Wildland/Urban Interface and Communities at Risk

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

08-14-2003

Chad Gentry, gentchad@isu.edu, Workstation: Borah

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 risk areas for Bannock County, Idaho. During this project models were created of specific individual risks associated with wildfires: slope, aspect, sun position, vegetation moisture, fuel load, rate of spread, suppression difficulty, number of structures at risk, and ignition source. These models were evaluated together to create a final fire risk model for Bannock County, Idaho. This report describes each of the WUI fire risk components and what affect each has on the final fire risk model. This final model is an accurate depiction of the spatial distribution of wildfire risk in Bannock County, and can be used by regional fire managers to manage wildfire risk.

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

Contents: Page

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 risk and make decisions regarding funding, development, and deployment of suppression resources. One very 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 these tools, we created 8 models that account for different types of fire risk. The first model created was Fuel Load/ Vegetation Moisture. This model takes into account how different levels of vegetation moisture affect fire risk. The second component model was Fuel Load/ Rate of Spread. This model takes into account how different fuel load classes spread and affect fire risk. The third component model Fuel Load/ Intensity describes how different fuel load classes release heat energy during a fire. The fourth component model, Slope/ Rate of Spread, takes into account how the angle of slope affects the rate of spread of a fire. The fifth component model, Slope/ Suppression Difficulty, takes into account how varying slope affects the effectiveness of suppression efforts of firefighters and their equipment. The sixth component model, Aspect/ Sun Position, takes into account different fire risks associated with aspect. The seventh model, Response Time, takes into account how areas that are within five minutes of a fulltime fire station are at lower risk than those beyond the five minute time frame. Finally the Structures at Risk component model takes into account structure density. Each of these component models are weighted and summed to produce the Final Fire Risk Model. The Bannock County, Idaho WUI fire risk 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) and for Clark County, Idaho (Gentry *et al*, 2003).

Methods:

Required data sets:

- Digital Elevation Model (DEM) of Bannock County
- Landsat 7 ETM+ imagery for Bannock County and environs – Path 039, Row 030
- Digital Orthophoto Quarter-Quads (DOQQs) for Bannock County
- Digital Raster Graphics (DRGs) for Bannock County
- Transportation dataset for Bannock County
- Census data for Bannock County from the year 2002

Data processing:

We defined the projection of all datasets as Idaho Transverse Mercator (GCS North American 1927) using Arc Toolbox → Data Management Tools → Projections → Define Projection.

The DEM for Bannock County was downloaded from http://srtm.usgs.gov/data/obtainingdata.html as a single seamless ArcInfo grid with 30m pixels. The Bannock County DEM was then clipped to the footprint of Bannock County using ArcInfo Workstation 8.2.

Landsat 7 ETM+ (Path 039, Row 030 and Row 031), bands 1, 2, 3, 4, 5, and 7 were retrieved from the GIS TReC's archives in Fast-L7A format and converted into ArcInfo grids. These ArcInfo grids were also clipped to Bannock County using ArcInfo Workstation 8.2.

The GIS TReC had all of the DOQQs and DRGs covering Bannock County. These datasets were used for visual purposes only, and no processing was necessary as they were already projected into IDTM.

The transportation dataset was also retrieved from the spatial library of the GIS TReC (http://giscenter.isu.edu/data/data.htm), and needed only to be clipped to the extent of Bannock County.

A polygon shapefile containing census data for Bannock County was downloaded from http://arcdata.esri.com/data/tiger2000/tiger_download.cfm and used to define structure density. This dataset was converted to an ArcInfo grid using ArcMap's Spatial Analyst extension.

Primary Models:

- NDVI model
- Fuel Load model
- Slope model
- Aspect model

Creating NDVI models

We estimated vegetation cover with satellite imagery using the Normalized Difference Vegetation Index (NDVI) for Landsat 7 ETM+, dated 07-28-2002. The NDVI, which is an estimation of photosynthetically active vegetation, was calculated from atmospherically corrected reflectance from the visible red (band 3) and near infrared (band 4) bands of Landsat 7 ETM +. The resulting NDVI has an interval of –1 to +1, where –1 is no vegetation and +1 is pure photosynthetically active vegetation. Equation 1 shows the argument used to calculate the NDVI grid in ArcMap → Spatial Analyst → Raster Calculator.

