Wildland/Urban Interface and Communities at Risk

Joint Fire Modeling Project for Fremont 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 the risk of 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 (GISTReC) at Idaho State University (ISU), have created a model to predict potential wildfire susceptibility areas for Fremont County, Idaho. During this project models were created of specific individual susceptibility associated with wildfires: topography, fuel load, and the number of vulnerable structures. These models were evaluated together to create a final fire susceptibility model for Fremont County, Idaho. This report describes each of the WUI fire susceptibility components and what affect each has on the final fire susceptibility model. This final model is an accurate depiction of the spatial distribution of wildfire susceptibility in Fremont County and can be used by regional fire managers to manage wildfire susceptibility.

Keywords: Fire, Wildfire, GIS, Fremont County, Idaho, BLM

Contents

Abstract: ... **1**
Keywords: ... **1**
Introduction: ... **3**
Methods: ... **4**
Utilized data sets: ... 4
Data Preprocessing: ... 4
DEM Data: ... 4
Landsat Imagery: ... 4
DLG Datasets: ... 4
Data Processing: ... 5
Topographic Sub-model Components ... 5
Creating the Topographic: Slope: Suppression Difficulty ... 5
Creating the Topographic: Slope: Rate of Spread ... 6
Creating the Topographic: Aspect: Sun Position ... 7
Fuel Load Sub-model Components ... 7
Creating the Fuel Load Fire Susceptibility Components ... 7
Fuel Load Model Validation ... 9
Fuel load: Vegetation Moisture ... 9
Fuel load: Rate of Spread ... 10
Fuel load: Intensity ... 10
Structure Sub-model Components ... 11
Structure Vulnerability ... 11
WUI fire susceptibility model ... 11
Results: ... **12**
Fire Regime Condition Class (FRCC) ... Error! Bookmark not defined.
Construction of the Fire Regime Condition Class Alternate Fire Susceptibility Model ... 23
Discussion: ... **25**
Assessments of error and bias: ... **27**
References cited: ... **29**
Acknowledgements: ... **29**
Appendices ... **31**
Appendix A – Cartographic Model ... 31
Appendix B – Weightings ... 32
Appendix C – Data dictionary ... 34

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 satellite imagery.

Using both GIS and remote sensing, we created a Wildland/Urban Interface (WUI) Fire Susceptibility model. It is comprised of 7 sub-models that describe different aspects of fire susceptibility:

- **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 these component models are weighted and summed to produce the Final Fire Susceptibility Model. The Fremont County, Idaho WUI fire susceptibility assessment is a continuation of WUI projects that have been completed and validated for the City of Pocatello, Idaho (Mattson et al., 2002) the city of Lava Hot Springs, Idaho (Jansson et al., 2002), Clark County, Idaho (Gentry et al., 2003), Bannock County, Idaho (Gentry et al., 2003), Power County, Idaho (Gentry et al., 2003), Oneida County, Idaho (Franks et al., 2004*)*, Caribou County, Idaho

(Bulawa et al., 2004), Bingham County, Idaho (Neves et al., 2004), and Bear Lake County, Idaho (Langille et al., 2005).

Methods:

Utilized data sets:

- Digital Elevation Model (DEM) of Fremont County
- Landsat 5 TM imagery for Bear Lake County and environs: Path 38 , Row 29 and Path 39, Row 29.
- Digital Orthophoto Quarter-Quads (DOQQs) for Fremont County (NAIP)
- Transportation, place and county boundary datasets for Fremont County
- Structures of Fremont County
- Fire Regime Condition Class data provided by Lance Brady, BLM, Idaho Falls Office.

Data Preprocessing:

DEM Data:

A 28.5 meter DEM for Fremont County area was obtained from http://seamless.usgs.gov/website/seamless/viewer.php and this dataset was ultimately the one used to produce the slope and aspect models used in the topography sub-models.

Landsat Imagery:

Landsat 5 imagery from Path 38, Row 29, and Path 39, Row 29 was used. The Landsat Imagery was ordered from the USGS website, http://edcsns17.cr.usgs.gov/EarthExplorer/ . The imagery included bands 1, 2, 3, 4, 5, and 7 (band 8 being the metadata). Path 38, Row 29 was taken on September 7, 2005 and Path 39, Row 29 was taken on August 29, 2005.

DLG Datasets:

The Idaho county boundaries and Idaho places datasets were downloaded from the Spatial Library (located on the ISU GIS Center website, http://giscenter.isu.edu/data/data.htm). The Fremont County boundary was selectively saved as a separate shapefile and re-projected as necessary. The roads dataset was also obtained from the Spatial Library, shown above. The city boundaries dataset was provided by Bonnie Moore of Fremont County.

Structures Data:

The data needed to indicate the structures in Fremont County was provided by Bonnie Moore of Fremont County. This data includes parcels data along with an attached table indicating the status of the parcels. From this the parcels containing structures was extracted and made into a point file and re-projected as necessary.

Data Processing:

The WUI fire susceptibility model consists of several sub-model susceptibility components (*italic*) that can be categorized as follows:

- Topographic
    - Slope
        - *Suppression difficulty*
        - *Rate of spread*
    - Aspect
        - *Sun Position*
- Fuel Load
        - *Rate of Spread*
        - *Fire Intensity*
        - *Vegetation Moisture*
- Structures
        - *Structure Vulnerability*

Each model component was treated separately to learn how each affected fire susceptibility. To be able to merge the models together easily, we normalized the value range of each model to a scale from 0 to 1000, where 1000 is the highest susceptibility. We used weightings based on 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 Fremont County, Idaho.

Topographic Sub-model Components

Creating the Topographic: Slope: Suppression Difficulty

Using the Fremont County DEM as input, a slope grid can be calculated using the ArcMap processing selection: Spatial Analyst → Surface Analysis → Slope. The resultant pixel intensity equates to the slope of the DEM at that point. The output pixel value unit of the resultant grids was degrees of slope, the z-factor was 1 and the output cellsize was set to 28.5 meters.

To create the Slope: Suppression Difficulty sub-model, we used the original slope and applied weightings for Slope: Suppression Difficulty following Mattsson et al. (2002) (table B-6 in Appendix B) using ArcMap → Spatial Analyst → Reclassify, shown in (fig. 1).

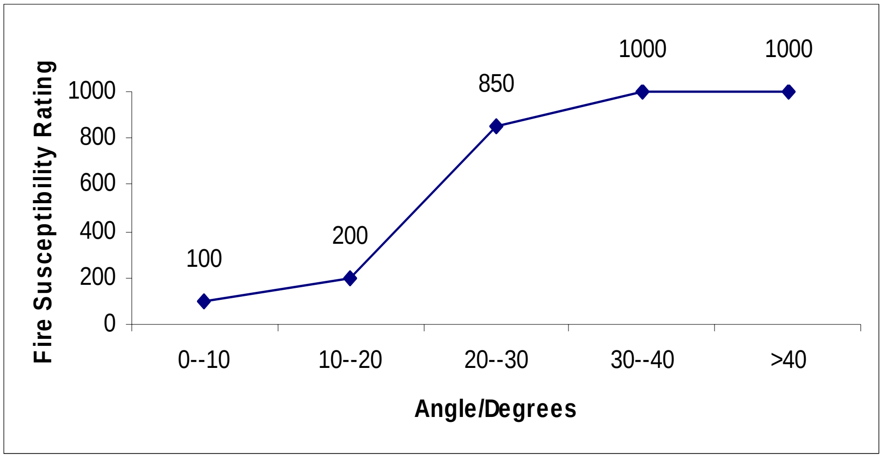

Figure 1*:* Weightings for slope/suppression difficulties describe how suppression difficulties are affected by the angle of slope (Mattsson et al., 2002).

