Wildland/Urban Interface Fire Susceptibility and Communities at Risk:

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

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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 a model to predict potential wildfire susceptibility areas for Bonneville County, Idaho. During this project models were created of specific individual susceptibility components associated with wildfire: topography, fuel load, and the number of vulnerable structures. These models were evaluated together to create a final fire susceptibility model for Bonneville 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 Bonneville County and can be used by regional fire managers to manage wildfire susceptibility.

Keywords:

GIS, Fire Regime, Slope, Aspect, Fuel Load

Contents

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.
- **Structure Vulnerability** – includes the density of man-made structures.

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

Methods:

GIS Data Sets:

- Digital Elevation Model (DEM) of Bonneville County
- Landsat 5 TM imagery for Bonneville County and environs – Path 38, Row 30, acquired August 12, 2007 and Path 39, Row 30, acquired July 18, 2007.
- National Agriculture Imagery Program (NAIP) images for Bonneville County acquired November, 2007
- Transportation, place and county boundary datasets for Bonneville County acquired November 20, 2007
- Structure density raster data was based on county wide parcel data for Bonneville County, supplied by the county.

Data Acquisition and Preparation:

Elevation Data

The DEM data for Bonneville County was obtained from Idaho State University (ISU) GIS Center's Spatial Library. Through the use of ArcMap 9.2 this data was 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 38, Row 30, acquired August 12, 2007 and Path 39, Row 30, acquired July 18, 2007). The Landsat Imagery was ordered from the USGS website. This imagery was then corrected for atmospheric effects using in house worksheets in combination with atmospheric correction tools in IDRISI Andes version 15.0.

Other Datasets

The Bonneville County boundaries and roads datasets were downloaded from the Inside Idaho website. The Bonneville County boundary was selectively saved as a separate shapefile and re-projected to IDTM-NAD83. The roads dataset was clipped to include only the roads within Bonneville 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, values were normalized 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). After completing these analyses, the impact each fire model component had on the overall fire susceptibility in Bonneville County, Idaho was examined.

Topographic Sub-Model Components

Creating the Topographic: Slope: Suppression Difficulty Component Model

Using the Bonneville County DEM as input, a slope grid was calculated using ArcMap (Spatial Analyst → Surface Analysis → Slope). The resulting pixel values equate to the slope of the DEM at that point. The output pixel value 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 with applied weightings for Slope: Suppression Difficulty following Mattsson *et al*. (2002) using ArcMap (Spatial Analyst → Reclassify) (figure 1).

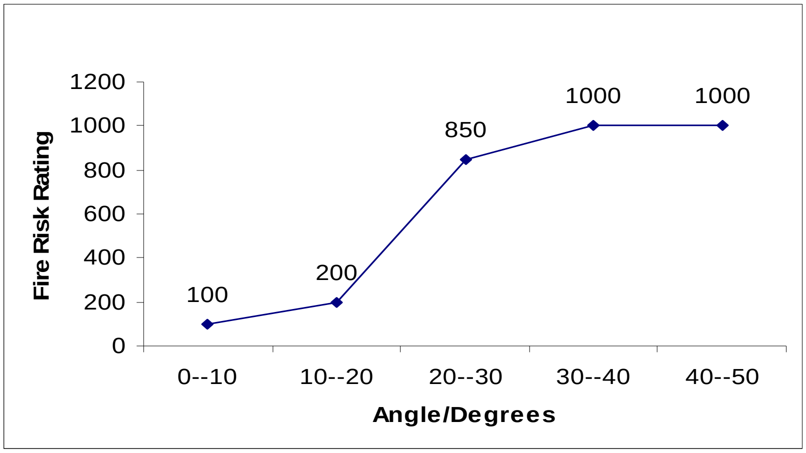

Figure 1. *Weighting for slope/suppression difficulties describe how suppression difficulties are affected by the angle of slope (Mattsson et al, 2002).*

Creating the Topographic: Slope: Rate of Spread Component Model

To make the Slope: Rate of Spread sub-model, the Slope model was reclassified based on weightings from Mattsson *et al*. (2002) using ArcMap (Spatial Analysis → Reclassify (figure 2)).

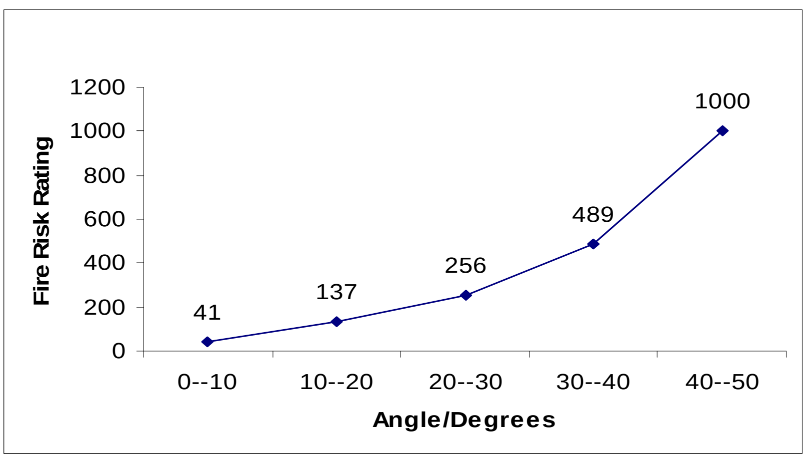

Figure 2. *Weightings describe how spread rate increase with angle of slope. The weight proportion is essentially exponential with slope angle (Mattsson et al., 2002).*

Creating the Topographic: Aspect Sun Position

Aspect indicates the horizontal *direction* of the instantaneous slope face. Using the Bonneville County DEM as input, an aspect model was calculated. The resulting pixel values equate to the angular horizontal direction of the landscape's slope at that point. The ArcMap processing selection was: Spatial Analyst → Surface Analysis → Aspect. The output units were degrees (where 0 is North, 90 is East, etc.) and the output cell size was 30 meters.

To create the Aspect: Sun Position component model, the aspect model was reclassified following Mattsson *et al.* (2002) using ArcMap (Spatial Analyst → Reclassify (figure. 3))

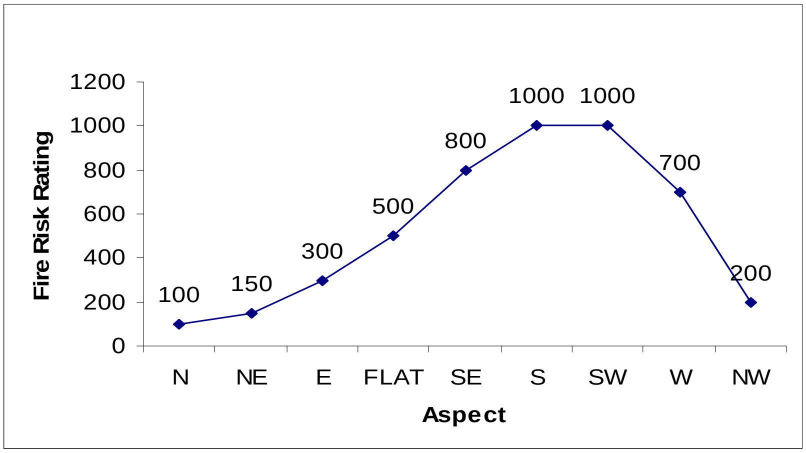

Figure 3. *Weightings for Aspect/Sun position describe how the sun desiccates the ground at different aspects (Mattsson et al, 2002).*

Fuel Load Sub-model Components:

Creating the Fuel Load Fire Susceptibility Components

The fuel load fire susceptibility components were derived from field based fuel load observations, a fuel load estimates raster model, and the Normalized Difference Vegetation Index (NDVI) calculated from the Landsat imagery.