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

Equation 1: Equation for calculating NDVI.

Once the NDVI grid was completed we made several raster calculations of the NDVI grid in ArcMap → Spatial Analyst → Raster Calculator to delineate wet vegetation, dry vegetation, and no vegetation. After each raster grid was made, we compared it to DOQQs. A visual assessment determined that values >0.6 reliably indicated areas of photosynthetically active wet vegetation, values between 0.6 and 0.15 indicated photosynthetically active dry vegetation, and values <0.15 indicated no photosynthetically active vegetation.

<u>Creating the Fuel Load Model</u>

Supervised classification of Landsat 7 ETM+ imagery was used for estimating fuel load in Bannock County. To estimate fuel load, we used 419 sample points. Forty-one of the sample points were collected in the summer of 2003 by Ben McMahan and Chad Gentry. The remaining 378 points used were collected by Ben McMahan and Joel Sauder in the summer of 2002. Each of the sample points were classified, by McMahan, Sauder, and Gentry, into one of 7 fuel load classes: 0 = 0 tons/acre (No vegetation), 0.74 tons/acre (Grassland), 1 ton/acre (Grassland with some Sagebrush), 2 tons/acre (Low Sagebrush), 4 tons/acre (Typical Sagebrush), and = >6 tons/acre (Forest).

To begin creating the fuel load model we imported bands 1, 2, 3, 4, 5, and 7 (Fast-L7A format) from two Landsat 7 ETM+ scenes (Path 39 Row 30 and Path 39 and Row 31) into ERDAS Software. The digital number values of each of the bands were converted into radiance and from radiance into reflectance using ERDAS → Model Builder. Once the bands were in reflectance we exported the files into grid format for use in ArcGIS 8.3. All identical bands, from each of the scences, were merged using Arc → Grid → Merge. The merged grids were then exported to Idrisi 32 Software in float file format.

To develope our training sites we used 378 of the sample points. These training sites were converted to raster using ArcView 3.3 → Spatial Analysis → Convert to grid (we used ArcView

3.3, because it allowed use to select the spatial extent of an exsisting grid and also let us determine pixel size). This grid was then exported to Idrisi in float file format.
Once all our data was in Idrisi we created a signature file using our training site grid and Landsat 7 ETM+ bands 1, 2, 3, 4, 5, and 7 using Idrisi 32→ Image Processing → Signature Development → MAKESIG. The signature file was used to make the fuel load model using Idrisi 32→ Hard Classifiers → Maxlikely. We checked this model using techniques described in the next section "Fuel load Model Validation". Our results showed that this fuel load model classified the higher fuel load classes well, but discriminated against the lower fuel load classes. To try and improve the model accuracy a second model was created using Landsat 7 ETM+ bands 4, 5, 7, the NDVI (Normalized Difference Vegataion Index), and a Principal Component Analysis consisting of all Landsat 7 ETM+ bands, PVI, NDVI, TSAVI, Tassled Cap Greeness, and Tassled Cap Brightness to create the signature file. This signature file was used to create the second fuel load model. This model classified the lower fuel load classes well, but discriminated against higer fuel load classes. These two fuel load model were then exported to ArcGIS 8.3 and the fuel load catagories with low accuarcy for each model were reclassified as No Data using ArcMap→ Reclassify. These two model were then merged to create the final fuel load model using Arc → Grid → Merge.

