIBILITY MODEL.

Component	Description	Percentage
Aspect	Sun position	5%
Slope	Rate of Spread	17%
Slope	Suppression Difficulties	11%
Fuel load	Vegetation Moisture	11%
Fuel load	Rate of Spread	17%
Fire Regime	Condition Class	17%
Structures	Structure Vulnerability	22%

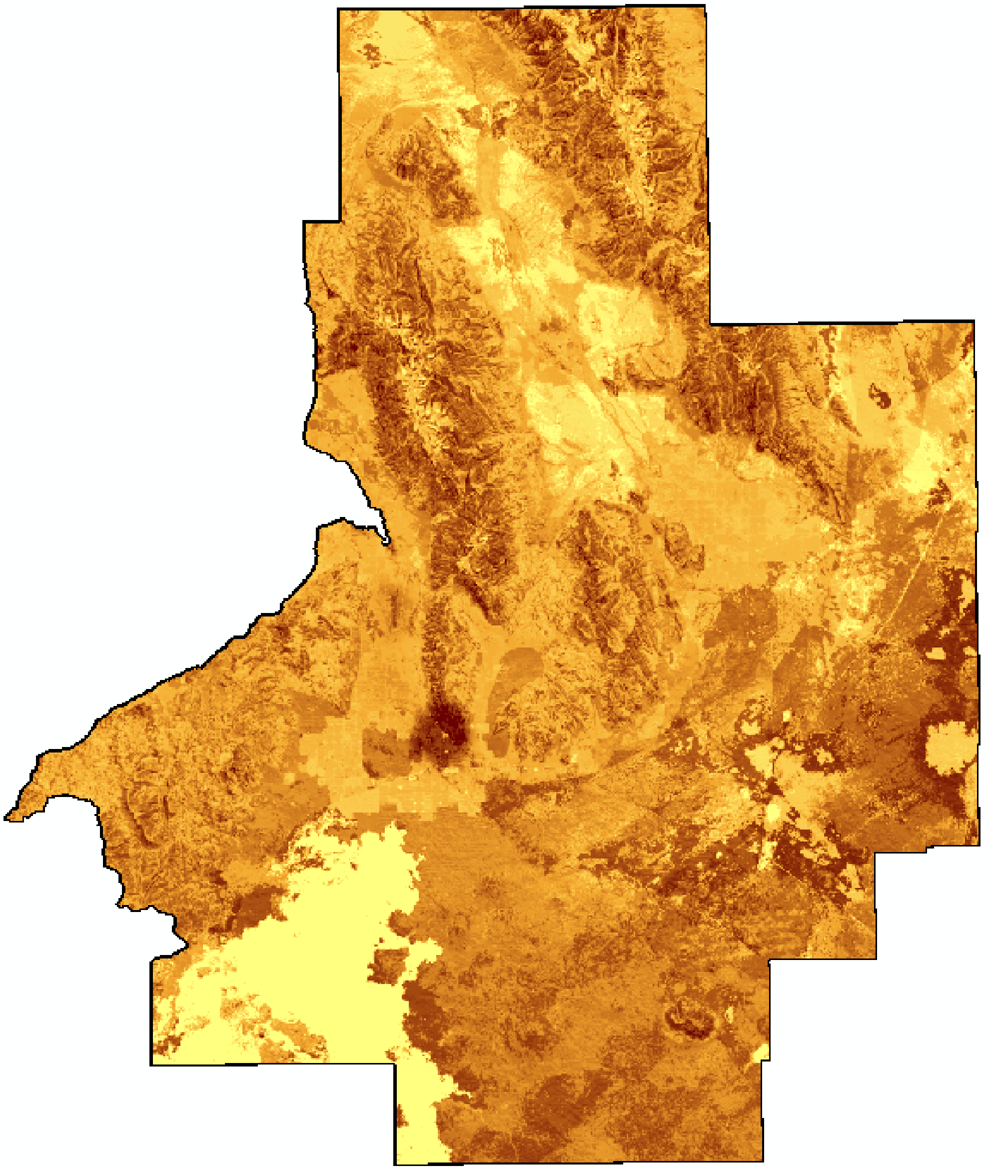

FIGURE 16 - ALTERNATE FIRE SUSCEPTIBILITY MODEL FOR BUTTE COUNTY USING THE FIRE REGIME CONDITION CLASS MODEL (darker colors indicate higher susceptibility)