We estimated general vegetation characteristics with satellite imagery using NDVI for Landsat Path 38, Row 30, acquired August 12, 2007 and Path 39, Row 30, acquired July 18, 2007. The NDVI, which is an estimation of photo-synthetically active vegetation, was calculated from band 3 (visible red) and band 4 (near infrared) of the original uncorrected Landsat imagery. The resulting NDVI has an interval of -1 to +1, where -1 is no vegetation and +1 is pure photo-synthetically active vegetation. We created the NDVI using Idrisi after bands 3 and 4 were stretched and then converted to “byte binary” format. The following equation was used to create the NDVI grid:

$$NDVI = \frac{Band4 - Band3}{Band4 + Band3}$$

Equation1. *Equation for calculating NDVI.*

To create the fuel load estimation model, Principal Components Analysis (PCA) was performed using Landsat bands 1, 2, 3 and NDVI using Idrisi Andes (Image Processing → Transformations → PCA). This produced 4 components raster layers. PCA components 1, 2, and 3 were subsequently used for image classification

The imagery was then classified using the maximum likelihood supervised classification procedure in IDRISI Andes (ver. 15.01). To estimate fuel load, we used a total of 413 field sample points collected in 2007. Each of the 413 sample points was initially classified into six fuel load categories based upon on-site estimates of fuel (0.74, 1, 2, 4, 6 and >6 tons per acre). These samples were then reclassified into four, more practical fuel load classes:

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)

Using Hawthe’s Tools in ArcMap 9.2, the fuel load samples were randomly subset into training (n = 205) and validations sites (n=208). An equal proportion of each fuel load class was retained in both the training and validation samples. Signature files were created for the training sites using the NDVI model produced from Landsat imagery (described above) and PCA Components 1, 2, and 3 (Idrisi → Image Processing → Signature Development → MAKESIG). The signature files were then used to create a fuel load model in Idrisi (Image Processing → Hard Classifiers → MAXLIKE).

Fuel Load Model Validation

The fuel load model was validated using a standard error matrix where each predicted (modeled) class was compared against the measured (field) class at all validation point locations (n = 208). In addition, a Kappa statistic was calculated which serves as an indicator of how much better or worse the classification performed compared to a random classification.

Fuel Load: Vegetation Moisture

The fuel load model (described above) was reclassified (to values 0, 1, 4, and 6) in ArcMap (Spatial Analyst → Reclassify). The vegetation moisture model was created through reclassification of the NDVI model using ArcMap (Spatial Analyst → Reclassify) to delineate wet vegetation, dry vegetation, and no vegetation. Values of <0.15 were reclassified to 100, 0.15-0.6 were reclassified to 200, and >0.6 were reclassified to 75 where 100 equals no vegetation, 200 equals dry vegetation, and 75 equals moist vegetation. This reclassified vegetation model was then multiplied by the fuel load model from above, the result being the Fuel Load: Vegetation Moisture sub-component model (Table 1).

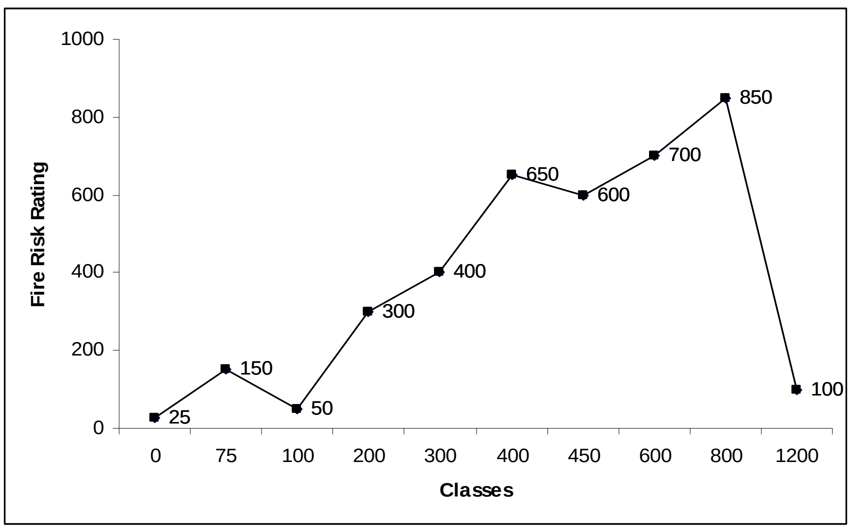

Figure 4. *Weightings for Fuel Load/ Vegetation Moisture (Jansson et al, 2002).*

Table 1: *Weighting data for Fuel Load/Vegetation Moisture component model (Jansson et al. 2002).*

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

Fuel load: Rate of Spread Component Model

The fuel load-derived Rate of Spread component model was created by reclassification of the fuel load grid, following Mattsson et al. (2002) using ArcMap (Spatial Analyst → Reclassify (figure 5)).

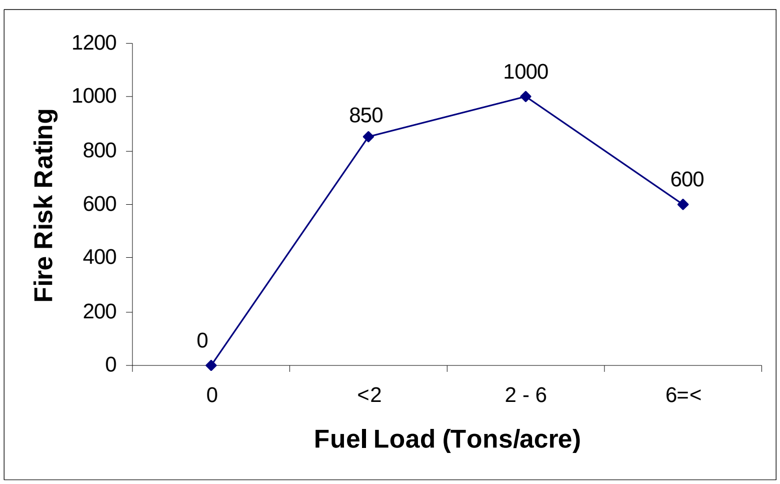

Figure 5. *Weightings for Fuel Load/ Rate of Spread (Mattsson et al, 2002).*

Fuel load: Fire Intensity Component Model

The fire intensity component model was derived by a reclassification of the fuel load grid, using values following Mattsson *et al*. (2002) with ArcMap (Spatial Analyst → Reclassify (figure 6)).