Fuel Load Model Validation

Each component was validated using a number of methodologies. 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 second validation method was a modified error matrix where similar classes were clumped together into sub-classes. These classes were based on Anderson (1982) United States Forest Service (USFS) fuel load classes. We also employed a third validation procedure using fuzzy set theory outlined in Congalton and Green (1999) whereby a threshold of acceptable error is established. In the case of our models, the fuzzy set threshold was +/-1 tolerance class. This procedure determined whether the predicted (modeled) class was within one class of the field-observed value. The results of these tests are reported in the text as standard/expanded, clumped, and fuzzy-set-theory accuracies, respectively.

We also completed a Kappa Statistic, using Keith T. Weber's "Chance" program, for our model. This program allowed use to calculate the observed proportion of agreement (Po), the chance expected proportion of agreement (Pc), the Kappa statistic (Kappa), 95% confidence intervals

(LO-95 and HI-95), standard error (SE), and a test of significance (Z). The Kappa statistic describes how much better --or worse-- a classification performed relative to chance alone.

Creating the Slope Model

Using the Bannock County DEM, we made a slope grid that calculated the surface steepness using ArcMap → Spatial Analyst → Surface Analysis → Slope.

Output measurement: degree

Z-factor: 1

Output cellsize: 30m

Creating the Aspect Model

Aspect shows what direction the surface faces. We made the aspect model from the Bannock County, Idaho DEM in ArcMap → Spatial Analyst → Surface Analysis → Aspect.

Output measurement: degree

Output cell size: 30m

Wildfire risk components:

- Fuel Load/ Vegetation Moisture
- Fuel Load/ Rate of Spread
- Fuel Load/ Intensity
- Slope/ Rate of Spread
- Slope/ Suppression Difficulty
- Aspect/ Sun Angle
- Response Time
- Structures at Risk

Creating the wildfire risk components

Each component model was treated separately to learn how each affected fire risk. To be able to merge the models together easily, we reclassified each model using equal scales from 0 to 1000, where 1000 is highest risk. 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 risk in Bannock County, Idaho.

Fuel load/ Vegetation Moisture

We reclassified the Fuel Load grid and NDVI grid using ArcMap → Spatial Analyst → Reclassify. Table B-1 in Appendix B shows the reclassification table. To create the Fuel Load/ Vegetation Moisture component model we multiplied the fuel model with the NDVI model using ArcMap → Spatial Analyst → Raster Calculator. These values were then weighted based on Jansson *et al.* (2002) using ArcMap → Spatial Analyst → Reclassify, shown in figure 1. The weightings used are shown in table B-2 in Appendix B.

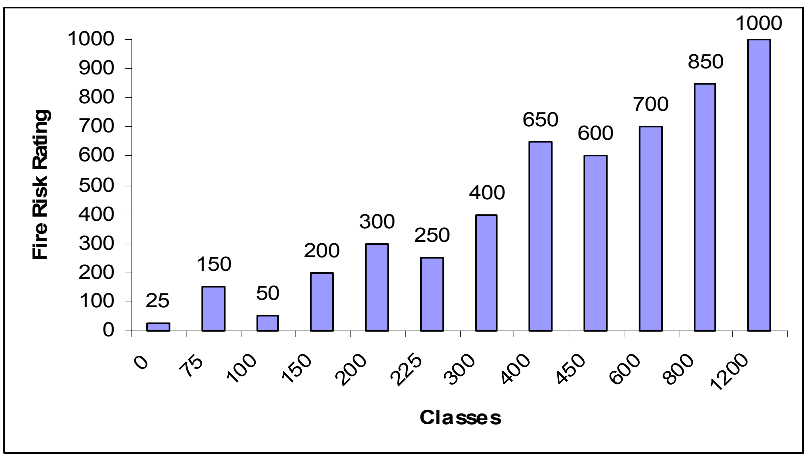


Figure1. Weightings for Fuel Load/ Vegetation Moisture (Jansson et al, 2002).

Fuel load/ Rate of Spread

We reclassified the Fuel load model, following Mattsson *et al*. (2002) (table B-3 in Appendix B), using ArcMap → Spatial Analyst → Reclassify (fig. 2).