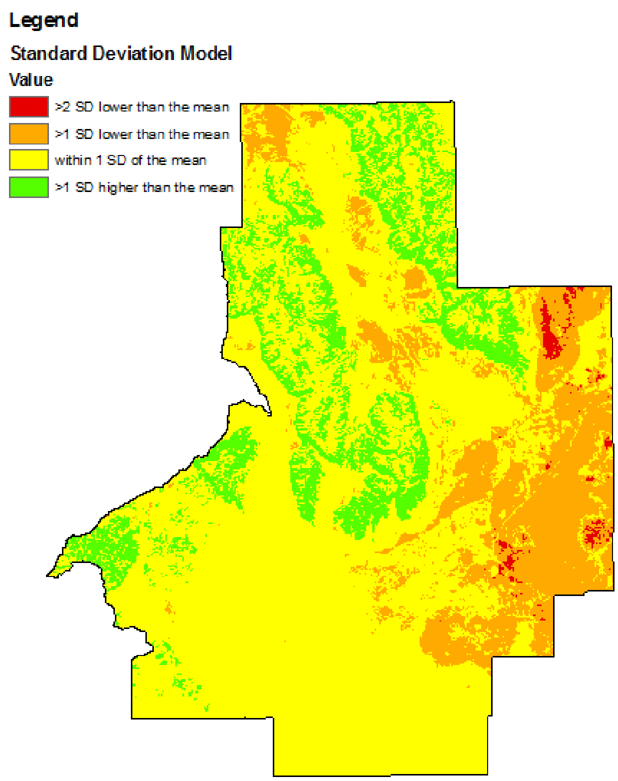

FIGURE 17 - STANDARD DEVIATION BETWEEN THE STANDARD MODEL AND THE FRCC ALTERNATIVE MODEL (CREATED BY FINDING THE DIFFERENCE BETWEEN THE STANDARD AND FRCC MODEL, WITH DIFFERENCES DISPLAYED IN SD FROM THE MEAN DIFFERENCE).

DISCUSSION:

We compared the WUI fire susceptibility models for Butte, Bonneville, Clark, Bannock, Power, Oneida, Caribou, Bingham, and Bear Lake counties (Idaho) by reclassifying the final fire susceptibility model into three distinct classes (0-333 = low susceptibility; 334-666 = medium susceptibility; 667-1000 = high susceptibility). The comparison between total acres classified as low, medium, and high fire susceptibility is shown in Table 5. Figure 18 shows portions of each county classified as low, medium, and high susceptibility relative to individual areas.

Lemhi, Bonneville, Teton, Fremont, Bannock, and Clark counties all contain high desert sagebrush steppe ecosystems, while both Lemhi and Butte Counties also contain areas of coniferous forest.

TABLE 4 - TOTAL ACRES CLASSIFIED AS LOW, MEDIUM, AND HIGH FIRE SUSCEPTIBILITY FOR BANNOCK, BONNEVILLE, BUTTE, CLARK, FREMONT, LEMHI, AND TETON COUNTIES.

