# Wildland/Urban Interface Fire Susceptibility and Communities at Risk:

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

December 17, 2008

Linda Tedrow,tedrlind@isu.edu

Keith Weber, webekeit@isu.edu

## KEYWORDS

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

## 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 Jefferson 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 Jefferson 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 Jefferson County and can be used by regional fire managers to manage wildfire susceptibility.

# Table of 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. 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 Jefferson 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 Jefferson County
- Landsat 5 TM imagery for Jefferson County and environs – Path 38, Row 30, acquired July 29, 2008, Path 39, Row 29, acquired July 20, 2008, and Path 39, Row 30, acquired July 29, 2008.
- 2004 National Agriculture Imagery Program (NAIP) images for Jefferson County acquired November, 2007
- Transportation, place and county boundary datasets for Jefferson County acquired February 10, 2008
- Structure density raster data was based on county wide parcel data for Jefferson County.

## DATA ACQUISITION AND PREPARATION

### ELEVATION DATA

The DEM data for Jefferson County was obtained from Idaho State University (ISU) GIS Center's Spatial Library. Through the use of ArcMap 9.3 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 July 29, 2008, Path 39, Row 29, acquired July 20, 2008, and Path 39, Row 30, acquired July 29, 2008). The Landsat Imagery was ordered from the USGS, via the EROS Data Center's Global Visualization website (http://glovis.usgs.gov/).

### OTHER DATASETS

The Jefferson County boundaries and roads datasets were downloaded from the Inside Idaho website. The Jefferson 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 Jefferson 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 Jefferson County, Idaho.

## Topographic Sub-Model Components

### Creating the Topographic: Slope: Suppression Difficulty Component Model

Using the Jefferson County DEM as input, a slope grid can be calculated using the ArcMap (Spatial Analyst → Surface Analysis → Slope). 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, we used the slope model created above 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 Figure 1.

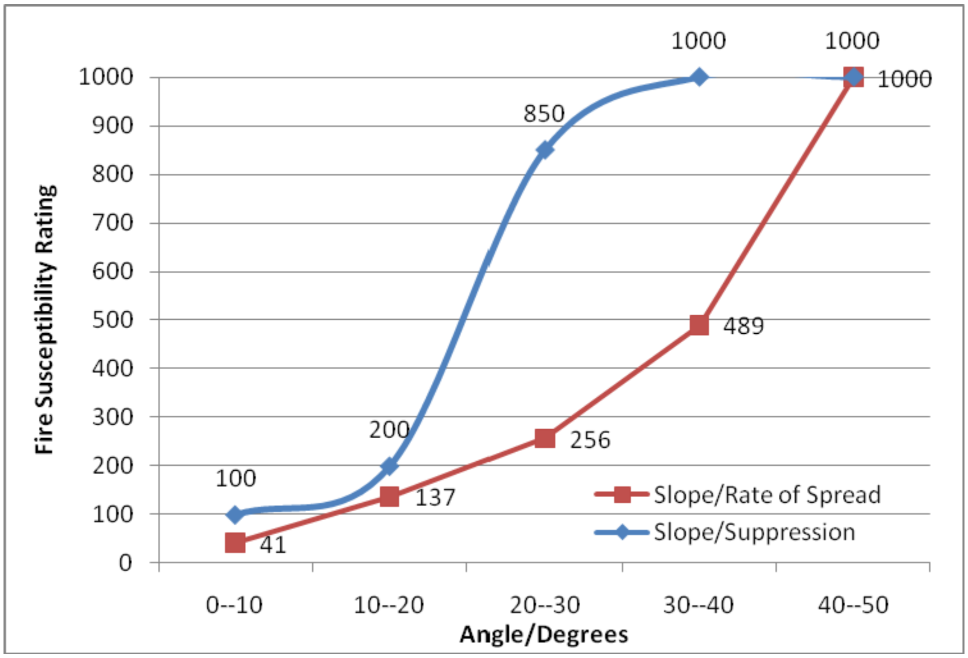



**FIGURE 1 - WEIGHTING FOR SLOPE/SUPPRESSION DIFFICULTIES DESCRIBE HOW SUPPRESSION IS IMPACTED BY THE ANGLE OF SLOPE. WEIGHTING FOR SPREADING RATE DESCRIBE HOW SPREADING RATES INCREASE WITH ANGLE OF SLOPE. (MATTSSON ET AL, 2002)**

## Creating the Topographic: Slope: Rate of Spread Component Model

To make the Slope: Rate of Spread sub-model, we reclassified the Slope based on weightings from Mattsson *et al.* (2002) using ArcMap → Spatial Analysis → 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 the instantaneous slope face. Using the Jefferson County area DEM as input, an aspect grid was 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 cell size was set to 30 meters.

To create the Aspect: Sun Position, we reclassified the aspect grid, following Mattsson *et al.* (2002) (table B-7 in Appendix B) using ArcMap → Spatial Analyst → Reclassify (Figure 2).

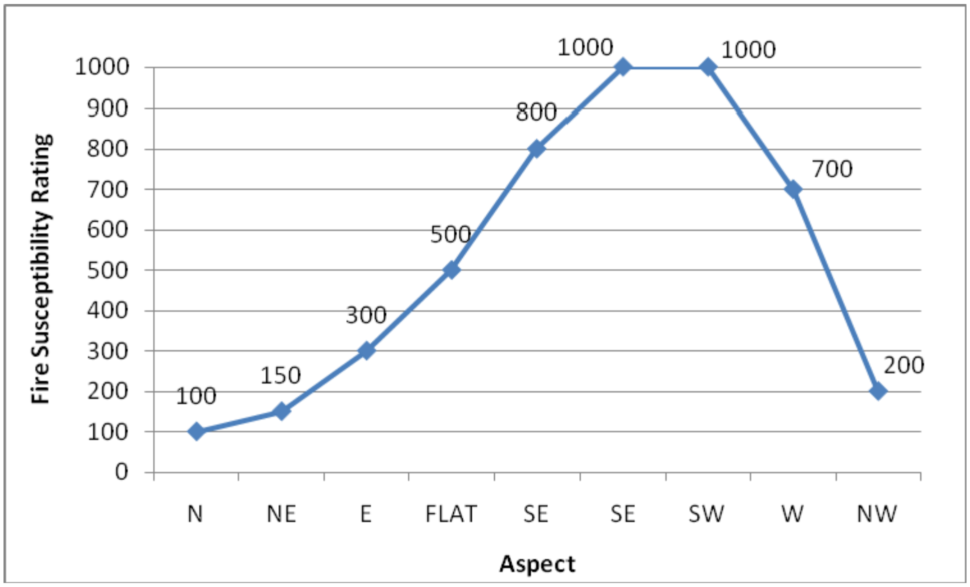



**FIGURE 2. WEIGHTING FOR ASPECT/SUN POSITION DESCRIBE HOW THE SUN DESICCATES VEGETATION AT DIFFERENT ASPECTS (MATTSSON ET AL, 2002).**

## FUEL LOAD SUB-MODEL COMPONENTS:

### CREATING THE FUEL LOAD FIRE SUSCEPTIBILITY COMPONENTS

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

We estimated vegetation cover with satellite imagery using the Normalized Difference Vegetation Index (NDVI) for Landsat Path 38, Row 30, acquired July 29, 2008, Path 39, Row 29, acquired July 20, 2008, and Path 39, Row 30, acquired July 29, 2008. 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”. The following equation was used to create the NDVI grid:

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

***Equation1.** Equation for calculating NDVI.*

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

Supervised classification of Landsat imagery through IDRISI Andes (ver. 15.01) was used for estimating fuel load in Jefferson County. To estimate fuel load, we used 728 fuel load estimates taken throughout the three Landsat scenes. These estimates were a combination of field sample points and a range of fuel load estimates. The field sample points included (640 sample points) collected within the O'Neal and Big Desert study sites during the summers of 2007 and 2008. An additional 88 supplemental fuel load estimates were collected throughout the three landsat scenes by L Tedrow and previous WUI researchers (Anderson and Weber, 2008, Anderson and Weber, 2007, Crats, et al 2006). The 728 sample points were classified into a fuel load grid with the following 4 fuel load classes:

**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) |

Using Hawthe's Tools (Beyer, 2004) in ArcMap 9.3, we randomly selected and divided the classified fuel load points into training and validations sites. In Idrisi, we created signature files for the field training sites using an NDVI model produced from Landsat imagery and PCA Components 1, 2, and 3 (Idrisi → Image Processing → Signature Development → MAKESIG). The signature files were then used to create a fuel load raster grid using Idrisi (Hard Classifiers → MAXLIKE). In addition, a fuel load model was created using Classification Tree Analysis to compare with the model created with the maximum-likelihood algorigthm. We validated the predictions of these models 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 (Table 3). A Kappa statistic was calculated. This statistic serves as an indicator of how much better or worse our classification performed compared to pure random classification.