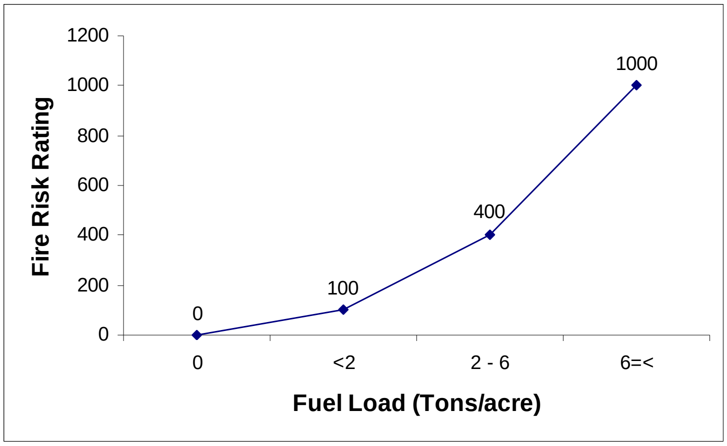

Figure 6. *This chart describes all weightings for Fuel Load/ Intensity (Mattsson et al, 2002).*

Structure Sub-Model Components: Structure Vulnerability Component Model

To create the Structure Vulnerability component model county parcel data was used to parse out ten structure types that are prone to wildfire at the urban interface, some of these include: Speculative Homesite, Agricultural Homesite, Rural Commercial Subdivision, Rural Residential Tracts, and Improved Cropland. No parcel polygon that lay inside or within 200 meters of boundaries of any Bonneville County municipality was used. These remaining polygons were extracted and converted to points based on their centroid. Those points were then used to create a point density raster. To make this component raster consistent with the other component-models, the range of pixel values was stretched to a range of 0 – 1000. It should be noted that all seven fire stations associated with Bonneville County were located within municipal boundaries and their locations did not significantly affect fire susceptibility at the wildland/urban interface.

WUI Fire Susceptibility Model:

After completing the above component models, the impact each model had on overall fire susceptibility in Bonneville County, Idaho was examined. The final fire susceptibility model was calculated as a multi-criteria evaluation using a weighted average (ArcMap → Spatial Analyst → Raster Calculator) of the seven component models. The weight assigned to each component is given in Table 2. The weights were determined through consultation with a regional fire manager, Fred Judd (personal communication).

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%

Fire Regime Condition Class (FRCC) and the Construction of an Alternate Fire Susceptibility Model:

There are 3 condition classes used in this study. The 3 condition classes are used with 5 fire regimes. The 5 fire regimes are essentially fuel models. The condition classes indicate what condition the area is in relation 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 out of whack due to too much fire (too many acres burned). The sagebrush steppe in 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).

In preparation for using the Fire Regime Condition Class data provided by the BLM in an alternate Fire Susceptibility Model, each category was weighted from 0– 1000 (figure 21). A normalized Fire Regime Condition Class sub model was then constructed (figure 22) for

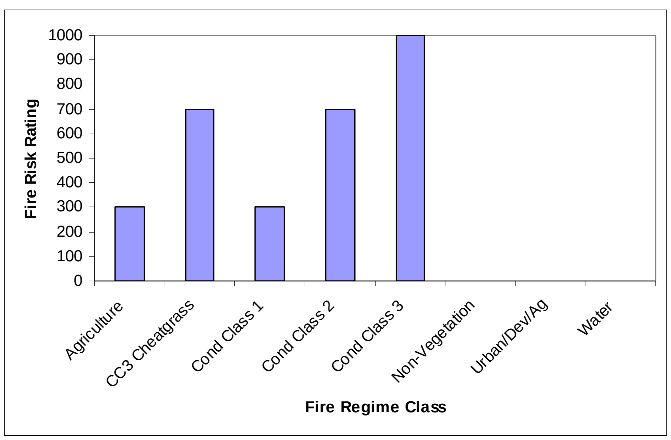

Figure 21*: Fire susceptibility ratings of Fire Regime Class component.*

use in construction of an Alternate Fire Susceptibility Model. An Alternate Fire Susceptibility Model was created by substituting the Fire Regime Condition Class sub model in place of Fuel Load: Fire Intensity. The sub model components and weights comprising the Alternate Fire Susceptibility model were multiplied by their own weighting percentage *(Table 2*). The resulting values were then added to produce the Alternate Fire Susceptibility Model (figure 23).

Figure 24 then illustrates the Standard Deviation between the Standard Model and the FRCC based Model.

<u>Results:</u>

The NDVI model is shown in figure 9. The reclassified NDVI estimating the location of wet vegetation, dry vegetation and no vegetation is shown in figure 10. Figure 11 illustrates the Fuel Load model derived from field training sites and Landsat satellite imagery. Table 3 shows the error matrix validation for the fuel load model. The overall Kappa statistic was 0.750 indicating that the classification was approximately 75% better than a random classification.

Table 3. *Error matrix for the fuel load model.*

		Field Measurement (tons/acre)					
		0	**<2**	**2-6**	**>6**	**Total**	**Commission Accuracy**
Modeled Fuel (tons/acre)	**0**	38	0	4	1	**43**	88%
	<2	0	25	23	0	**48**	52%
	2-6	0	8	70	0	**78**	90%
	>6	0	0	0	34	**34**	100%
	Total	**38**	**33**	**97**	**35**	**203**	**Overall Accuracy**
	Omission Accuracy	100%	76%	72%	97%		**75%**

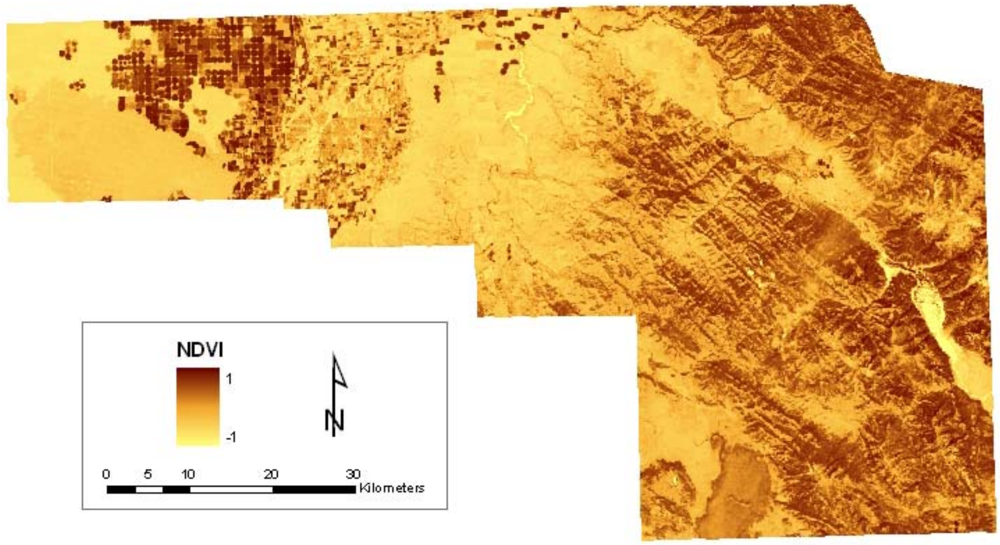

Figure 9. *The NDVI has an interval of -1 to +1, where -1 is no vegetation and +1 is pure vegetation.*