Creating the Topographic: Slope: Rate of Spread

To make the Slope: Rate of Spread sub-model, we reclassified the Slope based on weightings from Mattsson et al. (2002) using ArcMap → Spatial Analyst → Reclassify (fig. 2).
These weightings are shown in table B-5 in Appendix B.

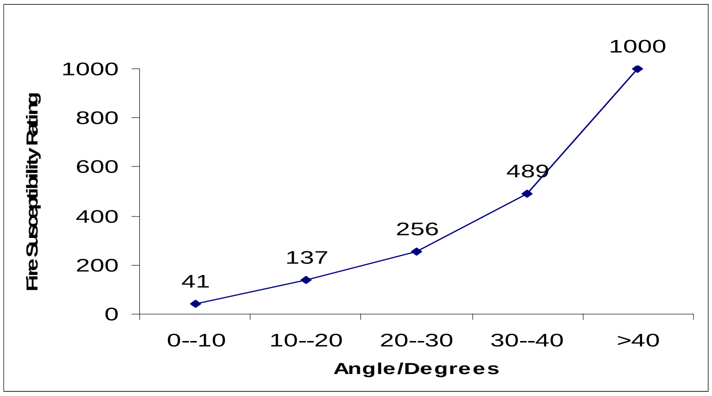

Figure 2: Weightings describe how spread rate increases with angle of slope. The weight proportion is essentially exponential with slope angle (Mattsson et al., 2002).

Creating the Topographic: Aspect: Sun Position

Aspect indicates the horizontal *direction* of the instantaneous slope face. Using the Fremont County area DEM as input, an aspect grid can be calculated. The resultant pixel intensity equates to the angular horizontal direction of the DEM 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 cellsize was set to 28.5 meters.

To create the Aspect: Sun Position sub-model we reclassified the aspect grid, following Mattsson et al. (2002) (table B-7 in Appendix B) using ArcMap → Spatial Analyst → Reclassify (fig. 3).

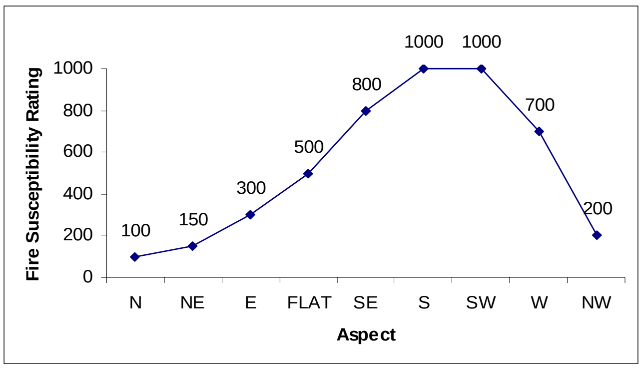

Figure 3: Weightings for Aspect/Sun position describe how the sun desiccates the ground at different aspects (Mattsson et al., 2002).

Fuel Load Sub-model Components

Creating the Fuel Load Fire Susceptibility Components

The fuel fire susceptibility components are all derived from the fuel load estimates determined from the Normalized Difference Vegetation Index (NDVI) calculated from the Landsat imagery.

We estimated vegetation cover with the Landsat 5 satellite imagery using the Normalized Difference Vegetation Index (NDVI). The NDVI, which is an estimation of photosynthetically active vegetation, was calculated from band 3 (visible red) and band 4 (near infrared) of the original uncorrected Landsat 5 imagery. The resulting NDVI has an interval of –1 to +1, where –1 is no vegetation and +1 is pure photosynthetically active vegetation. Idrisi → Image Processing→ Transformation→ VEGINDEX was used to calculate the NDVI grid using the following equation:

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

Equation 1: Equation for calculating NDVI.

Supervised classification of Landsat 5 imagery through Idrisi Kilimanjaro was used for estimating fuel load in Fremont County. To estimate fuel load, we used the sample points 321 sample points. 264 of these sample points were collected in the summer 2005 in the Hitching Post Pasture of the USSES near Dubois, Idaho by Jill Norton and Jamen Underwood. The remaining were digitized using the NAIP DOQQ of Fremont County. While the field training sites taken at the USSES are not located in Fremont County, they are within the Landsat scene used for the Fremont County study and therefore produced acceptable results.

Each of the sample points collected at the USSES was initially classified into 3 fuel load categories based upon on-site estimates of ground-cover (1=1 ton or less per acre, 2= 2-3 tons per acre and 4= 4 or more tons per acre). For this project, these categories were reclassified into a fuel load grid with the following 4 fuel load classes:

- 0 tons/acre (No vegetation)
- < 3 tons/acre (Grassland with some Sagebrush)
- 3-6 tons/acre (Low and Typical Sagebrush, shrubs)
- > 6 tons/acre (Forest)

Using Idrisi, we created signature files for the field training sites using the NDVI model produced from the Landsat 5 imagery (Image Processing → Signature Development → MAKESIG). The signature files were then used to create a fuel load raster grid (Image Processing→ Hard Classifiers → MAXLIKE). We validated the predictions of this model using techniques described in the next section "Fuel load Model Validation".

Alternative Fuel Load Model Technique

Based on Zambon et al. (2006) a new technique for creating the fuel load model was used. The training sites were seperated into 10 groups. Using only 9 of the groups, the classification was done using the same process mentioned above (in *Creating the Fuel Load Fire Susceptibility Components*). The 10^{th} group was then used for the validation. The process was repeated 10 times until each of the training site groups was used for validation. The training sites in each classification which produced the most error were removed and the resulting classifications were added together to produce the final classification. The overall error produced was 92.23%. The accuracy was better using the standard technique, so this fuel load model was *not* used when creating the Fuel Load Model Component models.

Fuel Load Model Validation

The fuel load model was validated using the following methodologies:

1. The first was a standard error matrix where each predicted (modeled) class was compared against the measured (field) class at all sample point locations. The results of these tests are reported in the text below (Table 3).
2. A Kappa statistic was also calculated for our model. This statistic serves as an indicator of the extent to which the percentage correct values of an error matrix are due to "true" agreement versus "chance" agreement.

Fuel load: Vegetation Moisture

The fuel load grid (described above) was reclassified (to values 0, 1, 4, and 6) using ArcMap → Spatial Analyst → Reclassify as described in table B-1 (Appendix B).
A vegetation moisture grid was created (with values 100, 200 and 75) through reclassification of the NDVI grid using ArcMap → Spatial Analyst → Reclassify to delineate wet vegetation (> 0.6), dry vegetation (0.15 – 0.6), and no vegetation (< 0.15) using the NDVI values (shown in parentheses above) as described in table B-1 of Appendix B.
The fuel load grid (with values 0, 1, 4, and 6) was then multiplied by the vegetation moisture grid, using ArcMap → Spatial Analyst → Raster Calculator, to produce an intermediate raster grid.
The intermediate grid was then reclassified using the weights based on Jansson et al. (2002) (figure 4). This latter part of the process is described in the heading of table B-2 in Appendix B.

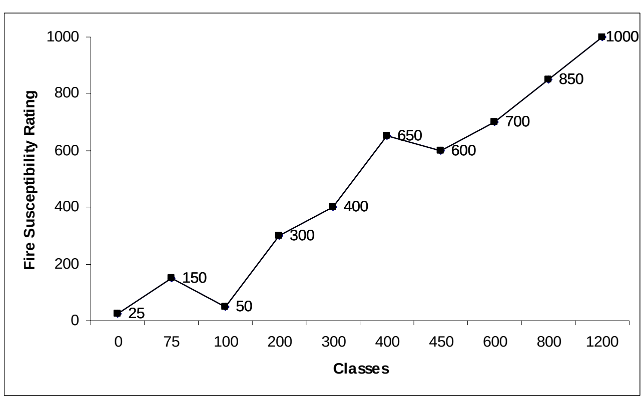

Figure 4: Weightings for Fuel Load/ Vegetation Moisture (Jansson et al., 2002).