### Fuel Load/Vegetation Moisture

The Fuel Load/Vegetation Moisture component incorporates the fuel load values and the vegetation moisture values. 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 through reclassification of the NDVI grid using ArcMap (Spatial Analyst → Reclassify) to delineate wet vegetation, dry vegetation, and no vegetation also described inTable B-1 of Appendix B.

The Fuel Load/Vegetation Moisture grid was created by multiplying the fuel load grid values with the vegetation moisture grid values using ArcMap →Spatial Analyst →Raster Calculator as described in Table B-2 of Appendix B.

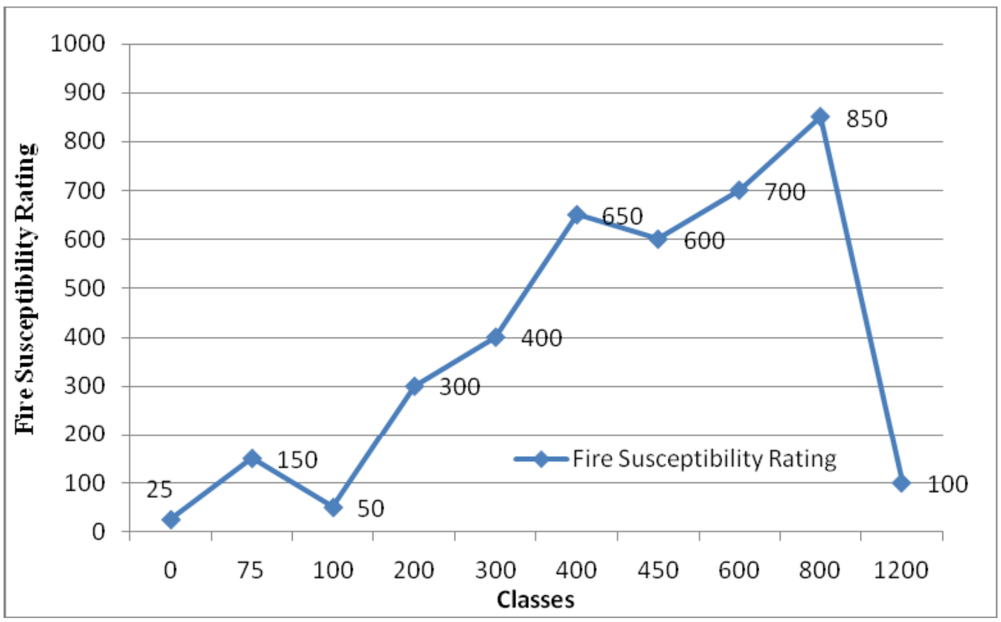



**FIGURE 3 - WEIGHTINGS FOR FUEL LOAD/ VEGETATION MOISTURE (JANSSON ET AL, 2002).**

### 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 grid, following Mattsson et al. (2002) (Table B-3 in Appendix B), using ArcMap → Spatial Analyst → Reclassify (Figure 4).

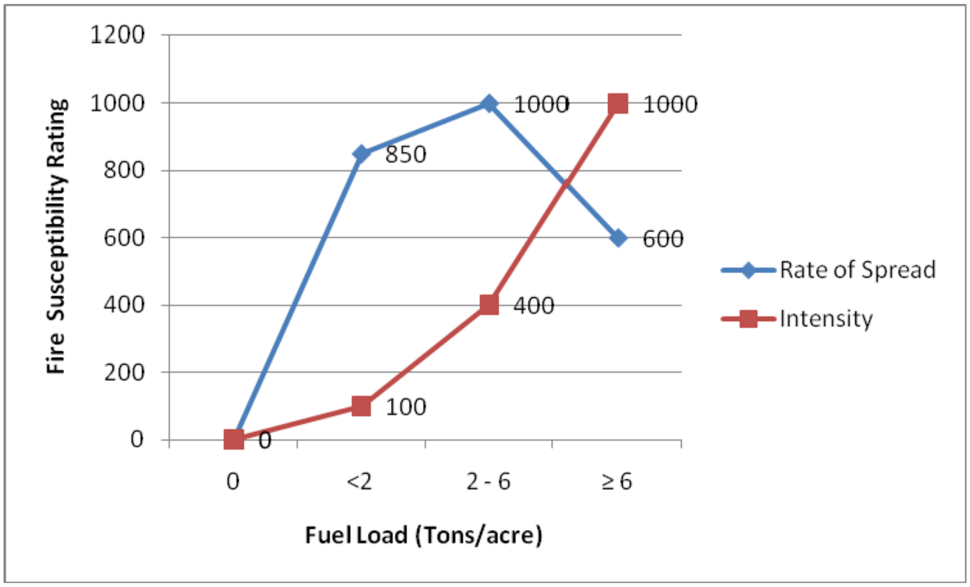



**FIGURE 4 - WEIGHTINGS FOR FUEL LOAD/RATE OF SPREAD AND FUEL LOAD/INTENSITY (MATTSSON ET AL, 2002).**

### FUEL LOAD: FIRE INTENSITY COMPONENT MODEL

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

## STRUCTURE SUB-MODEL COMPONENTS:

### STRUCTURE VULNERABILITY COMPONENT MODEL

To create the Structure Vulnerability sub model we used County Assessor provided parcel data for Jefferson County. Each parcel of a type appropriate to this study (those with structures in non urban settings) was selected and then converted into a single vector point. A simple point density raster was then derived from this dataset. To make this component consistent with the other sub-models, the range of pixel values was stretched to a range of 0 – 1000.

### WUI FIRE SUSCEPTIBILITY MODEL

After completing the above analyses, we examined the impact each fire model component had on the overall fire susceptibility in Jefferson County, Idaho. The final fire susceptibility model was determined as a weighted average (using ArcMap → Spatial Analyst → Raster Calculator) of the 7 component models. The weight of 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% |

## RESULTS:

The NDVI grid used to classify the fuel load model is shown in Figure 5. Table 3 shows the error matrix validation for the fuel load model produced using classification tree analysis as this approach outperformed maximum-likelihood in this instance. The overall Kappa statistic was determined to be 0.842 indicating that the classification was approximately 84% better than chance.