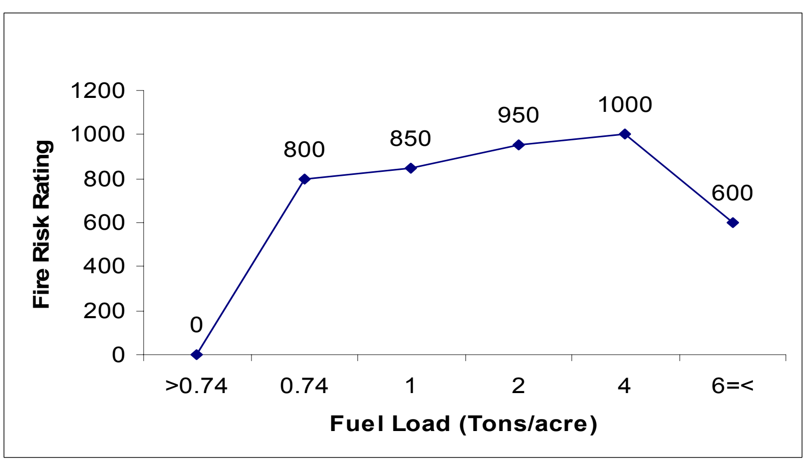


Figure2. Weightings for Fuel Load/ Rate of Spread (Mattsson et al, 2002).

Fuel load/ Intensity

We reclassified the Fuel load model using values following Mattsson *et al*. (2002) (table B-4 in Appendix B) using ArcMap → Spatial Analyst → Reclassify (fig. 3).

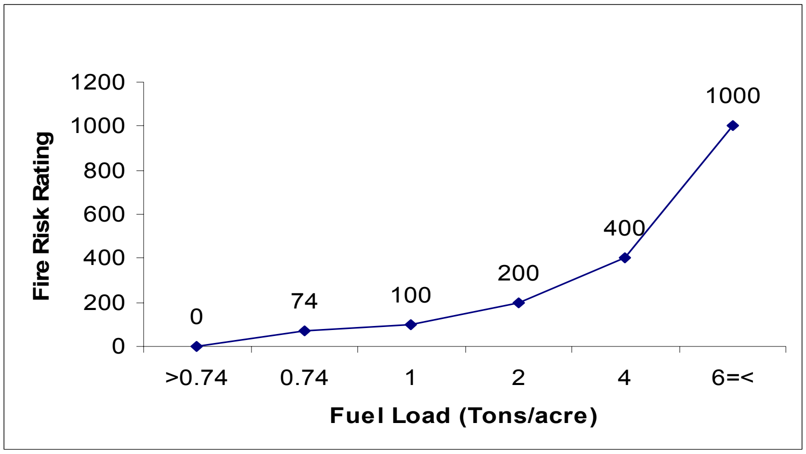


Figure 3. This chart describes all weightings for Fuel Load/ Intensity (Mattsson et al, 2002).

Slope/ Rate of Spread

To make the Slope/Rate of Spread model, we reclassified the Slope model based on weightings from Mattsson *et.al.* (2002). These weightings are shown in table B-5 in Appendix B. We used ArcMap → Spatial Analyst → Reclassify (fig. 4).

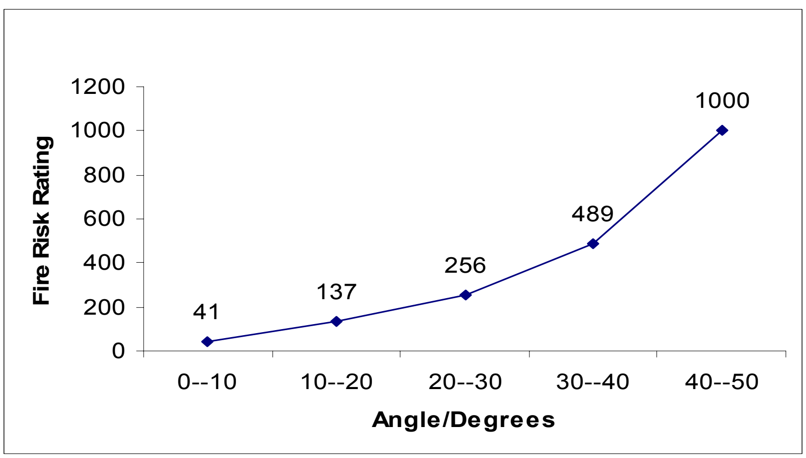


Figure 4. Weightings describe how spread rate increase with angle of slope. The weight proportion is essentially exponential with slope angle (Mattsson et al., 2002).