Total Acres Classified as Low, Medium and High Fire Susceptibility				
	Low	**Medium**	**High**	**Total**
Bannock	413,146	277,805	21,370	712,321
Bonneville	645,926	430,617	119,616	1,196,160
Butte	825,522	601,672	1,301	1,427,194
Clark	395,360	666,464	67,776	1,129,600
Fremont	570,608	598,237	32,434	1,201,280
Lemhi	1,348,323	1,436,257	146,556	2,931,136
Teton	46,094	187,261	54,737	288,092

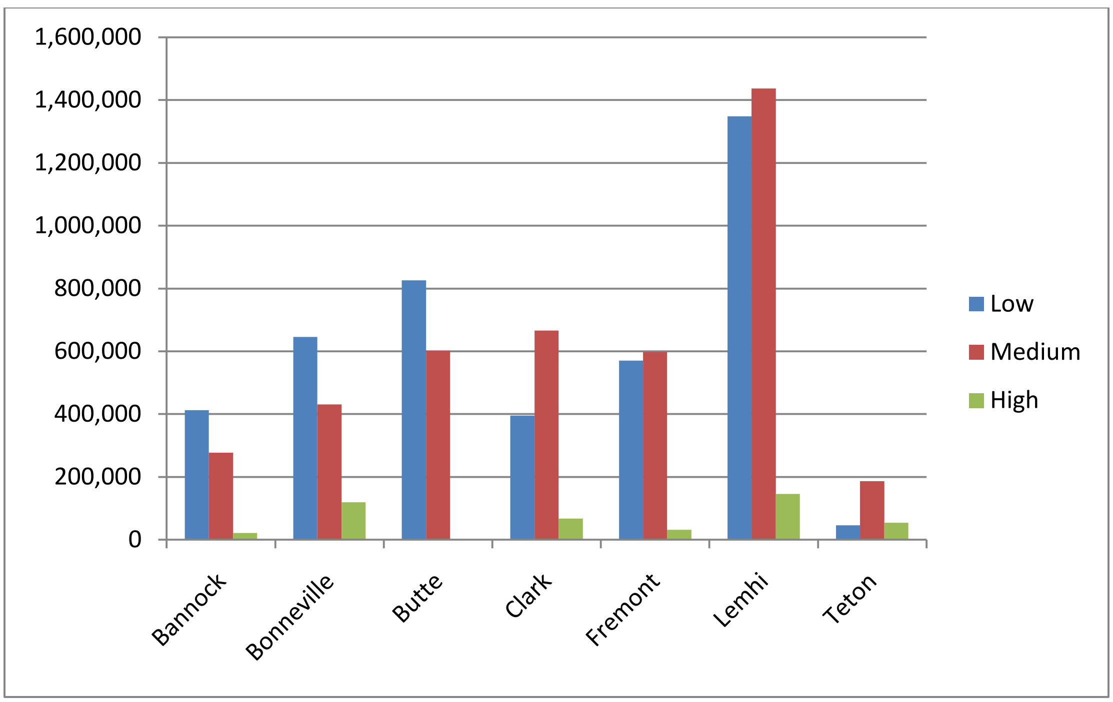

FIGURE 18- BANNOCK, BONNEVILLE, BUTTE, CLARK, FREEMONT, LEMI, AND TETON COUNTIES CONSIDERED LOW, MEDIUM AND HIGH FIRE SUSCEPTIBILITY BASED ON THE STANDARD FIRE SUSCEPTIBILITY MODEL.

Of these counties, Teton County has the smallest area, with 450 square miles, and Lemhi has the largest area, with 4,564 square miles. Butte County totals 2,232 square miles, and Bannock County has a spatial area of 1,113 square miles.

Butte County has the lowest total acres, just over 1,000, classified as high fire susceptibility. Lemhi County has the highest total acres classified as high fire susceptibility with 146,556 acres, Bonneville County has the second largest area classified as high susceptibility with 119,616 acres, and Clark County follows with 67,776 acres classified as high susceptibility. The high fire susceptibility classification for these six counties is concentrated in the mountainous areas. This is due to the influence of the topography component models Aspect/ Sun Position, Slope/ Suppression Difficulty, and Slope/ Rate of Spread, as well as the fuel load >6 tons/acre.
Butte County has the third highest total acres classified as medium fire susceptibility with 601,672 acres in this range. Lemhi County has the largest area classified as medium fire susceptibility with 1,436,257 acres.