**TABLE 3- ERROR MATRIX FOR THE FUEL LOAD MODEL.**

**Field Measurement (tons/acres)**

| | | **0** | **<2** | **2-6** | **>6** | **Total** | **Commission Accuracy** |
|---|---|---|---|---|---|---|---|
| **Modeled Fuel (tons/acre)** | **0** | 27 | 0 | 0 | 0 | **27** | 100% |
| | **<2** | 3 | 22 | 3 | 0 | **28** | 79% |
| | **2-6** | 0 | 8 | 26 | 0 | **34** | 76% |
| | **>6** | 0 | 0 | 0 | 30 | **30** | 100% |
| | **Total** | **30** | **30** | **29** | **30** | **119** | **Overall Accuracy** |
| | **Omission Accuracy** | 90% | 73% | 90% | 100% | | **88%** |

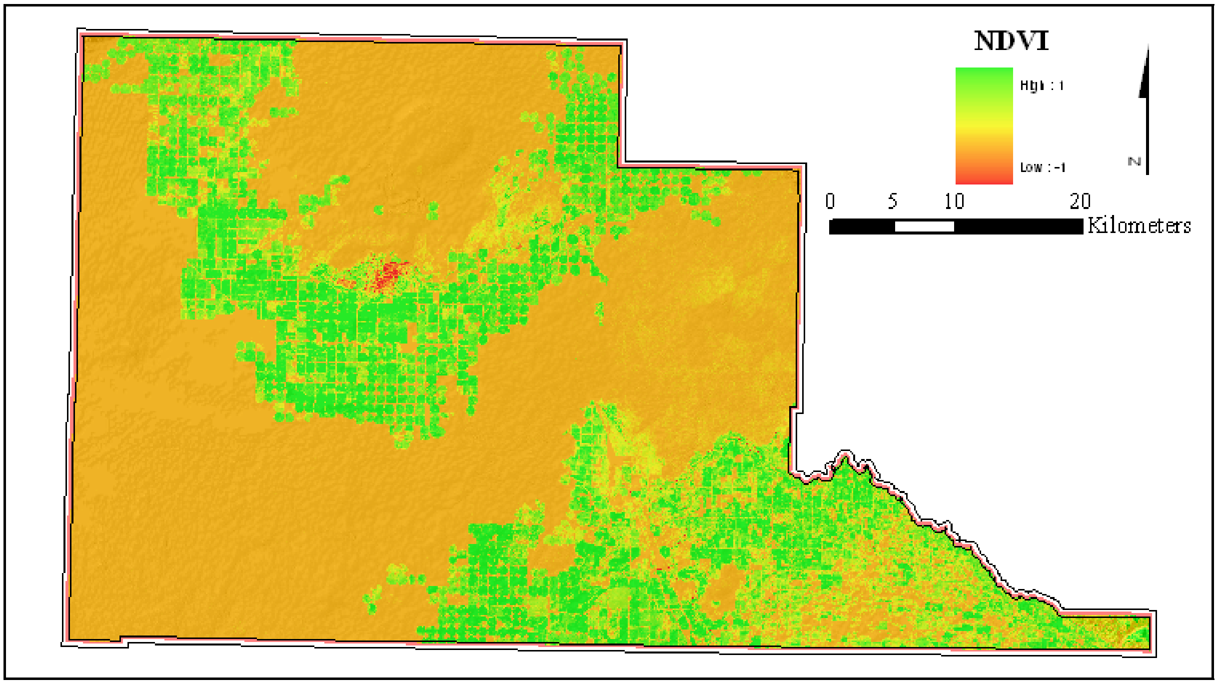



**FIGURE 5 - THE NDVI INTERVAL RANGES FROM -1 TO +1, FROM NO VEGETATION TO PURE PHOTOSYNTHETICALLY ACTIVE VEGETATION.**

The three component models derived from the fuel load model are shown in figures 6, 7, and 8. Figure 6 is the vegetation moisture model, irrigated and riparian areas contain the lowest susceptibility values, while the grasses and shrubs throughout Jefferson 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 effect of fuel load on fire’s spread rate is reported in figure 7. 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 8 is the intensity model. Confers in the highlands comprise the highest susceptibility for the most intense fires.