Slope/ Suppression Difficulties

To create the Slope/Suppression Difficulties model, we used the original slope and applied weightings for Slope/ Suppression Difficulties following Mattsson *et al.* (2002) (table B-6 in Appendix B). ArcMap → Spatial Analyst → Reclassify, shown in (fig. 5).

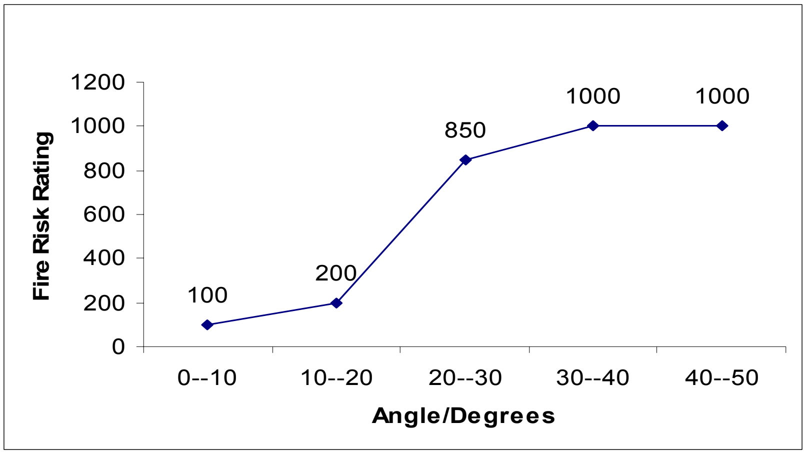


Figure 5. Weightings for slope/suppression difficulties describe how suppression difficulties are affected by the angle of slope (Mattsson et al, 2002).

Aspect/ Sun position

To create the Aspect/ Sun Position we reclassified the aspect grid, following Mattsson *et al* (2002) (table B-7 in Appendix B). We used ArcMap → Spatial Analyst → Reclassify (fig. 6).

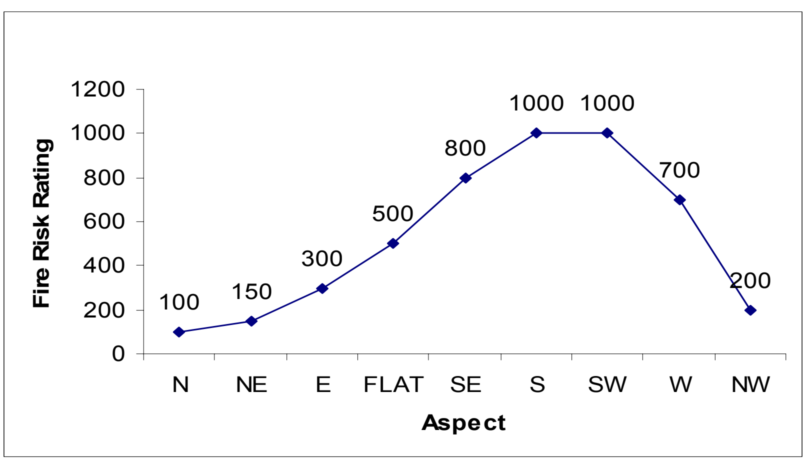


Figure 6. Weightings for Aspect/Sun position describe how the sun desiccates the ground at different aspects (Mattsson et al, 2002).