Fuel load: Rate of Spread

The fuel load-derived Rate of Spread was determined by a reclassification of the fuel load grid, following Mattsson et al. (2002) (table B-3 in Appendix B), using ArcMap → Spatial Analyst → Reclassify (fig. 5).

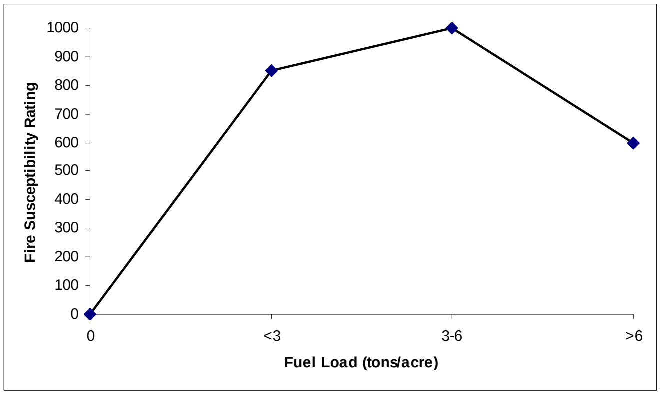

Figure 5: Weightings for Fuel Load/ Rate of Spread (Mattsson et al., 2002).

Fuel load: Intensity

The fire intensity was similarly derived by a reclassification of the fuel load grid, using values following Mattsson et al. (2002) (table B-4 in Appendix B) with ArcMap → Spatial Analyst → Reclassify (fig. 6).

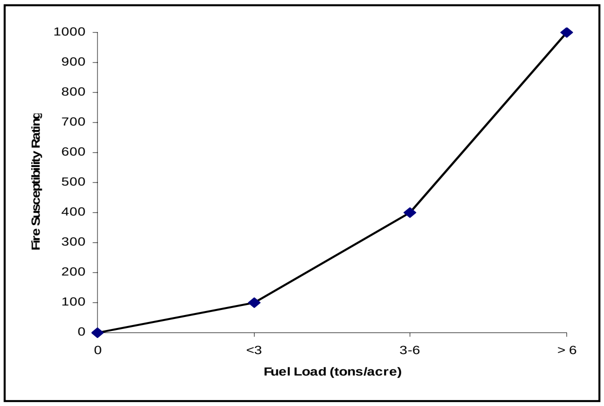

Figure 6: This chart describes all weightings for Fuel Load/ Intensity (Mattsson et al., 2002).

Structures Component Model

Structure Vulnerability

Using the parcels data provided by Bonnie Moore of Fremont County (mentioned earlier in 'Data Processing') we were able to create the structures vulnerability component model. We downloaded the one meter full color NAIP imagery available through the State of Idaho. Its original projection was NAD 83 UTM 12 N. It was reprojected to IDTM and is located on the ISU GIS Center website, http://giscenter.isu.edu/data/data.htm. Structures within 150 meters of the city boundaries were removed to better depict the wildland urban interface. To calculate the structure density from the shapefile, using ArcMap→ Spatial Analyst → Density. To make this component consistent with the other sub-models, the range of pixel values was stretched to a range of 0 - 1000.

Another technique for creating a density model was done using Spatial Statistics in ArcToolbox. First we integrated the structures points following Data Management Tools → Feature Class → Intergrate. We then used the Collect Events tool on the integrated file following Spatial Statistics Tools → Utilities → Collect Events. Using the weights provided from the collect events we ran a Spatial Autocorrelation following Spatial Statistics Tools → Analyzing Patterns → Spatial Autocorrelation (Morans I). We ran this several times using different distances until we found a peak in the Z value. Our peak was reached at 120,000 ft. Using this distance we ran a Hot Spot Analysis following Spatial Statistics Tools → Mapping Clusters → Hot Spot Analysis with Rendering. This process picks out clusters in the structures data and decides where the clusters are more dense relative to less dense areas. The output model contained one pixel with a value for each cluster so it is not compatable with our other models. However, it is a good resource for validating our density model.

WUI fire susceptibility model

The final fire susceptibility model is determined as a simple summation, using ArcMap → Spatial Analyst → Raster Calculator, of the 7 sub-model components. The weight of each component is described below. The weights were determined through consultation with a regional fire manager, Fred Judd (personal communication). See Table 1.

Table 1: 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:

We compared the WUI fire susceptibility models for Clark, Bannock, Power, Oneida, Caribou, Bingham, Bear Lake and Fremont County, Idaho. Figure 8 shows portions of each county classified as low, medium, and high susceptibility relative to individual areas. We did this 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 1. Figure 9 describes the fuel load distribution for each county. Table 2 show total acres of BLM Land classified as low, medium, and high fire susceptibility.