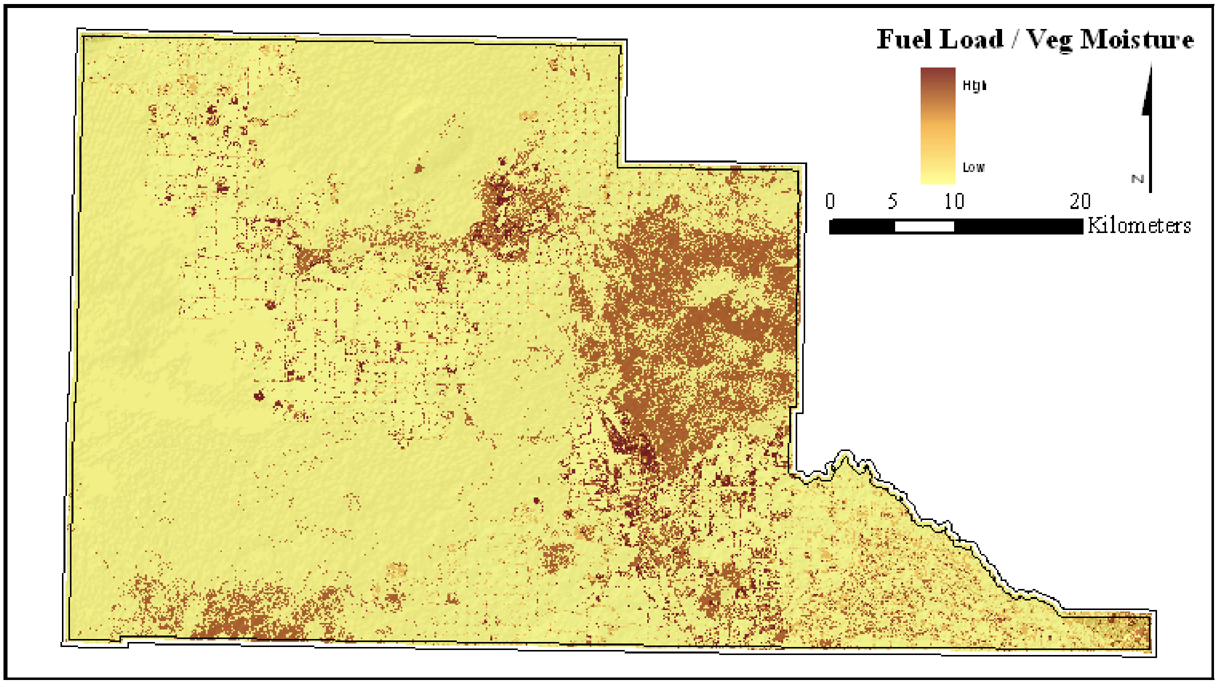



**FIGURE 6 - FUEL LOAD - VEGETATION MOISTURE**

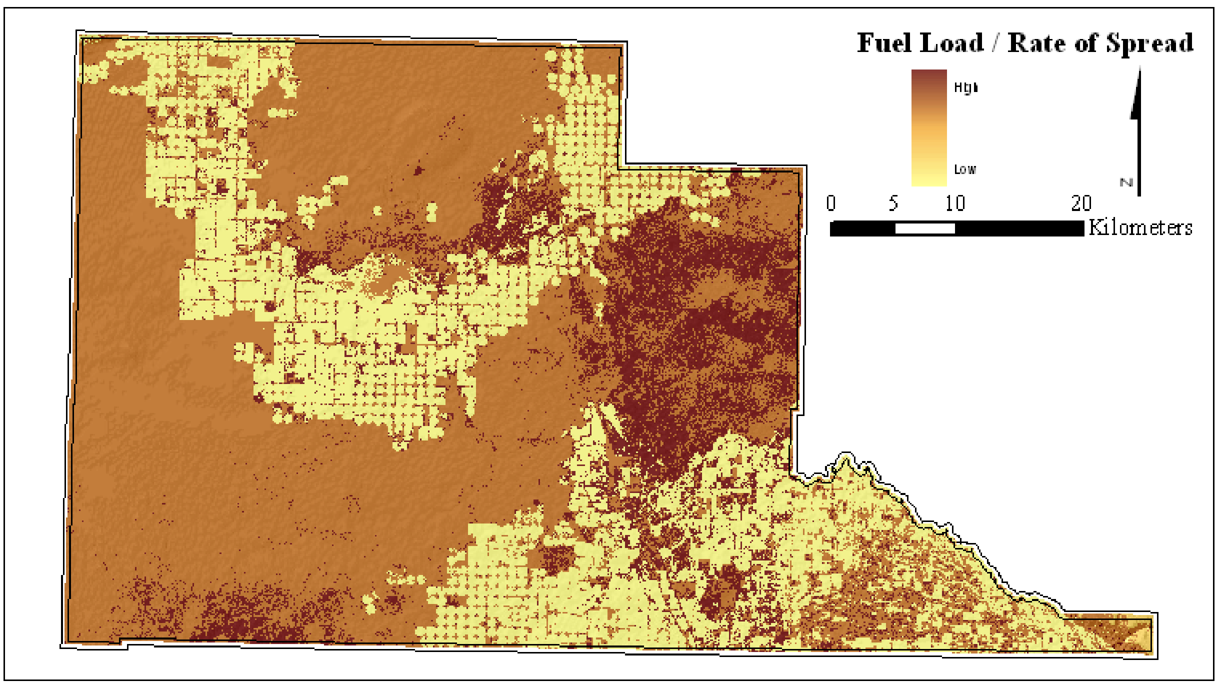



**FIGURE 7 EFFECT OF FUEL LOAD ON FIRE'S SPREAD RATE**

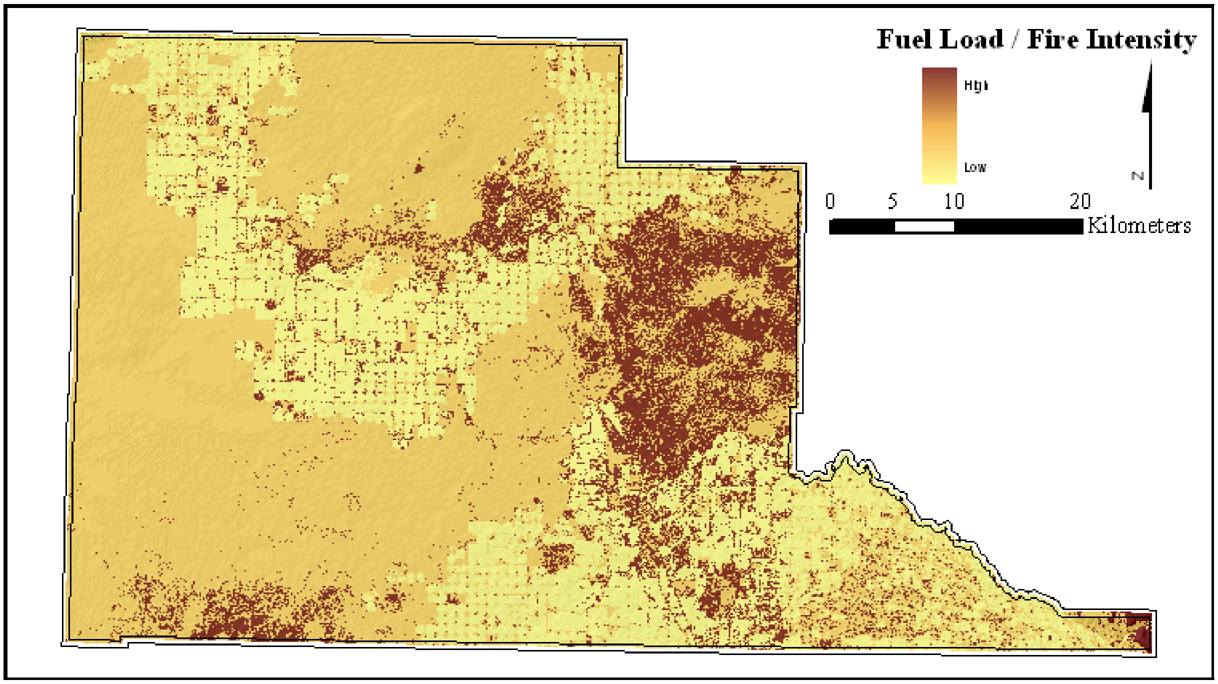



**FIGURE 8 - FUEL LOAD/FIRE INTENSITY**

Figures 9-11 are the component models generated using the Jefferson County DEM. Figure 9 assesses the susceptibility of fires spreading quickly due to steep slopes. The only steep slopes in Jefferson County are at the Northwest, Northeast and Southeast 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 wind through much of the day, contain the lowest fire susceptibility.

Figure 12 is the Structure Density model built from data supplied from the Jefferson County Assessors Office. The highest structure density coincides with areas of highest urbanization.