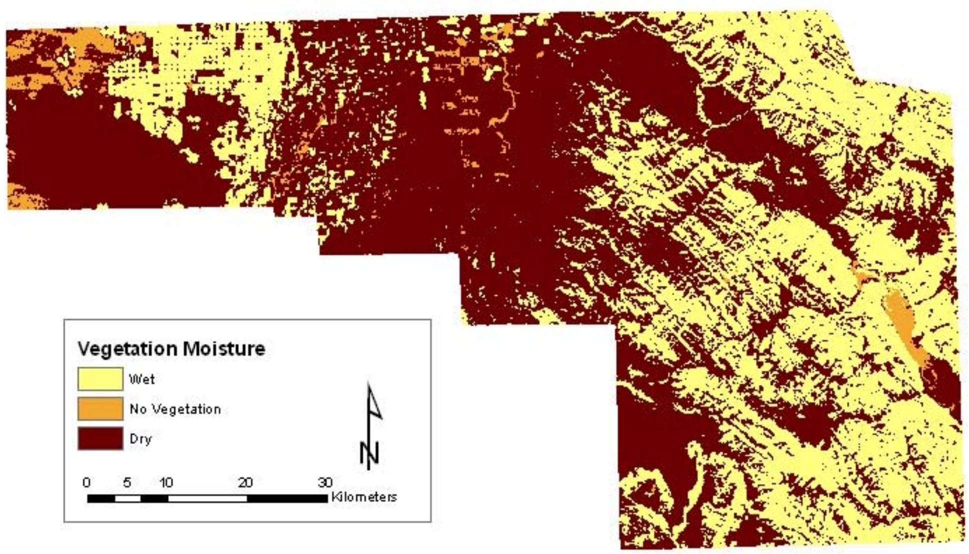

Figure 10. *The results of the reclassification of NDVI into no vegetation (100), dry vegetation (200), and wet vegetation (75).*

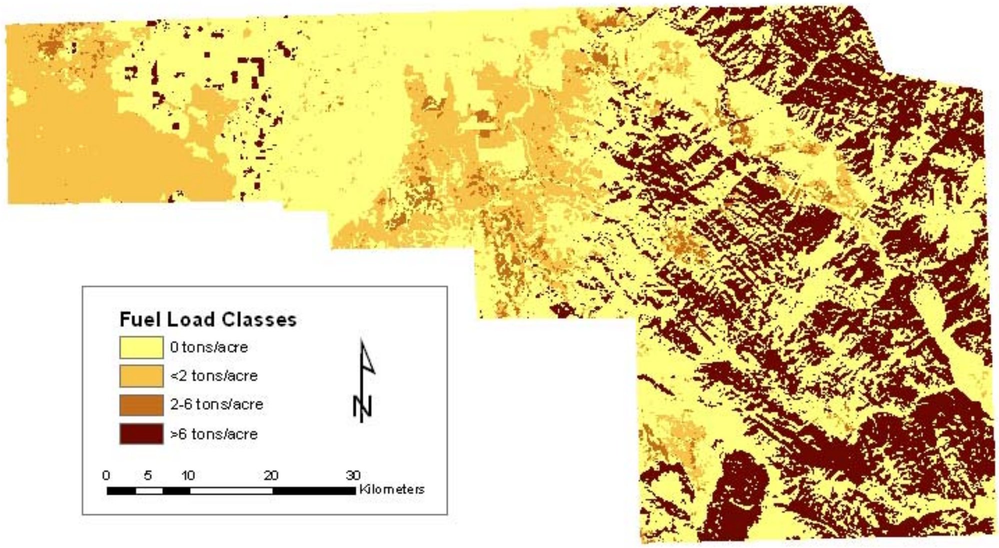

Figure 11. *The fuel load model and the distribution of different fuel load classes for Bonneville County, Idaho.*

The three Fuel Load component models (Vegetation Moisture, Rate of Spread, and Fire Intensity) derived from the fuel load model are shown in figures 12, 13, and 14, respectively. Figure 12 is the vegetation moisture model, irrigated and riparian areas contain the lowest susceptibility values, while the greases, shrubs, and mountainous areas throughout Bonneville County contain the highest values. The high susceptibility areas are due to the low moisture content associated with sagebrush steppe that dominates the area. The predicted effect of fuel load on fire spread rate is reported in figure 13. Mountainous areas, with larger fuel loads, contain the lowest values, where grasses and shrubs contain the highest values. The high susceptibility areas are due to the high concentration of 2-6 tons/acre fuels. Finally, figure 14 is the intensity model. Conifers in the highlands comprise the highest susceptibility for the most intense fires.

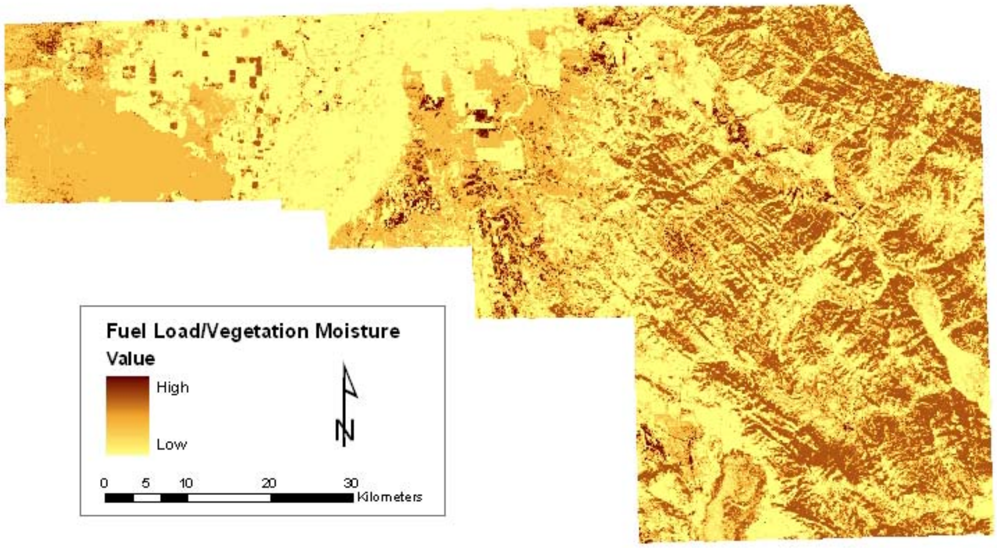

__Figure 12.__ Fuel Load/Vegetation Moisture model. This model expresses how low vegetation moisture and the combination of different fuel load classes affect fire susceptibility. This model was given an overall weighting of 11% of the final model.