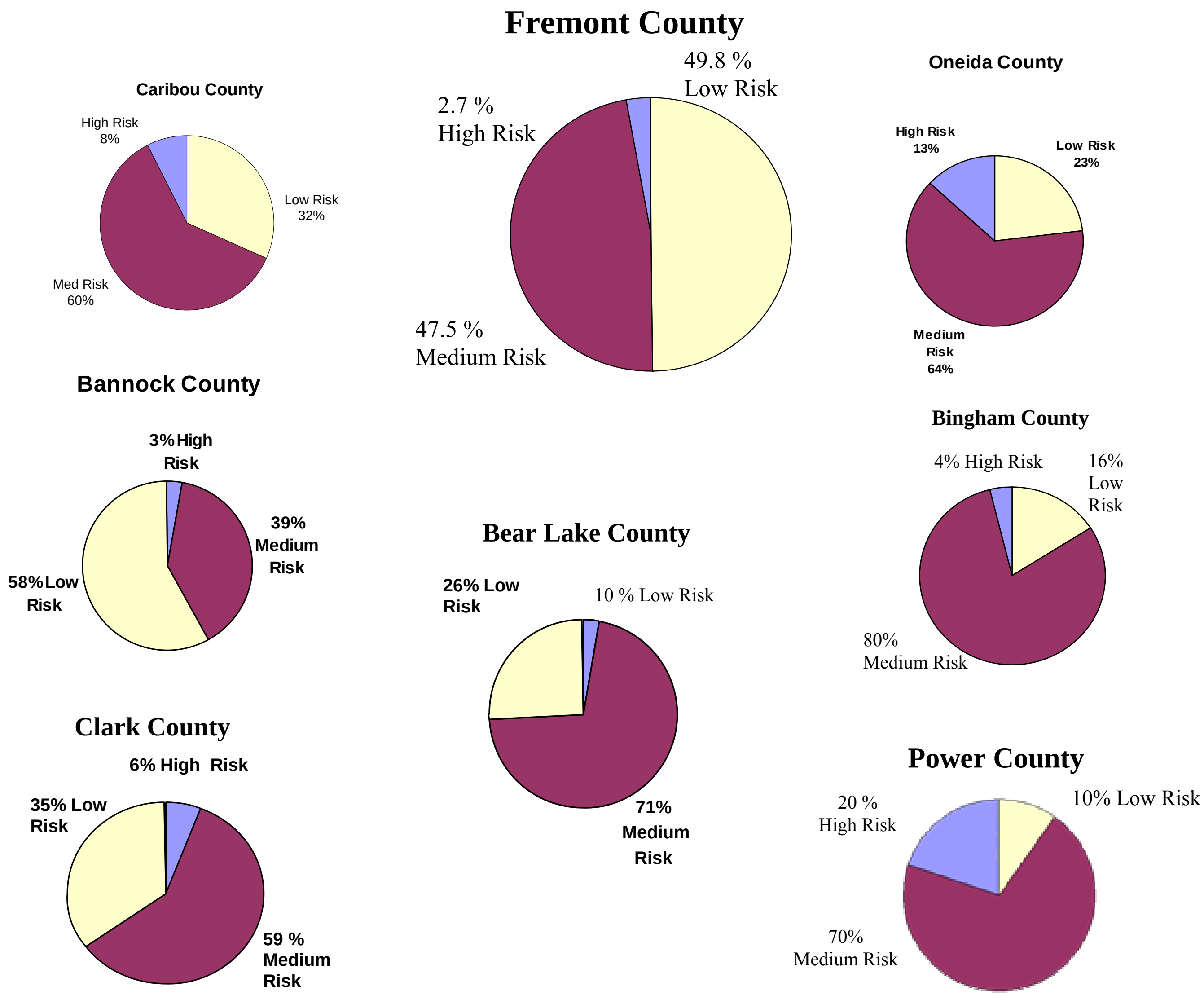

Figure 8: Percent of Clark, Bannock, Power, Oneida, Caribou, Bingham, Bear Lake and Fremont County considered low, medium, and high fire susceptibility based on the standard fire susceptibility model.

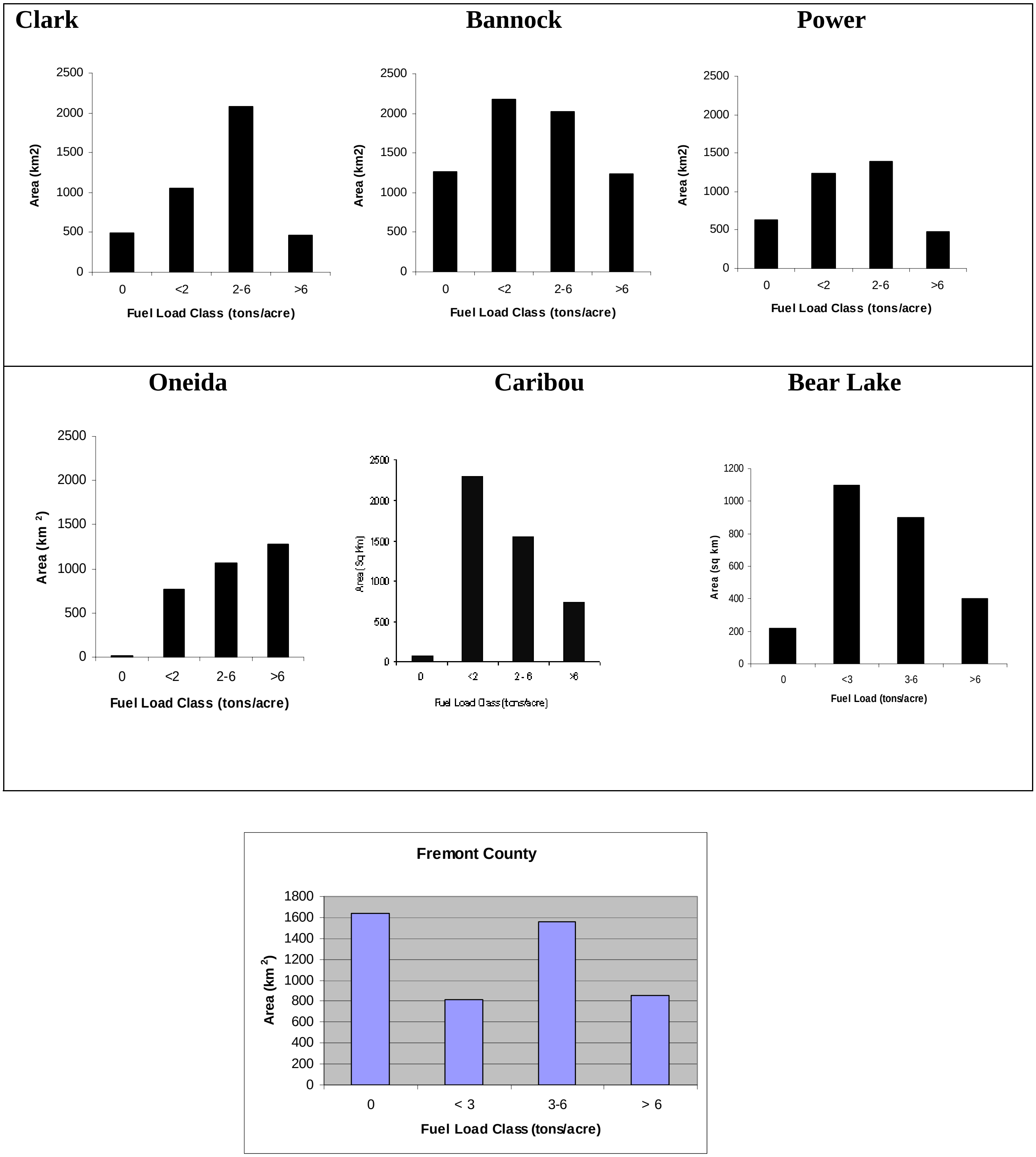

Figure 9: Comparison of fuel load distribution for Clark County, Bannock County, Power County, Oneida County, Bingham County, Caribou County, and Bear Lake County.

Table 2: Total acres classified as low, medium, and high fire susceptibility for Clark, Bannock, Power, Oneida, and Caribou County.

Total Acres Classified as Low, Medium and High Fire Susceptibility							
	Fremont County	**Bear Lake County**	**Clark County**	**Bannock County**	**Power County**	**Oneida County**	**Caribou County**
Low	570,608	62,080	395,360	413,146	233,958	175,761	356,923
Medium	598,237.4	435,008	666,464	277,805	638,886	495,089	688,575
High	32,434.6	124,288	67,776	21,370	26,996	97,599	84,806
Total	**1,201,280**	**621,376**	**1,129,600**	**712,321**	**899,840**	**768,449**	**1,130,304**

The NDVI grid used to generate the fuel load model is shown in figure 9. The reclassified NDVI grid 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 5 satellite imagery. Table 4 shows the error matrix validation for the fuel load model. The overall Kappa statistic was determined to be 0.8843 indicating that the classification was approximately 88.4% better than chance.

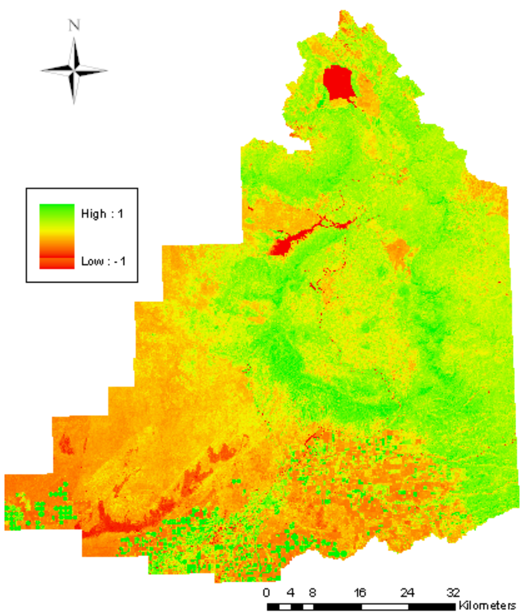

Figure 10: The NDVI has an interval of –1 to +1, where –1 is no vegetation and +1 is pure active vegetation.