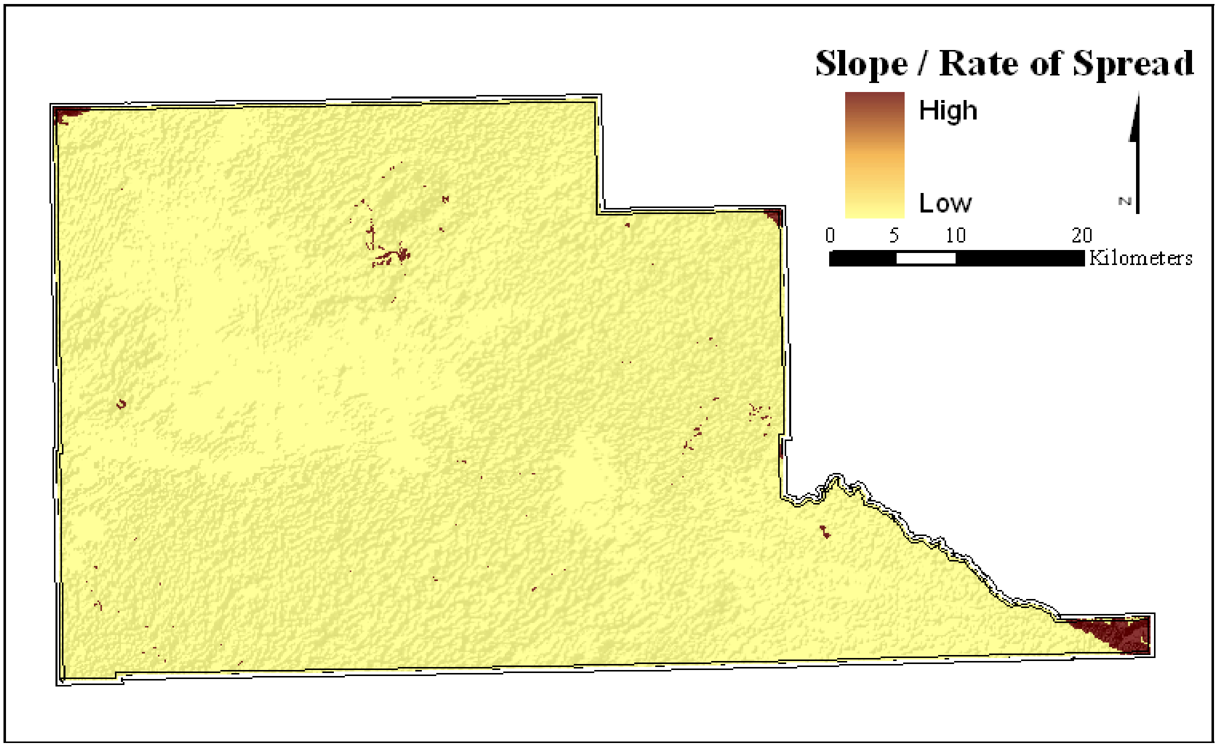



**FIGURE 9 - SLOPE / RATE OF SPREAD**

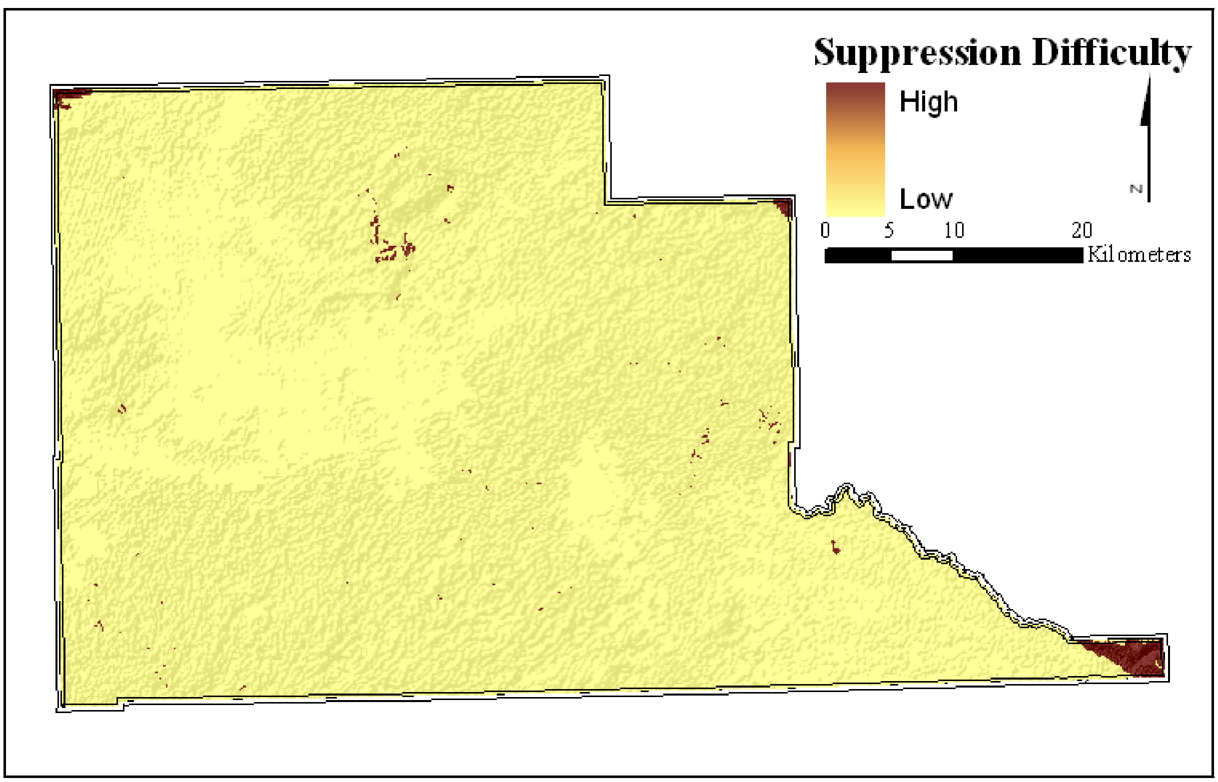



**FIGURE 10 - THE SLOPE/SUPPRESSION DIFFICULTY MODEL. THIS MODEL EXPRESSES HOW DIFFERENT SLOPE ANGLES AFFECT**

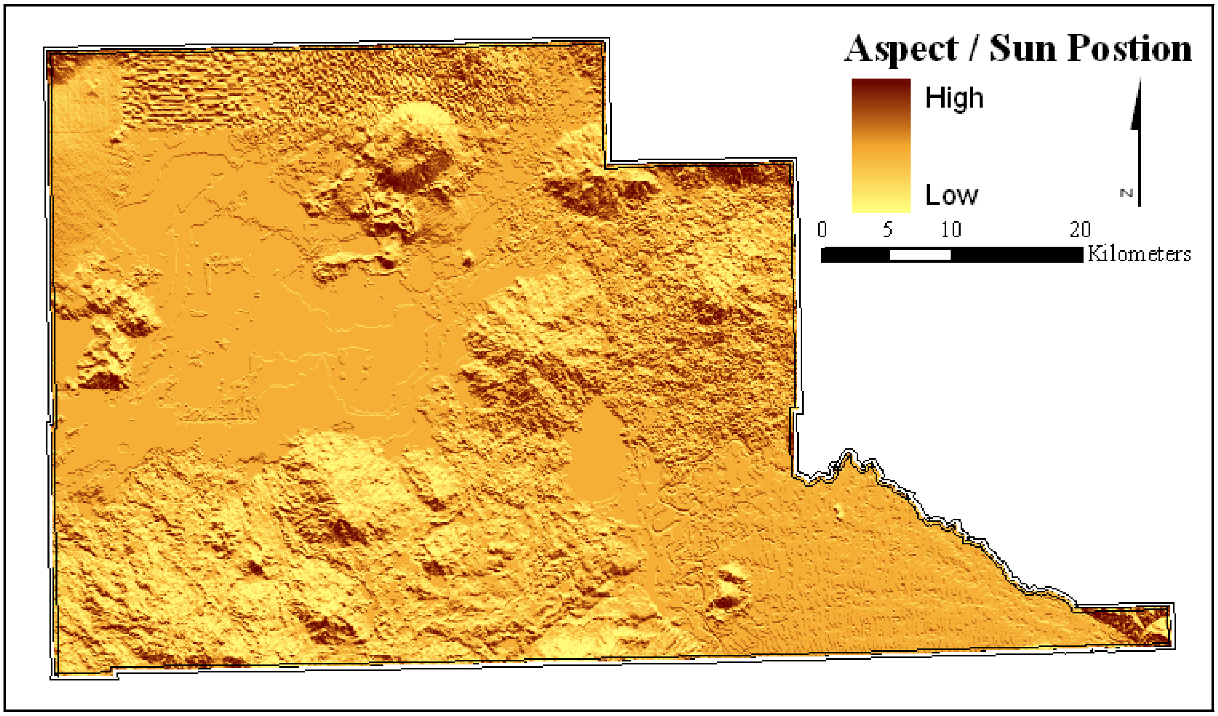



**FIGURE 11 - THE ASPECT: SUN POSITION. THIS MODEL EXPRESSES HOW DIFFERENT ASPECTS AFFECT FIRE SUSCEPTIBILITY.**

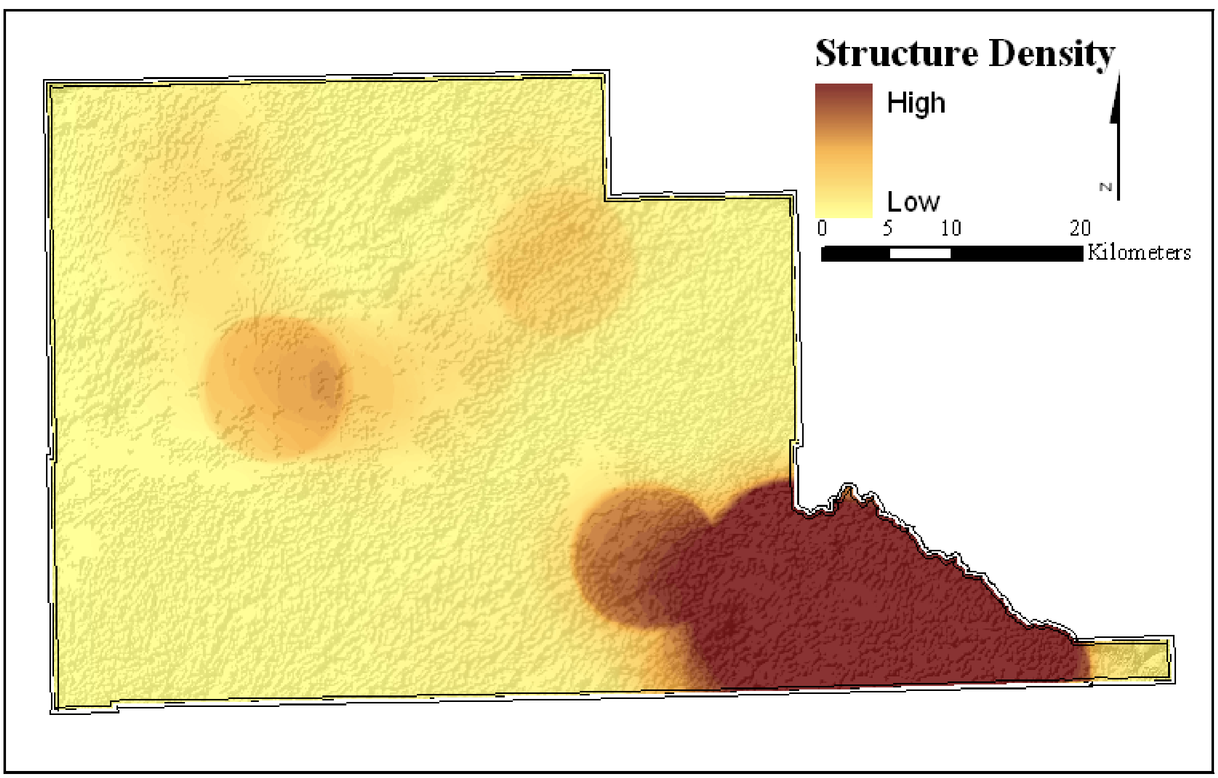



**FIGURE 12 - THE STRUCTURE VULNERABILITY MODEL. THIS MODEL EXPRESSES AREAS THAT ARE HIGH SUSCEPTIBILITY DUE TO STRUCTURE DENSITY.**

The Final Fire Susceptibility Model for Jefferson 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.