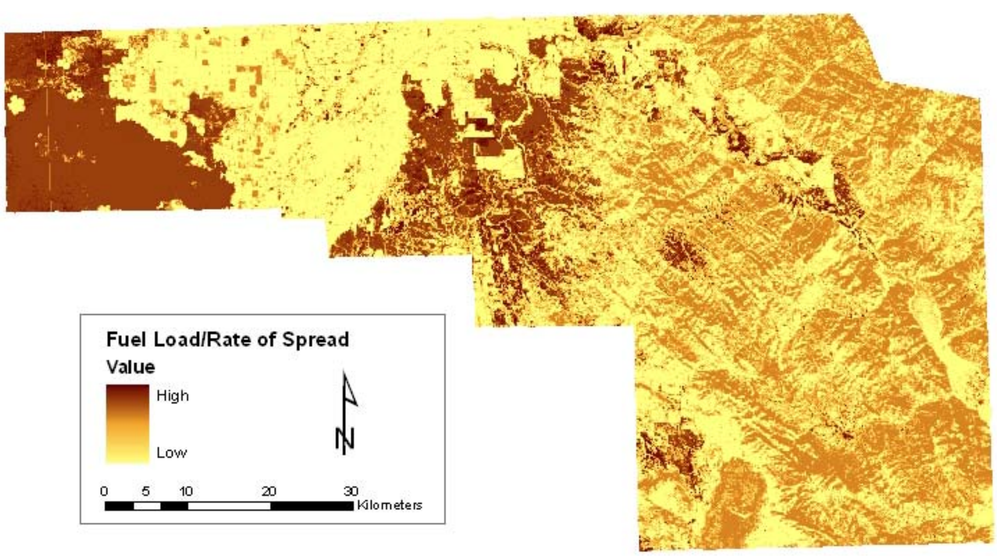

__Figure 13.__ The Fuel Load/Rate of Spread model. This model expresses the fire susceptibility associated with the spread rate of different load classes. This model was given an overall weighting of 17% of the final model.

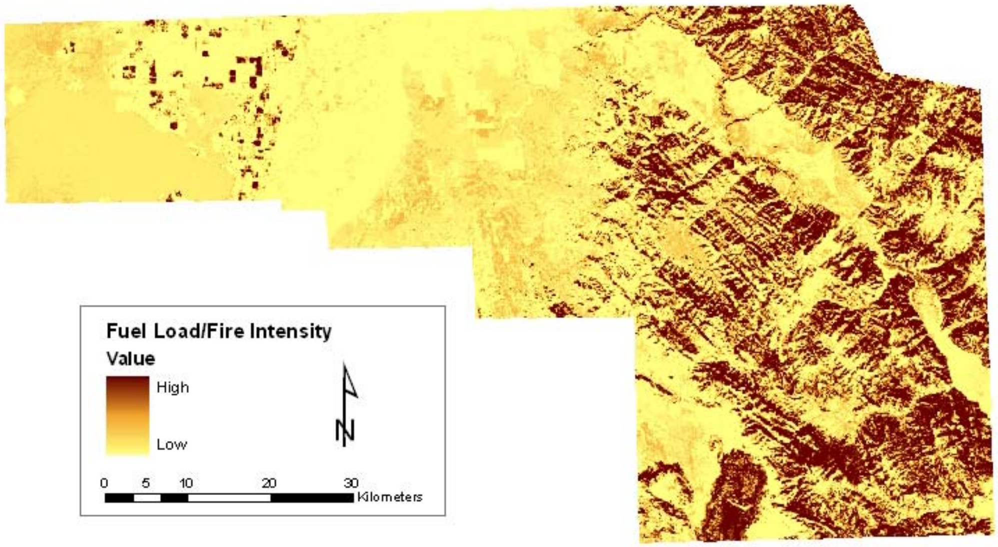

Figure 14. *The Fuel Load/Intensity model. This model expresses the fire susceptibility associated with the amount of heat energy (intensity) each fuel load class gives off. This model was given an overall weighting of 17% of the final model.*

Figures 15-17 are the component models generated using the Bonneville County DEM. Figure 15 assesses the susceptibility of fires spreading quickly due to steep slopes. Here, the highlands throughout the county received the highest values and the lowlands received the lowest values. Next is the suppression difficulty model (figure 16), where steeper slopes pose increasingly greater problems to fire fighters attempting to access fires in order to suppress them. The steeper terrain is weighted the highest susceptibility. Figure 17 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 wind through much of the day, contain the lowest fire susceptibility.

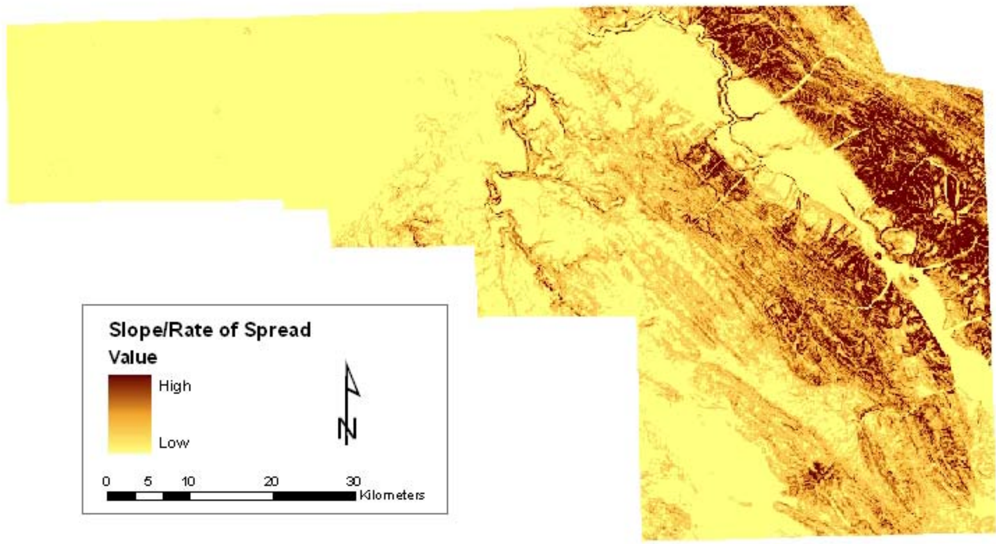

__Figure 15.__ The Slope/Rate of Spread model. This model expresses how different angles of slope affect the spread rate of fire. Steeper slopes are given the highest fire susceptibility. This model was given an overall weighting of 17% of the final model.