Butte County has the second highest percentage of total acres classified as low fire susceptibility (Figure 18) with 825,522 acres found within this range. This may be due to the influence of the structures susceptibility model which has a weight of 22% and the relatively low population density of the county. In Butte County the areas of highest structure density are confined to the mid-west section of the county.

NDVI values vary with absorption of red light by plant chlorophyll and the reflection of infrared radiation by water-filled leaf cells. It is correlated with Intercepted Photo-synthetically Active Radiation (IPAR) (Land Management Monitoring, 2003). In most cases (but not all) IPAR and hence NDVI is correlated with photosynthesis. Because photosynthesis occurs in the green parts of plant material the NDVI is normally used to estimate green vegetation. The NDVI is a nonlinear function which varies between -1 and +1 but is undefined when RED and NIR are zero (Land Management Monitoring, 2003). Early in this project we determined thresholds for no-vegetation, dry-vegetation, and moist vegetation using NDVI. We chose the value 0.15 as a threshold between no vegetation and general vegetation based on where and how well the NDVI values matched a DOQQ. We chose the second threshold (separating dry vegetation from moisture vegetation) using similar methods. The NDVI value of 0.6 was the threshold limit between dry vegetation and moist vegetation.

The Structure Vulnerability component was weighted most heavily (22%). Due to the nature of this project, we were most interested in quantifying susceptibility for the Wildland/Urban Interface. This model allowed us to emphasize the interface areas. Areas of high structure density received the highest fire susceptibility values and areas of low or no structure got the lowest fire susceptibility values. Bonneville County has the largest population with 94,630. The next largest by population is Bannock County with 78,443 people. Fremont has a population of 12,369, Lemhi has a population of 7,930, Teton County has a population of 7,838. Butte County has the second lowest population with 2,751 people, and lastly Clark County's population is 920 (U.S. Census Bureau Quick Facts 2006). Though each county has a relatively large area, the Structure Vulnerability component model for Bonneville County shows the highest risk to structures because of the number of wildland urban interface areas within the county. Butte County's population ranges as the second lowest among the counties studied with the areas of highest structure density contained in the midwestern section of the county.

The Fuel Load/Rate of Spread model takes into account how fast a fire will spread depending on different fuel load classes. The lower fuel load classes were considered to be the primary carrier of fire (e.g. grasses) and have the fastest spread rate. Fuel Load class 3-6 tons/acre received the highest fire susceptibility value, because of its high load of fine, low-standing fuels. Fuel Load class >6 tons/acre received the lowest fire susceptibility value since these fuels are of a larger size and higher moisture content, so they will not ignite as quickly.

The Slope/ Rate of Spread component model takes into account how different angles of slope affect the rate of spread of a fire. When fire moves across flat land it moves more slowly than fire moving up a mountainside (Amdahl, 2001). The steeper angles in this model have the highest fire susceptibility values, because fire increases exponentially with slope. Correspondingly, shallower angles have lower fire susceptibility values.

The Fuel Load/ Vegetation component accounts for moist vegetation and different fuel load classes that may be abundant but not readily flammable. Areas with dry vegetation and high fuel load (>6 tons/acre) had the highest fire susceptibility value. Areas that had wet vegetation and lower fuel load had the lowest fire susceptibility values.

The Fuel Load/ Intensity component takes into account how intense a fire of different fuel load classes affects fire susceptibility. Intensity is considered the amount of energy a fire produces. The more energy the fire produces, the more difficult it is for the firefighters to suppress it. Intense fires create their own wind system, drying out fuel ahead of the fire. This intensity depends on fuel load and other factors such as wind and ground conditions at the time of the fire. Thus, if firefighters do not suppress the fire, it will keep spreading. The fuel load class >6 tons/acre had the highest fire susceptibility value, due to the high intensity fires associated with these larger fuels.