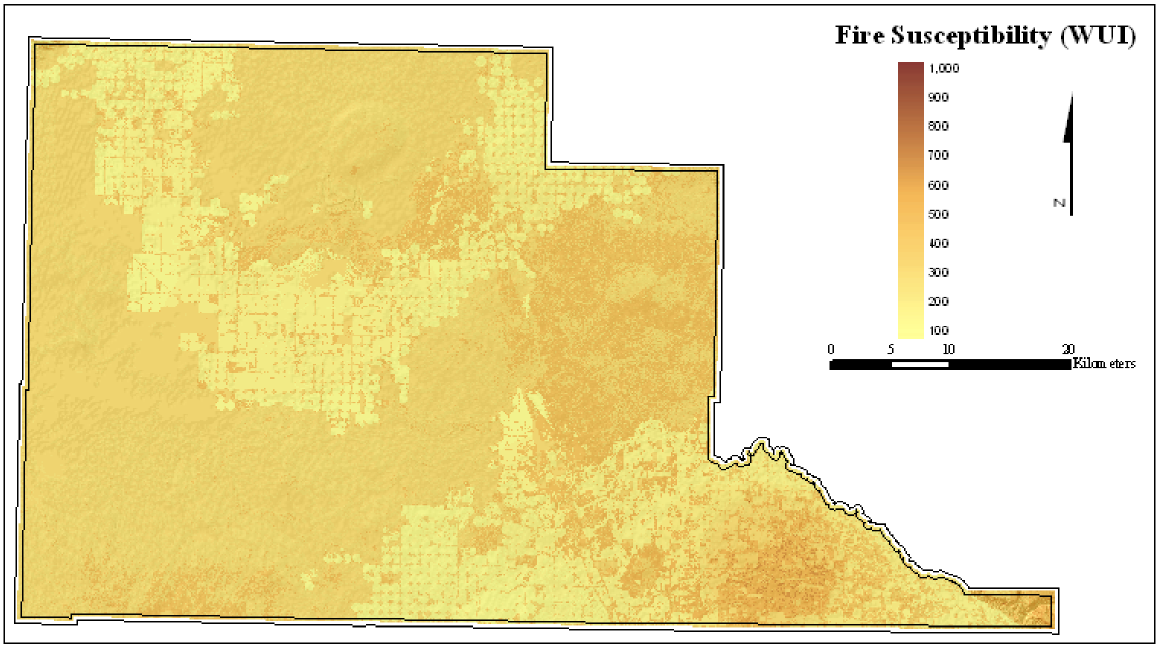



**FIGURE 13 - THE FINAL FIRE SUSCEPTIBILITY MODEL FOR JEFFERSON COUNTY, IDAHO.**

## The Fire Regime Condition Class

The Fire Regime Condition Class (FRCC) is 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 non-standard 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).

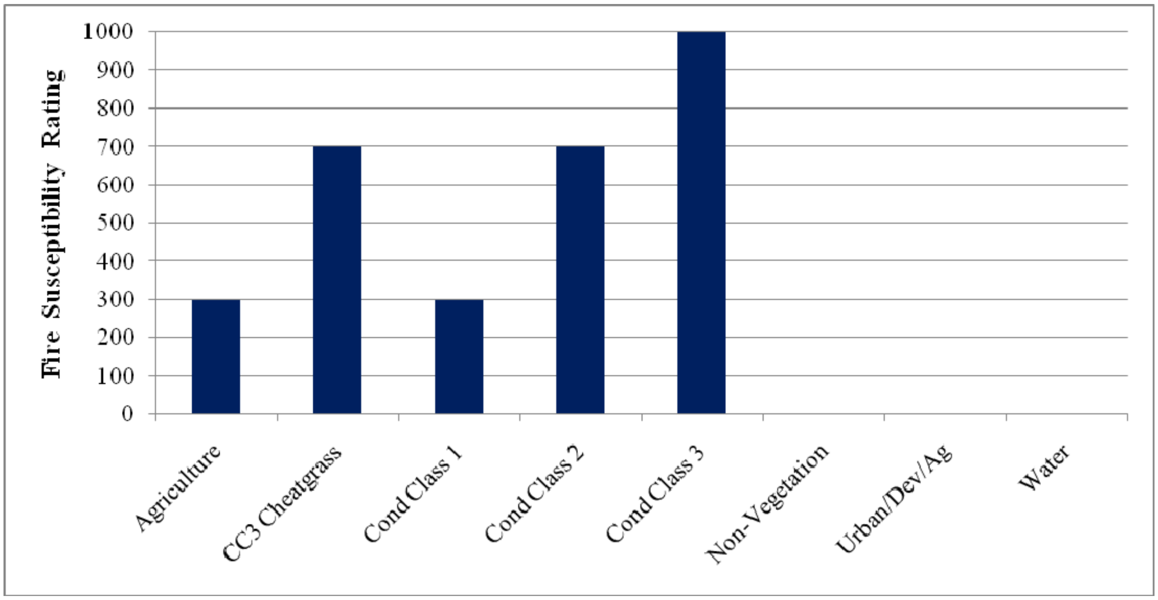



**FIGURE 14 - FIRE SUSCEPTIBILITY RATINGS OF THE FIRE REGIVE CLASS COMPONENT.**

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 of the Alternate 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 their own weighting percentage (Table 5). The resulting values were then added to produce the Alternate Fire Susceptibility Model (Figure 16).

A comparison of the two models is illustrated in Figure 17 which depicts the standard deviation between the standard model and the alternative model based on the FRCC.