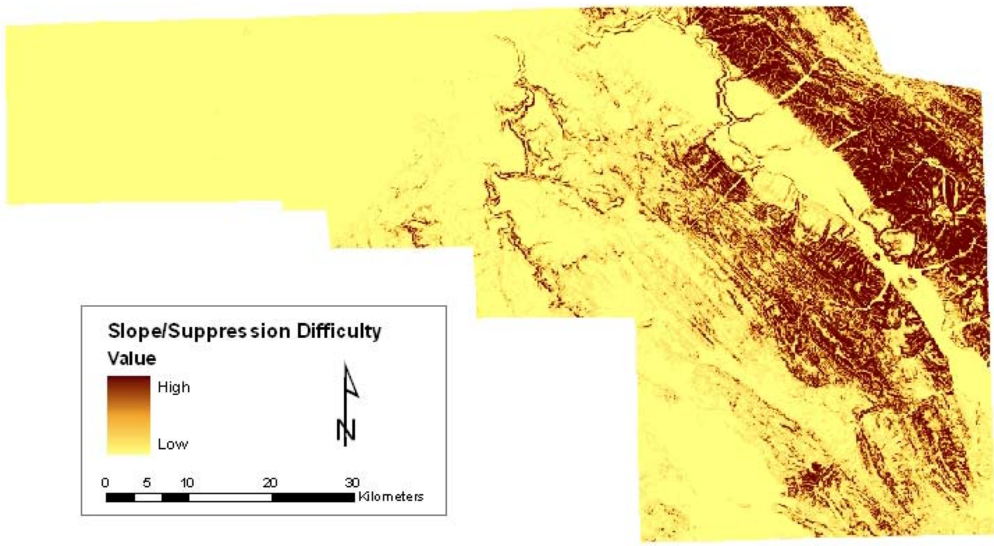

__Figure 16.__ The slope/Suppression Difficulty model. This model expresses how different slope angles affect suppression efforts of firefighters. This model was given an overall weighting of 11% of the final model.

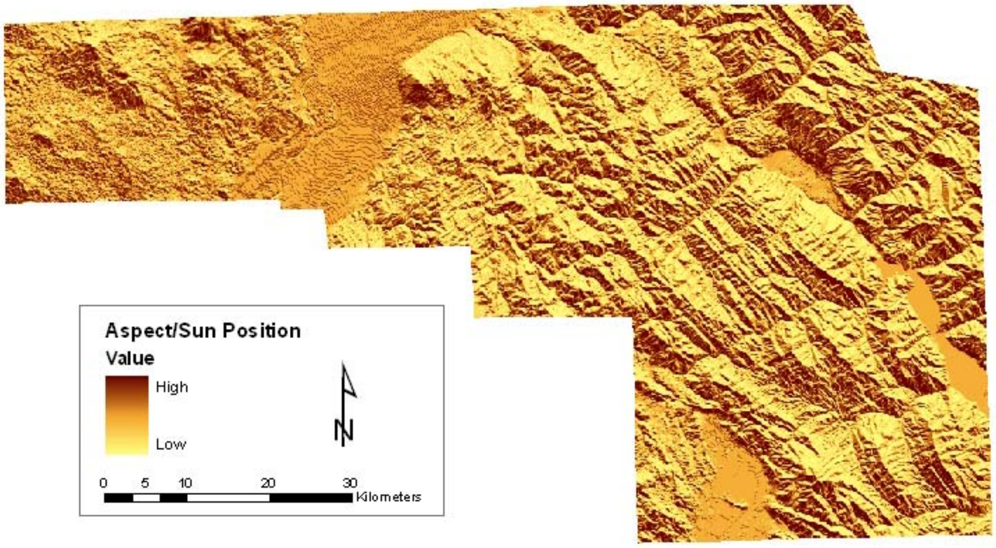

Figure 17. *The Aspect: Sun Position. This model expresses how different aspects affect fire susceptibility. Southern aspects have the highest fire susceptibility. This model was given an overall weighting of 5% of the final model.*

Figure 18 shows the Structure Vulnerability Component model. Here, of course, are the population centers of Bonneville County.

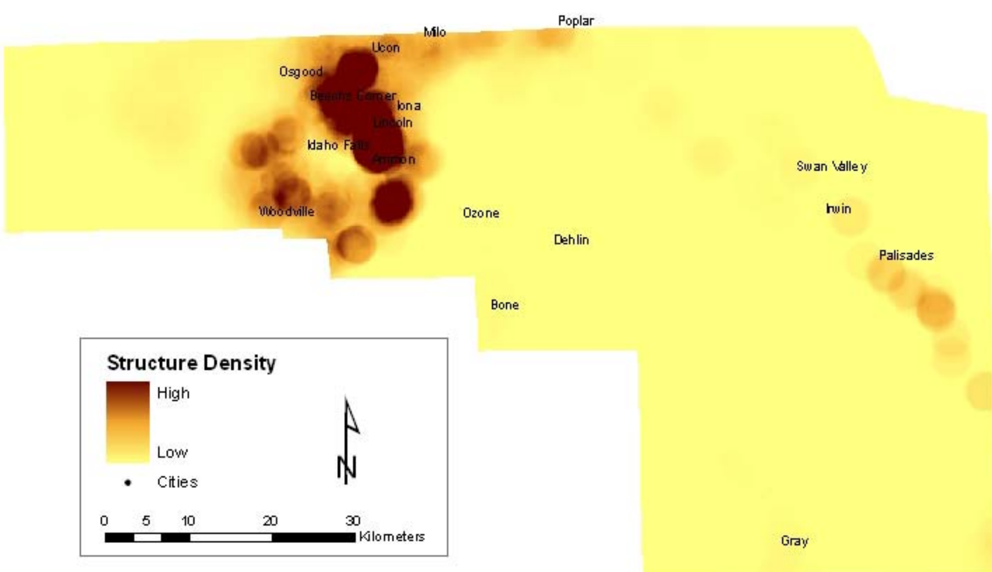

Figure 18. *The Structure Vulnerability model. This model expresses areas that are high susceptibility due to high structure density and is given an overall weighting of 22% of the final model.*

The Final Fire Susceptibility Model for Bonneville County is shown in Figure 19. Figure 20 shows the fire history on public lands within Bonneville County from 1955 – 2006. This was constructed from data available in the ISU GIS Center's spatial library.