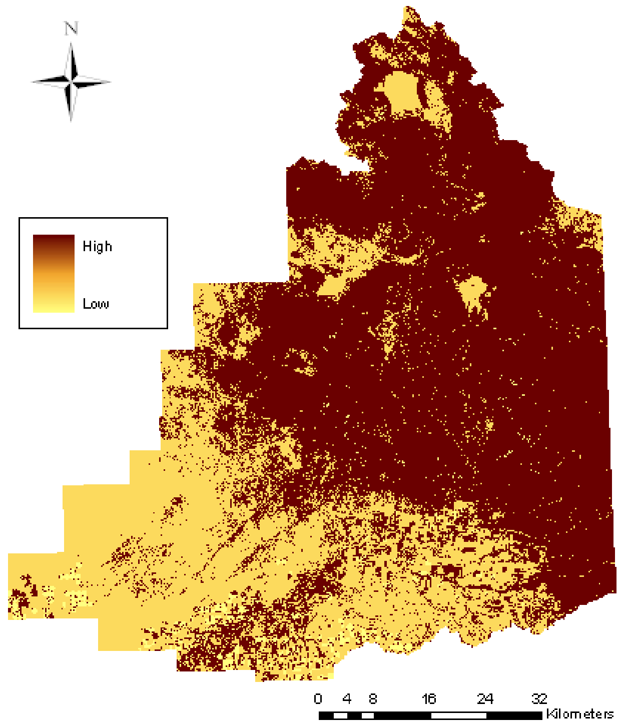

Figure 11: The results of the reclassification of NDVI into no vegetation (100), dry vegetation (200) and wet vegetation (75).

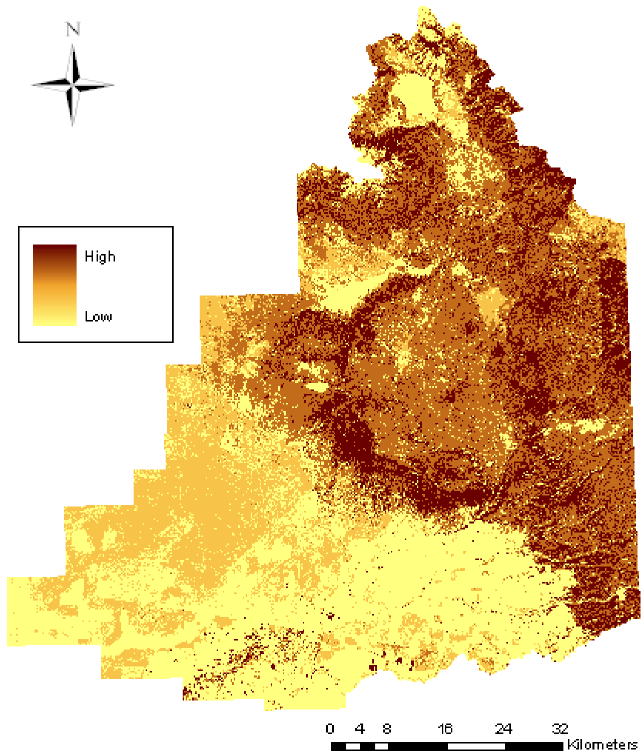

Figure 12: The fuel load model and the distribution of different fuel load classes for Bear Lake County, ID.

Table 3: Error matrix for the fuel load model.

		Field Measurement (tons/acre)					
		0	<3	3-6	>6	Total	Commission Accuracy
Modeled Fuel Load (tons/acre)	0	34	4	0	1	39	87.18%
	<3	0	197	0	0	197	100%
	3-6	4	0	16	6	26	61.54%
	>6	0	0	1	23	24	95.83%
	Total	38	201	17	30	286	Overall Accuracy
	Omission Accuracy	89.47%	98.01%	94.12%	76.67%		94.41%

The three component models derived from the fuel load model are shown in figures 13, 14, and 15. Figure 13 is the vegetation moisture model. The sand, grass, irrigated and riparian areas contain the lowest susceptibility values, while the shrubs, and mountainous areas of Fremont County contain the highest values. The high susceptibility areas are due to the low moisture content associated with the sagebrush steppe and the dry mountainous areas. The effect of fuel load on fire's spread rate is reported in figure 14. Mountainous areas with larger fuel loads and the areas containing no fuel loads (such as the sand dunes) contain the lowest values, where grasses and shrubs contain the highest values. The high susceptibility areas are due to the high concentration of 3-6 tons/acre fuels. Finally, figure 15 is the intensity model. The forested areas in the highlands comprise the highest susceptibilities for the most intense fires.

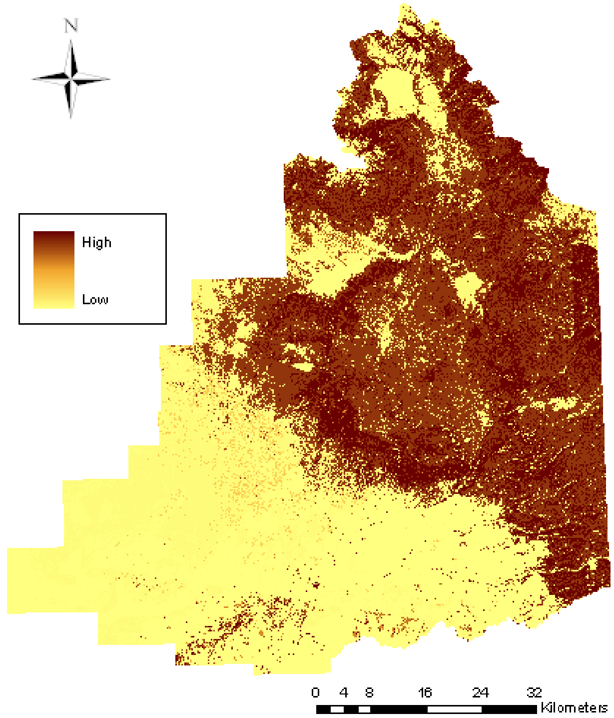

Figure 13: The Fuel Load/ Vegetation Moisture model. This model expresses how vegetation moisture (or lack of moisture) and the combination of different fuel load classes affect fire susceptibility. This model was given an overall weighting of 11% of the final model.

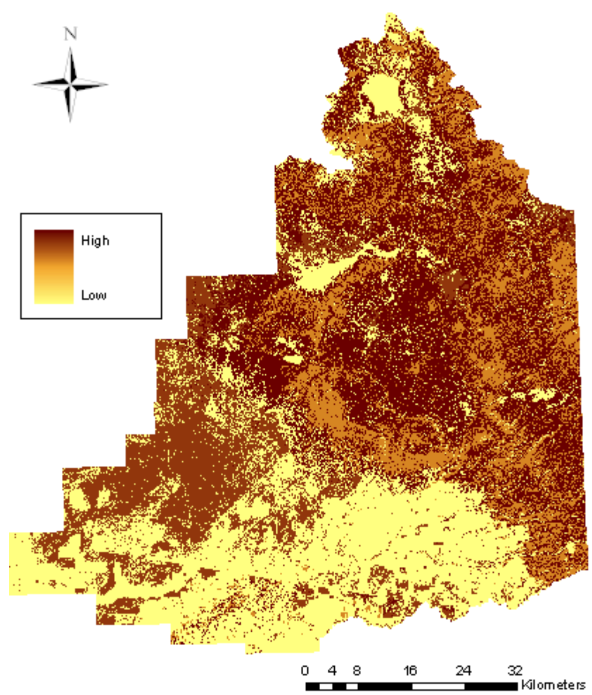

Figure 14: The Fuel Load/ Rate of Spread model. This model expresses the fire susceptibility associated with the spread rate of different fuel load classes. This model was given an overall weighting of 17% of the final model.