The Slope/Suppression Difficulties component describes how difficult it is for firefighters to suppress fire based on slope/terrain steepness. If firefighters cannot reach the fire, it will keep burning even though it may be a low susceptibility area according to other criteria. Slopes that are > 20 degrees affect wheeled vehicle support and slopes > 30 degrees affect tracked vehicle support. Without the aid of motorized equipment support suppression efforts are slowed, allowing the fire to spread. Slopes with the greatest degree of inclination had the highest fire susceptibility values and shallow slopes received the lowest fire susceptibility values.

The Aspect/ Sun position component models the direction each slope faces and the extent to which the sun desiccates the ground/vegetation. The sun will desiccate the ground/vegetation more on southern aspects and least on northern aspects. Southern aspects received the highest fire susceptibility values and northern aspects received the lowest.

ASSESSMENTS OF ERROR AND BIAS:

All estimations in this report are made based upon our knowledge of the criteria and the expert knowledge of Keith T. Weber, Felicia Burkhardt, Fred Judd, Lance Brady, Kevin Conran, Sarah Heide, and Josse Allen. We have discussed our analyses and results with these people and believe our results to be valid.

The goal for our model is as a tool to assist fire managers and decision-makers. As we treated each analysis separately, we believe the results have accuracy adequate to fit this purpose. We further believe our model gives a good overview of the fire susceptibility in the study area and that it is easy to understand. Because the model is easy to understand, it can be applied for other uses, which was a primary objective of this study.

Not all conditions affecting wildfire could be accurately modeled in this study. Factors not taken into account, such as wind direction and wind speed, are difficult to model without building many assumptions into the model (e.g., yearly weather patterns). Since the scope of this study is broad, we felt that removing these factors from the final model helped its overall effectiveness as a management tool. This also allowed us to place more emphasis on the factors we, Fred Judd, and Kevin Conran (personal communication) felt were more important.

ACKNOWLEDGEMENTS

Kevin Conran from the Idaho Bureau of Land Management suggested that we incorporate Vegetation Condition Classes into our Fire Susceptibility model. Shortly thereafter Lance Brady, also from the Idaho Bureau of Land Management, supplied the ISU GIS Center with Condition Class Data. This data has been used to develop an alternate Fire Susceptibility Model for Fremont County and for previous counties where WUI studies were conducted, and where appropriate data was available. The same criteria used in the original model were used to construct this alternate Fire Susceptibility Model with one exception. In the alternate model the Fire Regime Condition Class sub model was used in place of the Fuel load/ Fire Intensity sub model.