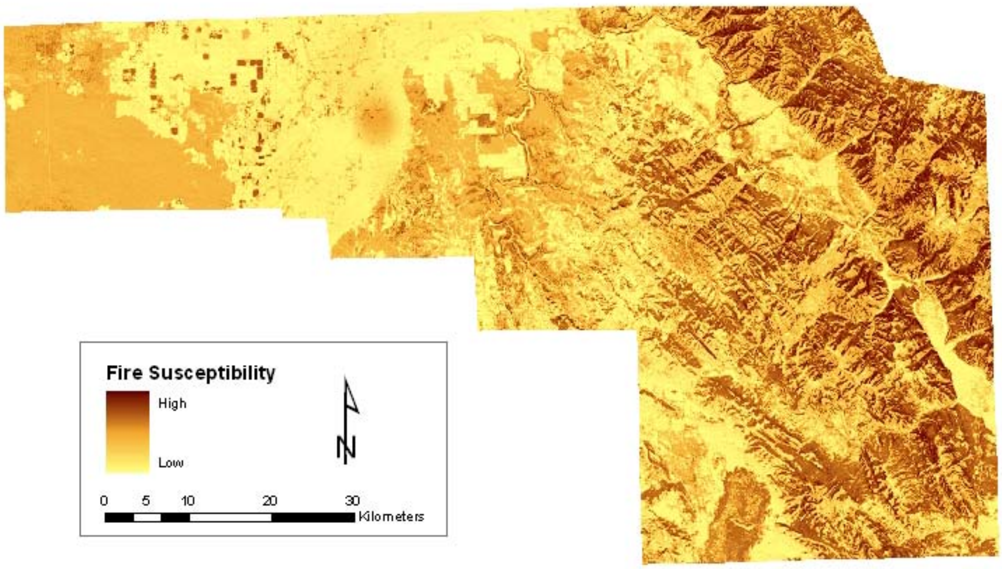

Figure 19. *The Final Fire Susceptibility Model for Bonneville County, Idaho.*

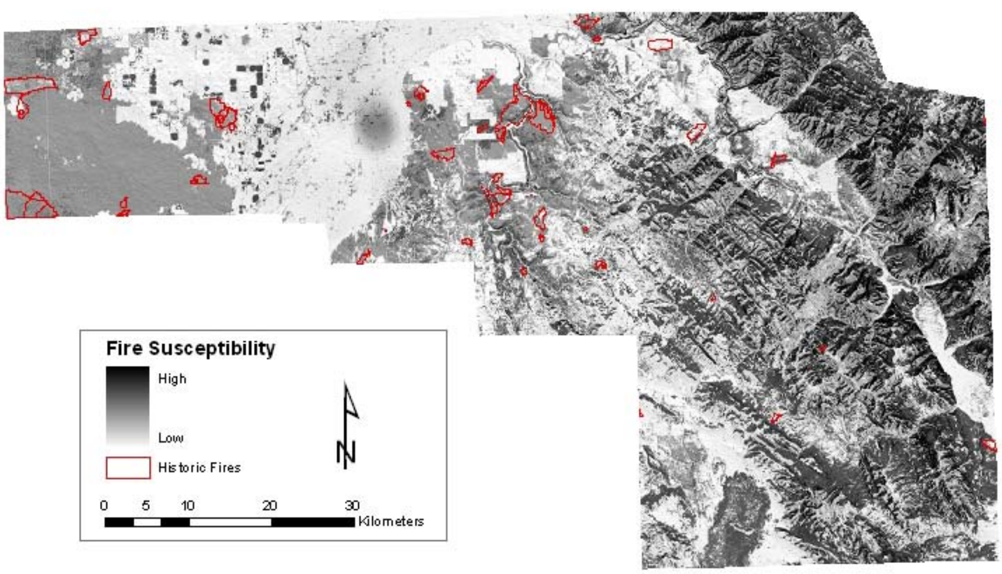

Figure 20. *Fire history for Bonneville County, 1955-2006.*

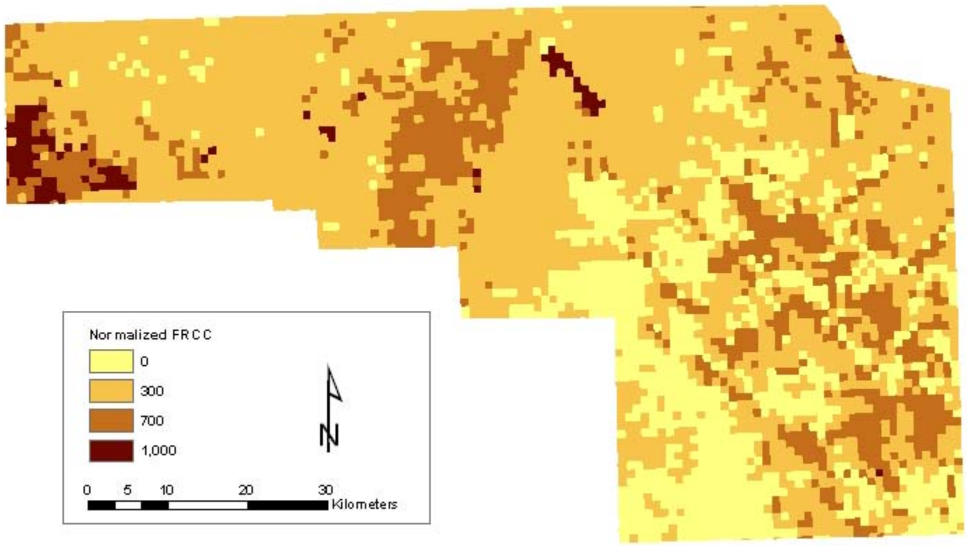

Figure 22*: Normalized Fire Regime Condition Class*

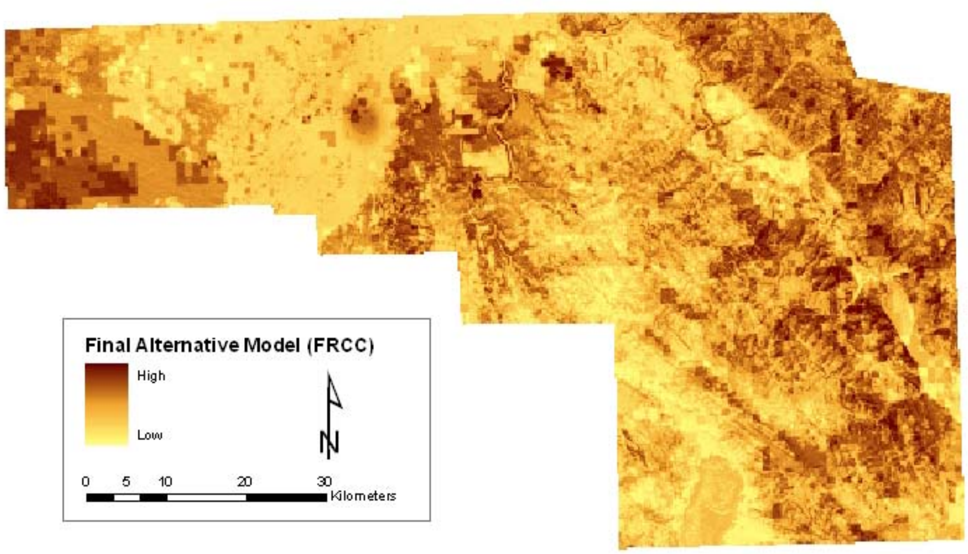

Figure 23*: Alternate Fire Susceptibility Model for Bonneville County using the Fire Regime Condition Class sub model in place of Fuel Load: Fire Intensity sub model.*