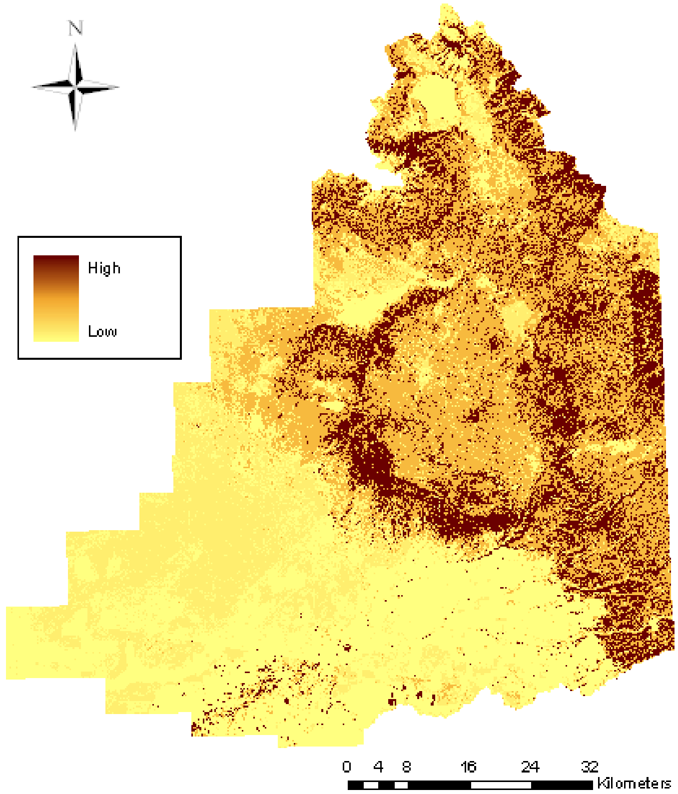

Figure 15: The Fuel Load/ Intensity model. This model expresses the fire susceptibility associated with the amount of heat energy (intensity) each fuel load class gives off. This model was given an overall weighting of 17% of the final model.

Figures 16-18 are the component models generated using the Fremont County DEM. Figure 16 assesses the susceptibility of fires spreading quickly due to steep slopes. Here, the highlands throughout the county received the highest values and the bottom lands throughout the county with shallow slopes, received the lowest values. Next is the suppression difficulty model (figure 17), where steeper slopes pose increasingly greater problems to fire fighters attempting to access fires in order to suppress them. The steeper terrain in the northeast is weighted the highest susceptibility. Figure 18 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.

The Structures Vulnerability component model is shown in figure 19. The main population centers of Fremont County include Island Park, St. Anthony, Warm River and Ashton. The Final Fire Susceptibility Model for Fremont County is shown in Figure 20.

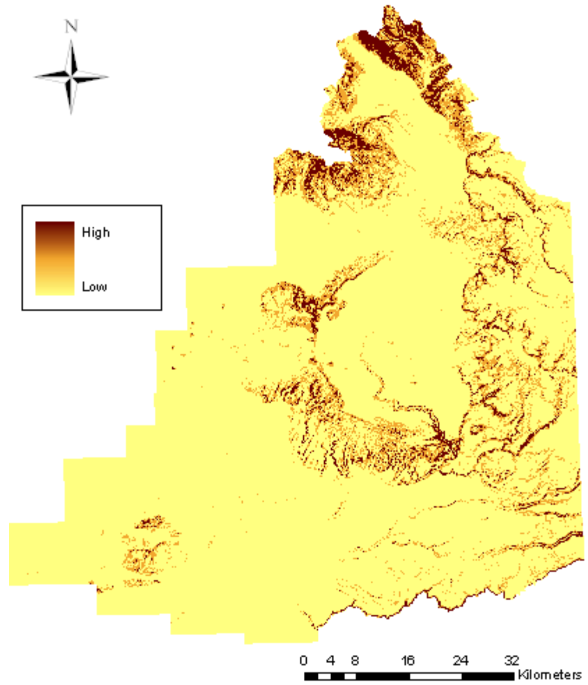

Figure 16: The Slope/ Rate of spread model. This model expresses how different angles of slope affect the spread rate of fire. Steeper slops are given the highest fire susceptibility. This model was given an overall weighting of 17% of the final model.

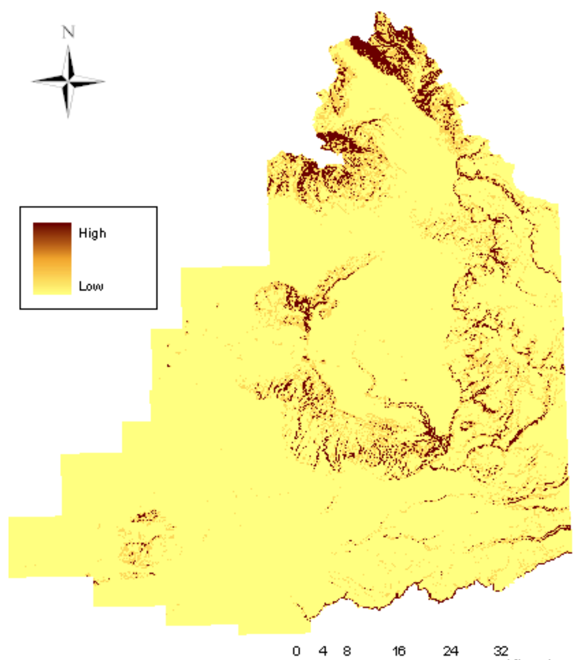

Figure 17: The Slope/ Suppression Difficulty model. This model expresses how different slope angles affect suppression efforts of firefighters. This model was given an overall weighting of 11% of the final model.

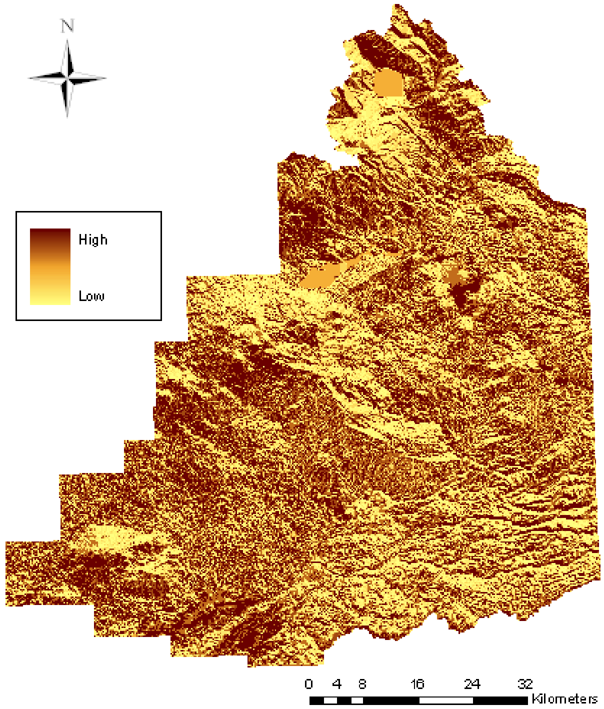

Figure 18: The Aspect: Sun Position. This model expresses how different aspects affect fire susceptibility. Southern aspects have the highest fire susceptibility. This model was given an overall weighting of 5% of the final model.