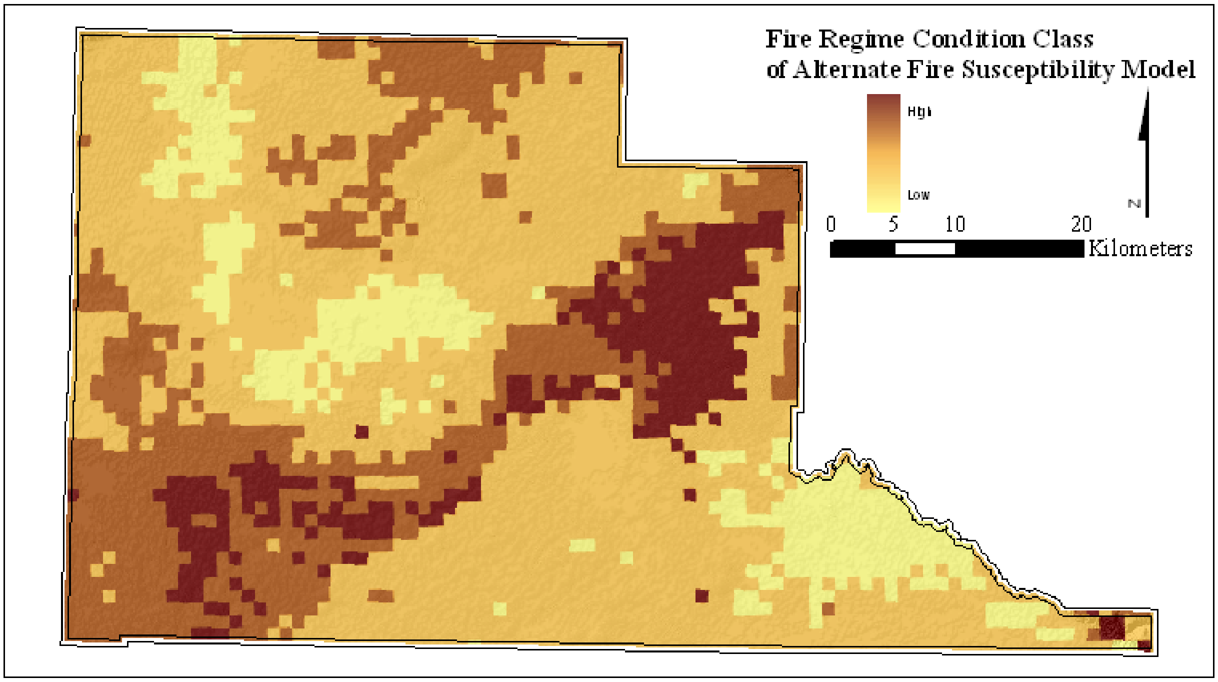


**FIGURE 15 - THE FIRE REGIME CONDITION CLASS (FRCC) IS AN ALTERNATE FIRE SUSCEPTIBILITY MODEL.**

**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% |

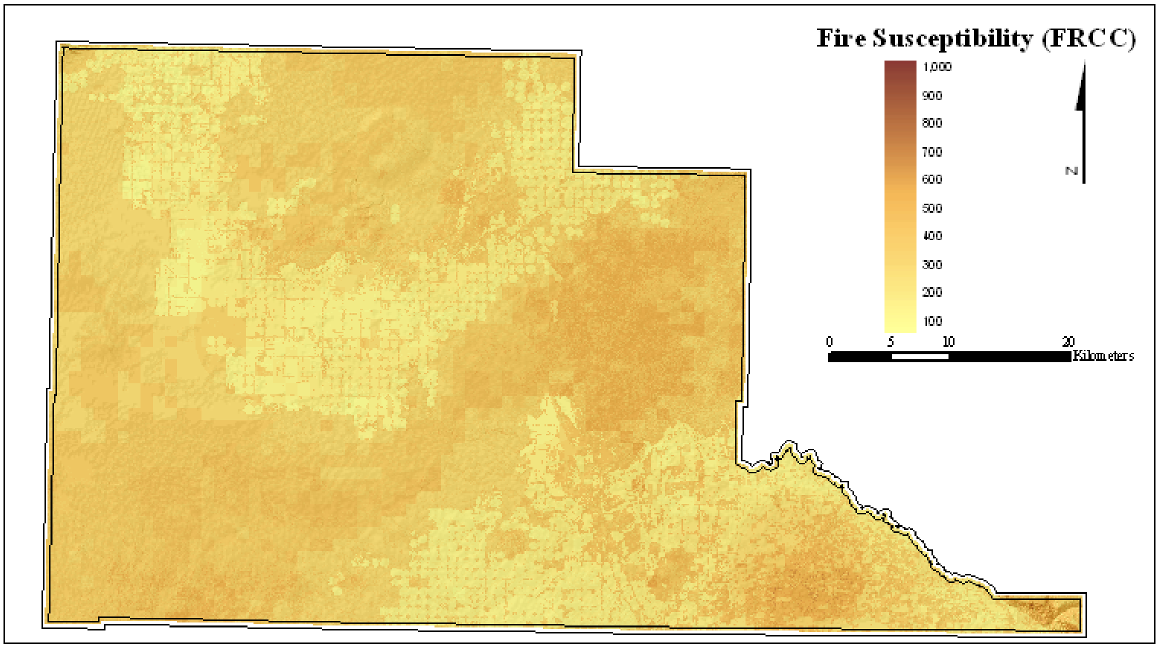



**FIGURE 16 - ALTERNATE FIRE SUSCEPTIBILITY MODEL FOR JEFFERSON COUNTY USING THE FIRE REGIME CONDITION CLASS**

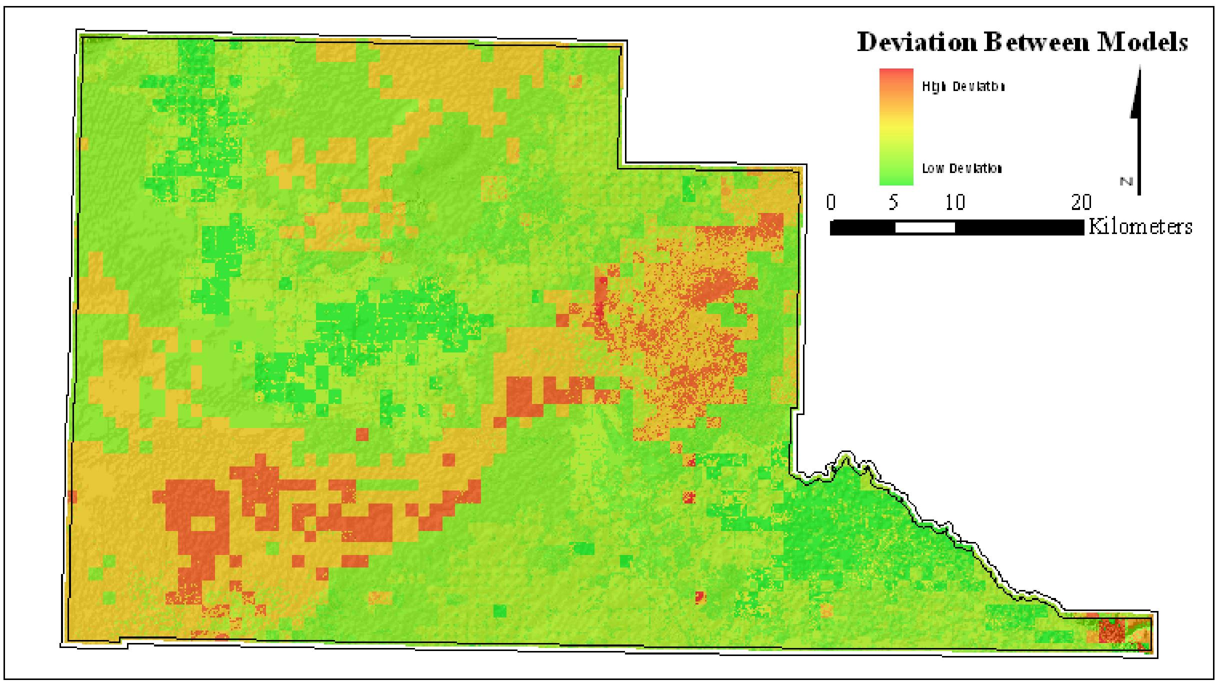



**FIGURE 17 - STANDARD DEVIATION BETWEEN THE STANDARD MODEL AND THE ALTERNATIVE MODEL BASED ON FRCC.**

## DISCUSSION:

We compared the WUI fire susceptibility models for Jefferson, 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; 333-666 = medium susceptibility; 666-1000 = high susceptibility). The comparison between total acres classified as low, medium, and high fire susceptibility is shown in Table 5. Figure 19 shows portions of each county classified as low, medium, and high susceptibility relative to individual areas. Table 4 - Total acres classified as low, medium, and high fire susceptibility for Bannock, Bonneville, Clark, Fremont, Jefferson, Lemhi, and Teton counties.