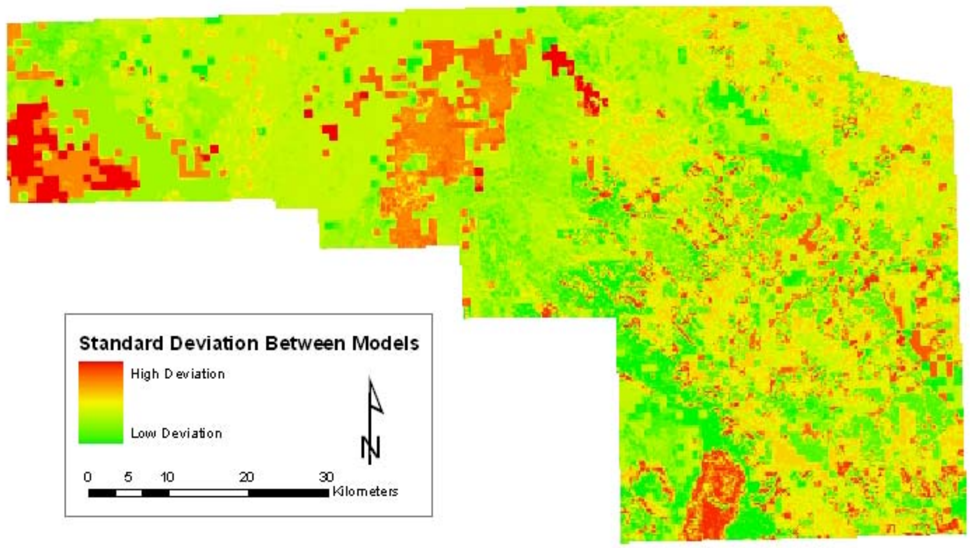

Figure 24: *Standard Deviation between the standard model and the alternative model based on FRCC.*

The Bonneville County WUI fire susceptibility model was compared with similar models created recently for Teton, Bear Lake and Fremont County, Idaho. Past WUI models not represented here are available from the GIS Training and Research Center at Idaho State University. Figure 7 shows the proportion of each county classified as low, medium, and high susceptibility. This relative breaks (low, medium, and high) were determined by reclassifying the final fire susceptibility model into three distinct classes (0-333 = low susceptibility; 333-666 = medium susceptibility; 666-1000 = high susceptibility). Comparison between total acres classified as low, medium, and high fire susceptibility is shown in Table 4. Figure 8 describes the fuel load distribution for each county.

Table 4: *Total acres classified as low, medium, and high fire susceptibility for Bonneville, Teton, Fremont and Bear Lake Counties.*

Total Acres Classified as Low, Medium and High Fire Susceptibility				
	Low	**Medium**	**High**	**Total**
Bonneville	645,926	430,617	119,616	1,196,160
Teton	46,094	187,261	54,737	288,092
Fremont	570,608	598,237	32,434	1,201,280
Bear Lake	62,080	435,008	124,288	621,376

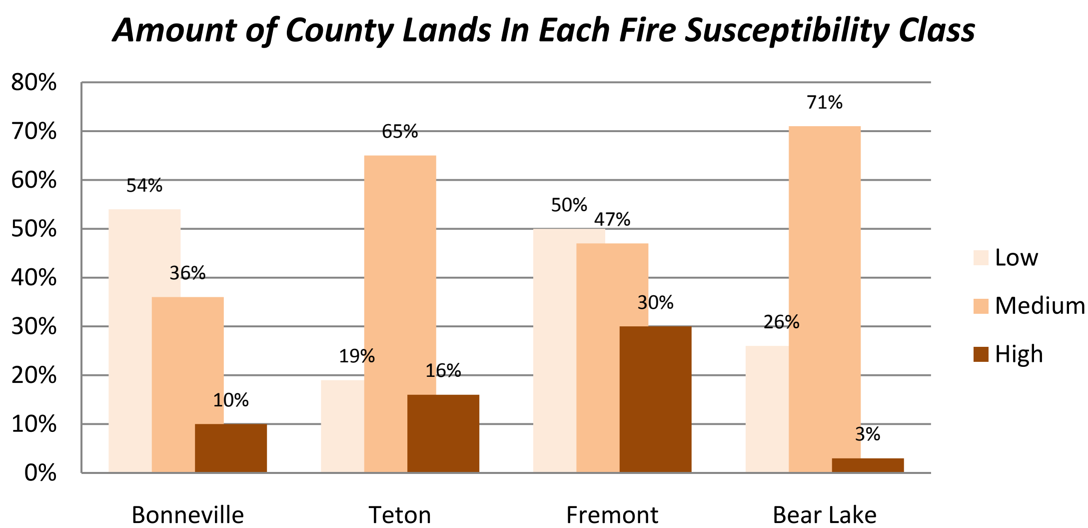

Figure 7: *Percent of Bonneville, Teton, Freemont, and Bear Lake Counties considered Low, Medium and High fire susceptibility based on the standard fire susceptibility model.*

<u>**Discussion:**</u>

Bonneville, Teton, Fremont, and Bear Lake Counties all contain high desert sagebrush steppe ecosystems.

Of these counties, Teton County has the smallest area with 450 square miles. Bear Lake County has the second-smallest area, with 971 square miles. In order of size Fremont has the largest area, with 1,877 square miles, and Bonneville with 1,869 square miles.

Bear Lake County has the highest total acres classified as high fire susceptibility with 124,288 acres. Bonneville County has the second largest area classified as high susceptibility with 119,616, Teton County has the third largest area classified as high susceptibility with 54,737, and Fremont County has 32,434.6 acres. The high fire susceptibility classification for all four 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.

Fremont County has the largest area classified as medium fire susceptibility with 598,237.4 acres. Bear Lake County and Bonneville County (495,089 acres, 435,008 acres respectively) have the next highest medium susceptibility classification. This is followed Teton County with 187,261 acres. It is important to note that the northwest portion of Bonneville County is located within the Snake River Plain which consists of primarily < 2 and 2-6 tons/acre fuels.

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, by far, has the largest population with 94,630. The next largest by population is Fremont County with 11,819 people. Teton has a population of 5,999 and Bear Lake County has a population of 6,411 (U.S. Census Bureau Quick Facts 2008).

The Fuel Load/ Rate of Spread 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 the results to be valid.

The goal of this research and resulting model was the development of a tool to assist fire managers and decision-makers. This model provides a good overview of fire susceptibility in the study area which is easy to understand.

Not all conditions affecting wildfire can 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 was fairly broad, removing these factors from the final model helped its overall effectiveness as a management tool. This also allowed more emphasis to be placed on the wildfire susceptibility factors.

Lastly, it is noted that the date (Path Path 38, Row 30, acquired August 12, 2007 and Path 39, Row 30, acquired July 18, 2007) on which satellite imagery was acquired plays a significant role in the outcome of all fuel load-based components of the final model as NDVI, in particular, is sensitive to even subtle moisture changes following a rainfall.

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Kevin Conran from the Idaho Bureau of Land Management suggested that we incorporate Vegetation Condition Classes into our Fire Susceptibility model. Shortly thereafter Kevin 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.

Appendices:

Appendix A – Cartographic Model