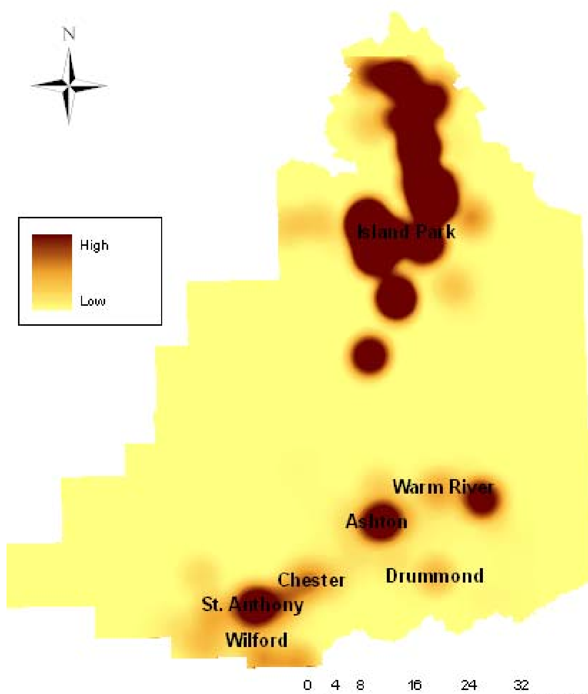

Figure 19: The Structures at Risk model. This model expresses areas that are highly susceptibility due to high structure density and is given an overall weighting of 22% of the final model.

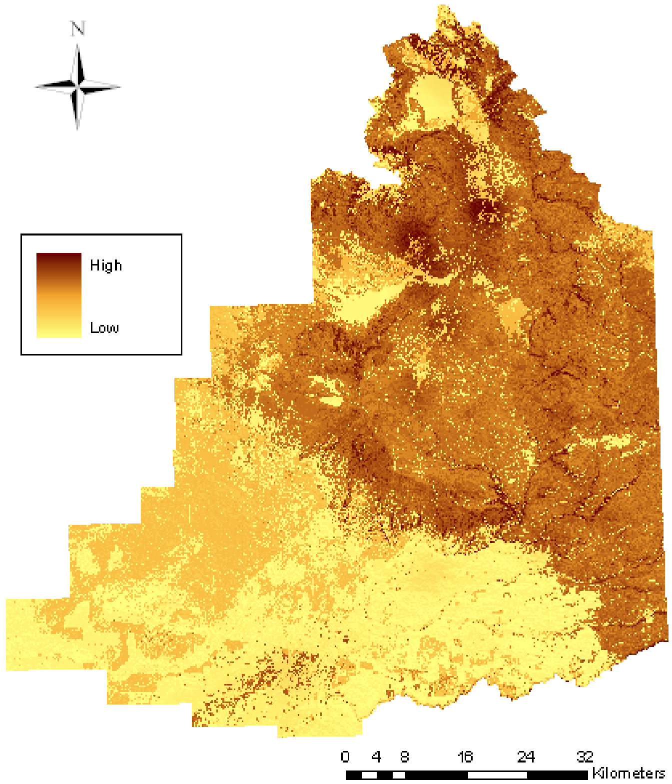

Figure 20: The Final Fire Susceptibility Model for Bear Lake County, Idaho.

Fire Regime Condition Class (FRCC)

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).

Construction of the Fire Regime Condition Class Alternate Fire Susceptibility Model

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 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 5*). The resulting values were then added to produce the Alternate Fire Susceptibility Model (Figure 23).

Table 5: 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%

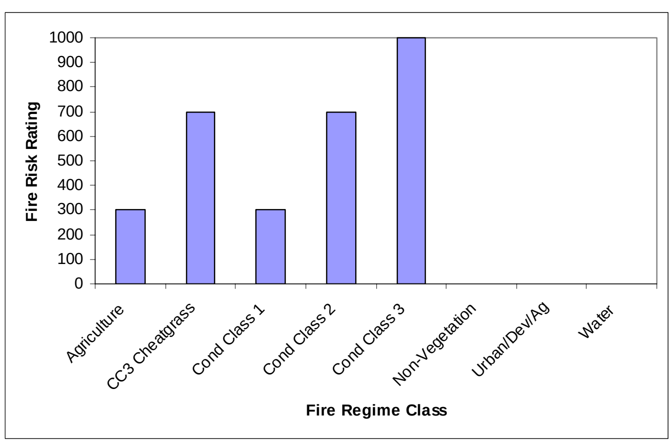

Figure 21: Fire susceptibility ratings of Fire Regime Class component.

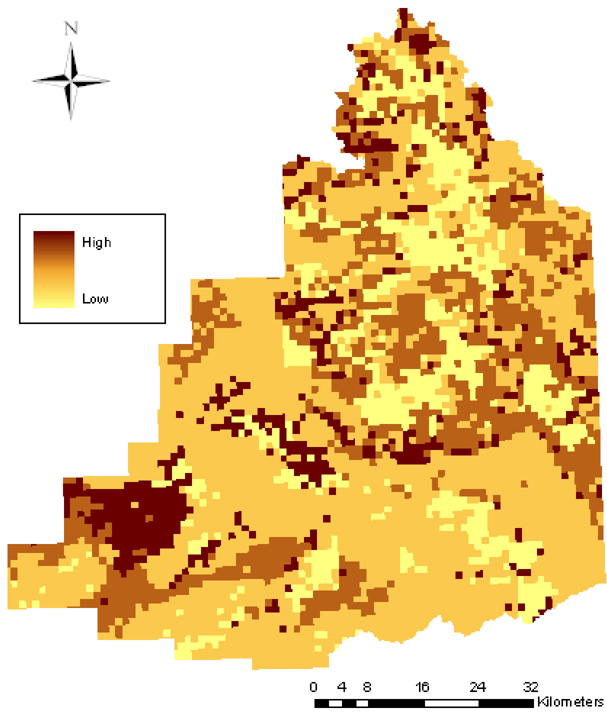

Figure 22: Normalized Fire Regime Condition Class sub model component.

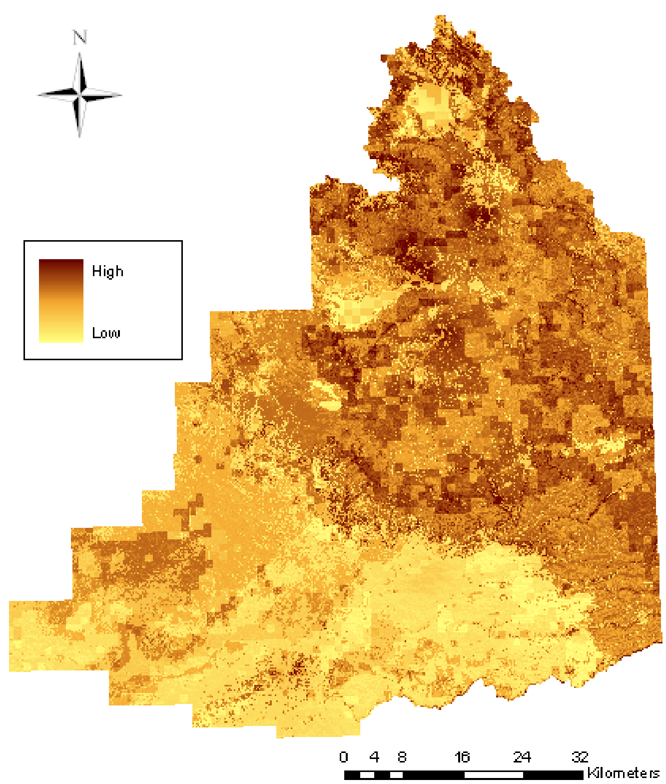

Figure 23: Alternate Fire Susceptibility Model for Bear Lake County using the Fire Regime Condition Class sub model in place of the Fuel Load: Fire Intensity sub model.

Discussion:

Fremont, Bear Lake, Clark, Bannock, Power, and Oneida counties all contain high desert sagebrush steppe ecosystems.