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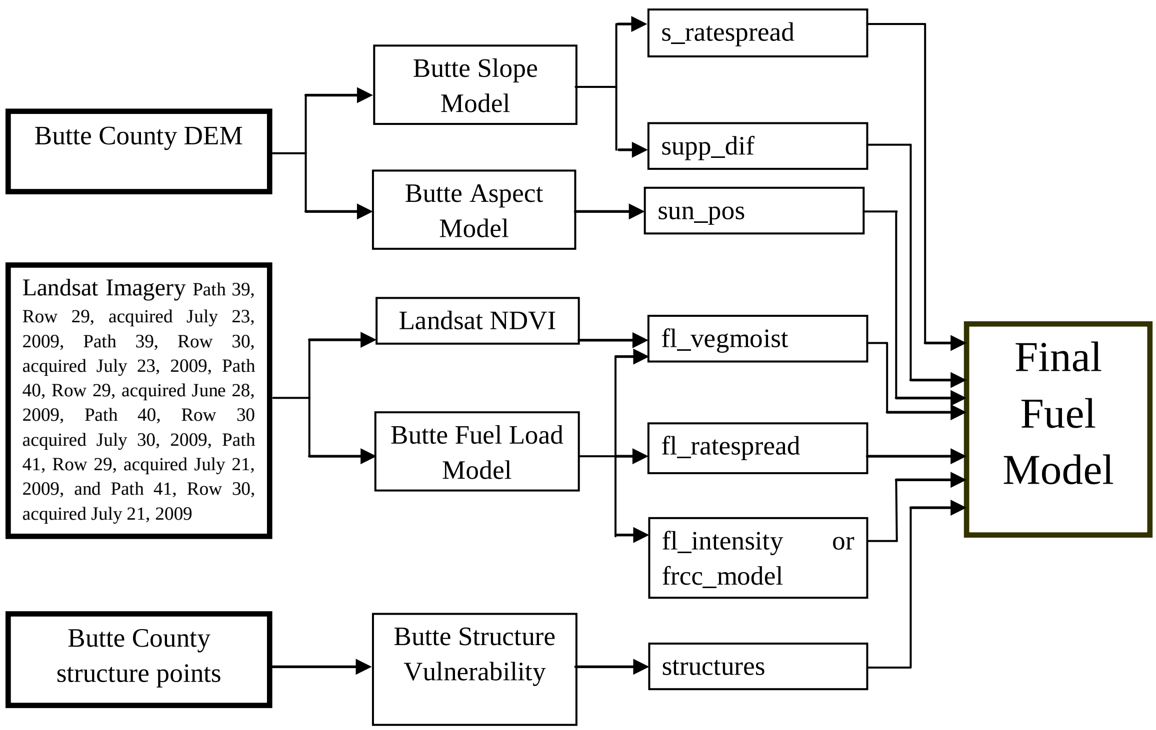
APPENDICES

APPENDIX A – CARTOGRAPHIC MODEL



APPENDIX B – WEIGHTINGS

These tables show the weightings we used to weight our fire susceptibility model components.

TABLE B 1 RECLASSIFICATION OF FUEL LOAD AND NDVI

Fuel Load	NDVI
0 = 0 tons/acre	100 = No Vegetation
1 = <3 tons/acre	200 = Dry Vegetation
4 = 3-6 tons/acre	75 = Moist Vegetation
6 = >6 tons/acre	

TABLE B 2 WEIGHTING DATA FOR FUEL LOAD/VEGETATION MOISTURE COMPONENT MODEL (JANSSON ET AL. 2002). COMPARE WITH FIGURE 3.

Fuel Load *	Vegetation =	Class	Weights
1	100	100	50
1	200	200	300
1	75	75	150
4	100	400	650
4	200	800	850
4	75	300	400
6	100	600	700
6	200	1200	100
6	75	450	600
0	*	0	25

TABLE B 3 WEIGHTING DATA FOR FUEL LOAD/RATE OF SPREAD. COMPARE WITH FIGURE 4

Classes (Tons/acres)	Weights
0	0
1	850
4	1000
6	600

TABLE B 4WEIGHTING DATA FOR FUEL LOAD/INTENSITY. COMPARE WITH FIGURE 4

Classes (Tons/acres)	Weights
0	0
1	100
4	400
6	1000

TABLE B 5: WEIGHTING DATA FOR SLOPE/ RATE OF SPREAD. COMPARE WITH FIGURE 1.

Angle/degree Intervals	Weights
0—10	41
10—20	137
20—30	256
30—40	489
40—50	1000

TABLE B 6WEIGHTING DATA FOR SLOPE/SUPPRESSION DIFFICULTIES. COMPARE WITH FIGURE 1.

Angle/degree Intervals	Weights
0—10	100
10—20	200
20—30	850
30—40	1000
40—50	1000

TABLE B 7: WEIGHTING DATA FOR ASPECT/SUN POSITION. COMPARE WITH FIGURE 2.

Degree Interval	Aspect	Weight
337.5--22.5	N	100
22.5--67.5	NE	150
67.5--112.5	E	300
112.5--157.5	SE	800
157.5--202.5	S	1000
202.5--247.5	SW	1000
247.5--292.5	W	700
292.5--337.5	NW	200