**TABLE 5 - TOTAL ACRES CLASSIFIED AS LOW, MEDIUM, AND HIGH FIRE SUSCEPTIBILITY FOR BANNOCK, BONNEVILLE, CLARK, FREMONT, JEFFERSON, 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 |
| **Clark** | 395,360 | 666,464 | 67,776 | 1,129,600 |
| **Fremont** | 570,608 | 598,237 | 32,434 | 1,201,280 |
| **Jefferson** | 598,960 | 111,730 | < 1 | 710,691 |
| **Lemhi** | 1,348,323 | 1,436,257 | 146,556 | 2,931,136 |
| **Teton** | 46,094 | 187,261 | 54,737 | 288,092 |

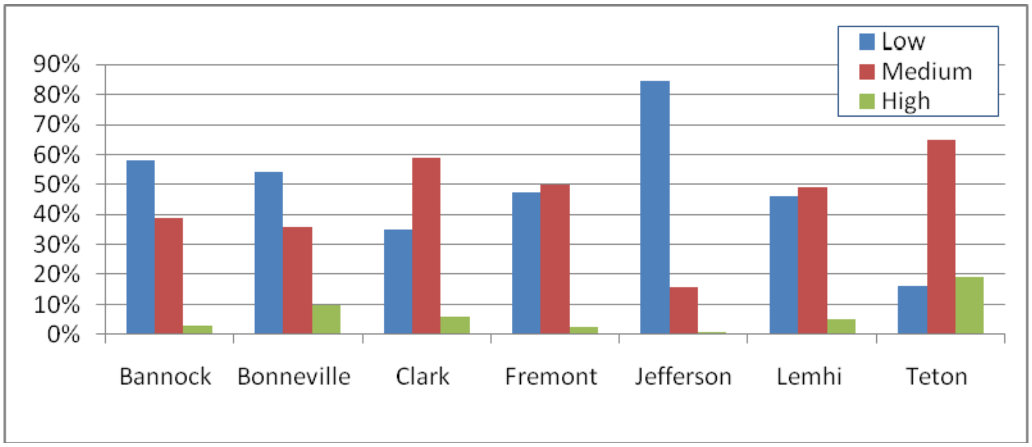



**FIGURE 18 - PERCENT OF BANNOCK, BONNEVILLE, CLARK, FREEMONT, JEFFERSON, LEMI, AND TETON COUNTIES CONSIDERED LOW, MEDIUM AND HIGH FIRE SUSCEPTIBILITY BASED ON THE STANDARD FIRE SUSCEPTIBILITY MODEL.**

Lemhi, Bonneville, Teton, Fremont, Bannock, and Clark counties all contain high desert sagebrush steppe ecosystems, while Lemhi County also contains vast areas of pine forest.

Of these counties, Teton County has the smallest area, with 450 square miles, and Lemhi has the largest area, with 4,564 square miles. Jefferson County and Bannock County have similar spatial areas of ~ 1,110 square miles.

Jefferson County has the lowest total acres, less than 1, 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.

Jefferson County also has the lowest total acres classified as medium fire susceptibility with 111,730 acres in this range. Lemhi County has the largest area classified as medium fire susceptibility with 1,436,257 acres.

Jefferson County has the highest percentage of total acres classified as low fire susceptibility (Figure 19). This may be due to the influence of the structure vulnerability model which has a weight of 22%. In Jefferson County the areas of high structure density are confined to the southeast 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.  Jefferson County has a middle of the range population of 22,350.  Fremont has a population of 12,369, Lemhi has a population of 7,930, Teton County has a population of 7,838 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.  Although Jefferson Counties population is in the middle of the range for the counties studied, the areas of high structure density are confined to the southeast section of 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.

## REFERENCES CITED

Allen, Josse; GIS Specialist, Godfrey, Dennis R.,Bear Lake County, *Personal Communications*

Amdahl, G. 2001. *Disaster Response: GIS for Public Safety* United States of America: ESRI PRESS.

Anderson Hal E. 1982. Aids to Determining Fuel Models for Estimating Fire Behavior. National Wildfire Coordinating Group.

Beyer, H. L. 2004. Hawth's Analysis Tools for ArcGIS. Available at http://www.spatialecology.com/htools.

Bulawa, Walt, Neves R., Garcia Gomez F.M., Weber K.T., Conran K. and Burkhardt F. 2003. Wildland/Urban Interface and Communities at Risk: Caribou County, Idaho

Congalton R.G and Green K. 1999. Assessing the Accuracy of Remotely Sensed Data: Principles and Practices. Lewis Publishers, Boca Raton.

Conran, Kevin; and Brady, Lance; Idaho Bureau of Land Management, Upper Snake River District, *Personal communications*

Gentry C., Narsavage D., Weber K.T., and Burkhardt F. 2003. Wildland/Urban Interface and Communities at Risk: Power County, Idaho

Heide, Sarah Crocker; Idaho Bureau of Land Management

Jansson, C., Pettersson, O., Weber K.T., and Burkhardt F. 2002. Wildland/Urban Interface and Communities at Risk: Lava Hot Springs, Idaho Land Management Monitoring. 2003. http://www.ea.gov.au/land/monitoring/ndvi.html

Mattsson, D.,Thoren, F., Weber K.T., and Burkhardt F. 2002. Wildland/Urban Interface and Communities at Risk: Pocatello, Idaho

Owens J. and Durland P. 2002. Wild Fire Primer/ A Guide for Educators. United States Government Printing Office.

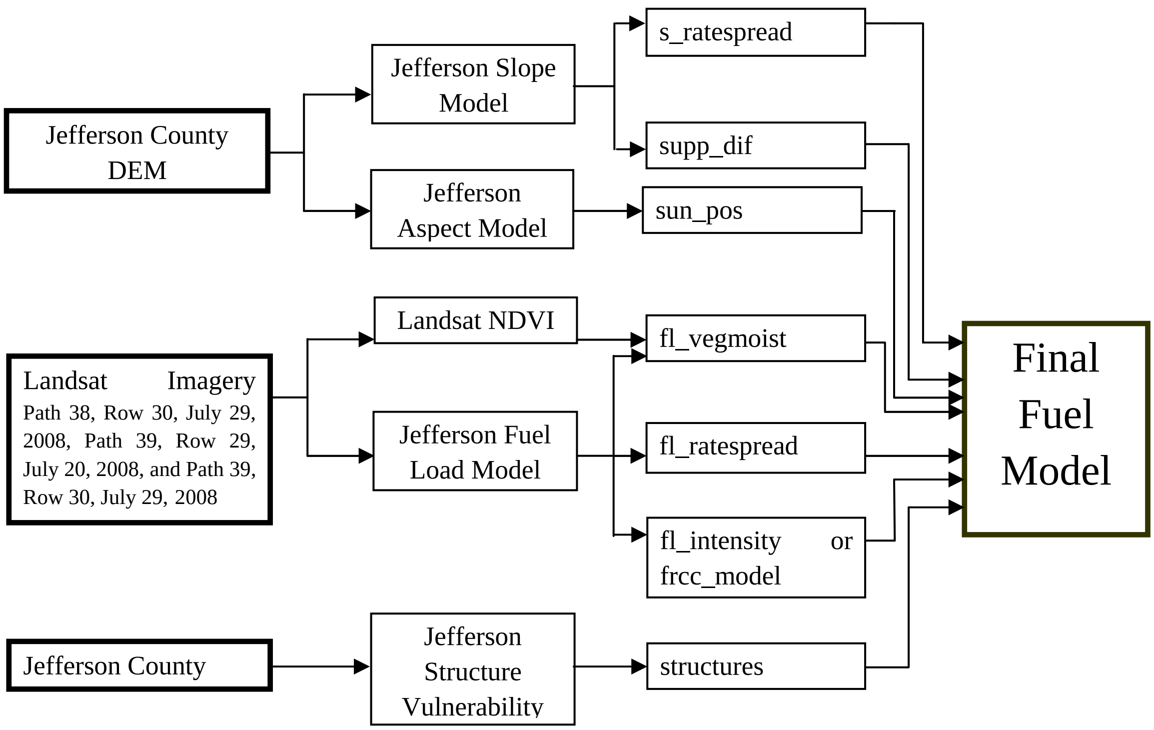
Zambon, M., Lawrence, R., Bunn, A., Powell, S., Effect of Alternative Splitting Rules on Image Processing Using Classification Tree Analysis, Photogrammetric Engineering & Remote Sensing, January 2006.

## 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.

## 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 |