Of these counties, Bear Lake County has the smallest area, with 971 square miles. In order of size Fremont has the largest area, with 1,877 square miles, Clark County with 1,765 square miles, Power County with 1,406 square miles, Oneida County with 1,200 square miles and Bannock County with an area of 1,113 square miles.

Bear Lake County has the highest total acres classified as high fire susceptibility with 124,288 acres. Oneida County has the second largest area classified as high susceptibility with 97,599 acres. Caribou County follows with 84,806 acres classified as high susceptibility, followed by Clark County with 67,776 acres, Fremont County with 32,434.6 acres and Power County with 26,996 acres. Bannock County has the least acres as high susceptibility at 21,370 acres. The high fire susceptibility classification for all 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.

Caribou County has the largest area classified as medium fire susceptibility with 688,575 acres. Clark County and Power County (66,464 acres and 638,886acres respectively) have the next highest medium susceptibility classification. This is followed by Fremont, Oneida, Bear Lake, and Bannock Counties (598,237.4 acres, 495,089 acres, 435,008 acres, and 277,805 acres respectively). The southern portion of Clark County and the northern portion of Power County are 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. Bannock, by far, has the largest population with 75,323. The next largest by population is Fremont County with 12,263 people. Bingham has a population of 7,397. Bear Lake County has a population of 6,409. Oneida County's population is 4,131 and Clark County has 971 (U.S. Census Bureau Quick Facts 2003). Though each county has a relatively large area, the Structure Vulnerability component model for Bannock County shows the highest risk to structures (U.S. Census Bureau Quick Facts 2003) because of the number of urban areas within the county.

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 our results to be valid.

The goal for our model is to be 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 our study area and that it is easy to understand. Because the model is easy to understand, it should be applied to other users, which was a primary objective with 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.

Lastly, the date (Path 38, Row 29 was taken on September 7, 2005 and Path 39, Row 29 was taken on August 29, 2005.) on which the Landsat 5 data was acquired plays a significant role in the outcome of the Fuel Load-based components of the final model.

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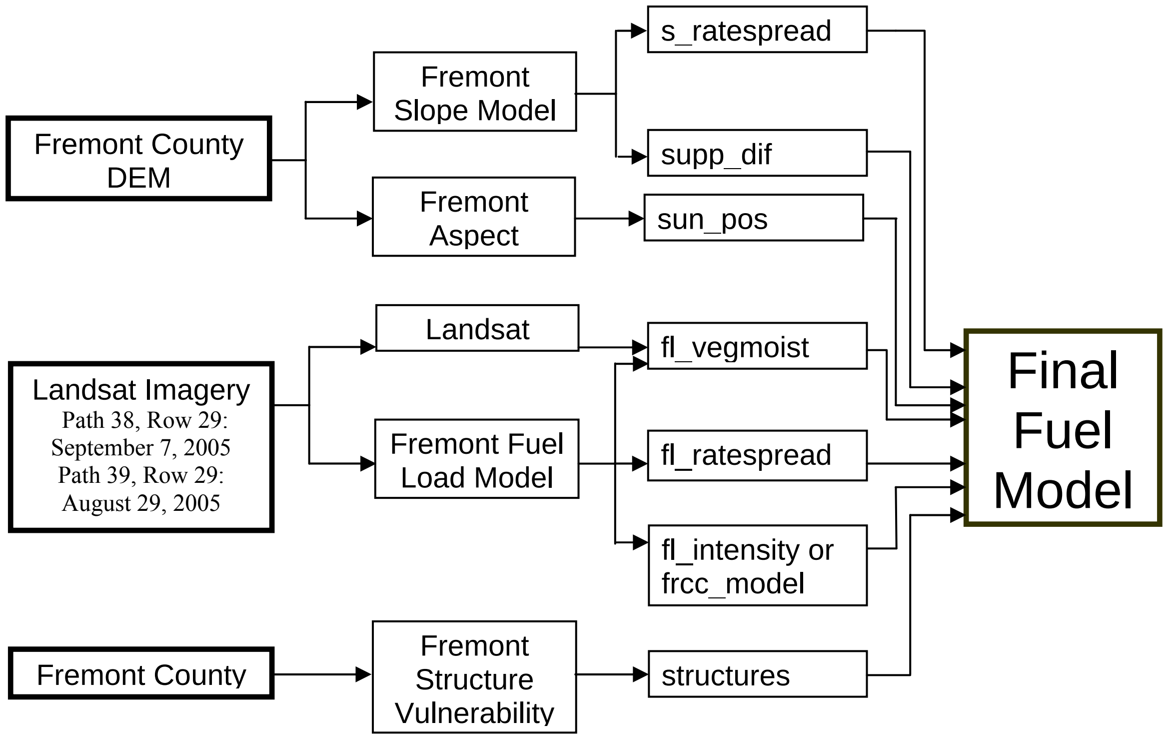
Acknowledgements:

At a meeting held on June 28, 2004, 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.

Appendices

Appendix A – Cartographic Model



Appendix B – Weightings

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

Table B-1: Reclassification system of the Fuel Load and NDVI grids. Compare with figure1.

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 1.

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 2.

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

Table B-4: Weighting data for Fuel Load/ Intensity. Compare with figure 3.

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 4.

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

Table B-6: Weighting data for Slope/ Suppression Difficulties. Compare with figure 5.

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 6.

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

Appendix C – Data dictionary

Data		File name		Description		Format
County boundary		Fremont_boun		Boundary of Fremont county		polygon coverage
County Roads		Fremont_rds		Roads of Fremont County		Shapefile
Structures Dataset		Structures		Data set of structures		Shapefile
Hot Spot Analysis Data		Hot_spot		Hot spot analysis for Fremont County structures, used to compare and validate with the structure density model (not used in the final WUI models).		Grid – 1017m pixels
Bands used for NDVI		Band_3		Landsat Band 3 for Fremont County		Grid - 28.5m pixels
		Band_4		Landsat Band 4 for Fremont County		Grid - 28.5m pixels
NDVI		C_NDVI		NDVI for Fremont County		Grid - 28.5 pixels
Fuel Load Model		fuel_load		Fuel Load model for Fremont County. Classes are 0 tons/acre, <3 tons/acre, 3-4 tons/acre, and 6> tons/acre		Grid - 28.5m pixels
DEM		Fremont_dem		Digital Elevation Model of Fremont County		Grid - 28.5m pixels
Condition Class Data		Condition_class		Condition class categories for Fremont County.		Shapefile
Component models		sun_pos		Susceptibility associated with aspect angle **i.e**. North, East, ...		Grid - 28.5m pixels
		s_ratespread		Susceptibility associated with how fire spreads with angle of slope.		Grid - 28.5m pixels
		supp_dif		Susceptibility associated with how suppression efforts are affected by angle of slope.		Grid - 28.5m pixels
		fl_ratespread		Susceptibility associated with how quickly different fuel load classes spread during a fire.		Grid - 28.5m pixels
		fl_intensity		Susceptibility associated with how intense (release of heat energy) different fuel load classes burn.		Grid - 28.5m pixels
		fl_vegmoist		Susceptibility associated with vegetation moisture.		Grid - 28.5m pixels
		structures		Susceptibility associated with structure density.		Grid - 28.5m pixels
		Frcc_model		Susceptibility due to condition classes base on the FRCC data.		Grid – 28.5m pixels
Final Model		Fnl_mdlc		Final susceptibility model		Grid - 28.5m pixels
FRCC Final Model		frcc_fnl_mdl		Final susceptibility model using condition classes		Grid - 28.5m pixels
Reports		Fremont_final_report		Report covering methods, results, & conclusions of WUI modeling		Word Document