Response Time

The Response time model was created using Pocatello streets and fire station shapefiles from the GIS TReC websites → Spatial Library. The Pocatello streets shapefile was clipped to the extent of Bannock County using the GeoProcessing Wizard → Clip one layer based on an other. Using ArcView 3.3 → Network Analysis → Find Service Area → Load Sites = Fire stations → Properties → Cost Field = Seconds, we ran a series of times (30, 60, 90, 120, 150, 180, 210, 240, 270, and 300 seconds) from each fire station. Each station response time was converted to a grid using ArcView 3.3 → Theme → Convert to Grid (we used ArcView 3.3, because it allowed us to select the spatial extent of an exsisting grid and also let us determine pixel size). The polygon shapefile for the boundary of Bannock County was also converted to a grid. To do this we first had to make a new field in the attributes table with the value of 1000 using ArcMap → Open Attributes Table → Options → Add Field → Name = Z → Calculate Values = 1000. Next, we used ArcMap → Spatial Analysis → Convert → Feature to Raster → Field = Z, Output cell Size = 28.5 to complete the grid convertion. These grids were then merged together using ArcInfo → Grid → Merge. The merged grid was then reclassified following Mattsson *et al* (2002), using ArcMap → Spatial Analyst → Reclassify (table B-8 in Appendix B) (fig. 7).

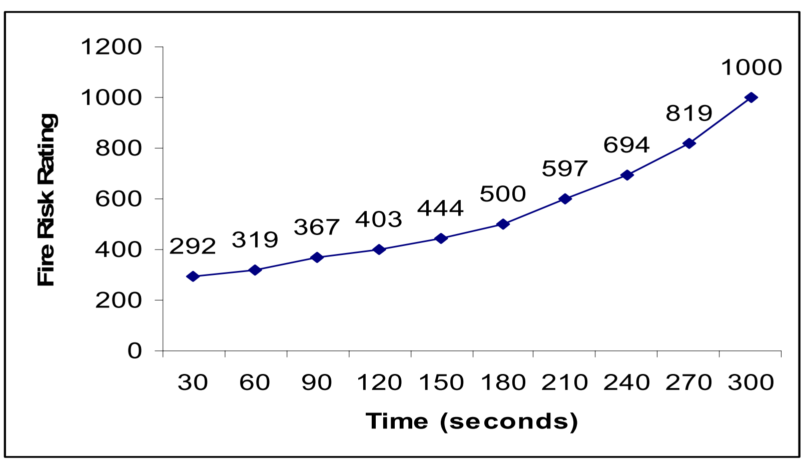


Figure 7. Weightings for Response Time describe how fire risk due to delayed travel time for the firefighters influences the risk (Mattsson et al, 2002).

Structures at Risk

We used census data for Bannock County, found on the ESRI website (http://arcdata.esri.com/data/tiger2000/tiger_download.cfm) in tabular form. These tables were then joined with a corresponding shapefile of census tracts, obtained from the same web site. The resulting dataset contained data on population as well as structures in each census tract. Using ArcMap's field calculator we divided the number of structures in each polygon by the area of that polygon to calculate structure density. Next, we converted the structure density polygons into a grid and applied a linear regression to fit the values between 0 and 1000 to generate the final structures at risk grid.

WUI fire risk model

After developing the different fire model components, we weighted and summed each component into the final fire risk model. Weightings were based on a regional fire manager, Fred Judd (pers. comm.). Beginning with the highest, we distributed each component as follows:

- Structure's at Risk 20%
- Fuel load/ Rate of Spread 15%
- Fuel load/ Intensity 15%
- Response Time 15%
- Fuel load/ Vegetation Moisture 10%
- Slope/ Rate of Spread 10%
- Slope/ Suppression Difficulties 10%
- Aspect/ Sun position 5%

These component models were weighted appropriately in a multi-criterion evaluation. This calculation was done in ArcMap → Spatial Analyst → Raster Calculator.

Results:

We compared the WUI fire risk models for Bannock County and Clark County, Idaho (Gentry *et al* 2003). These results are shown in figure 8.

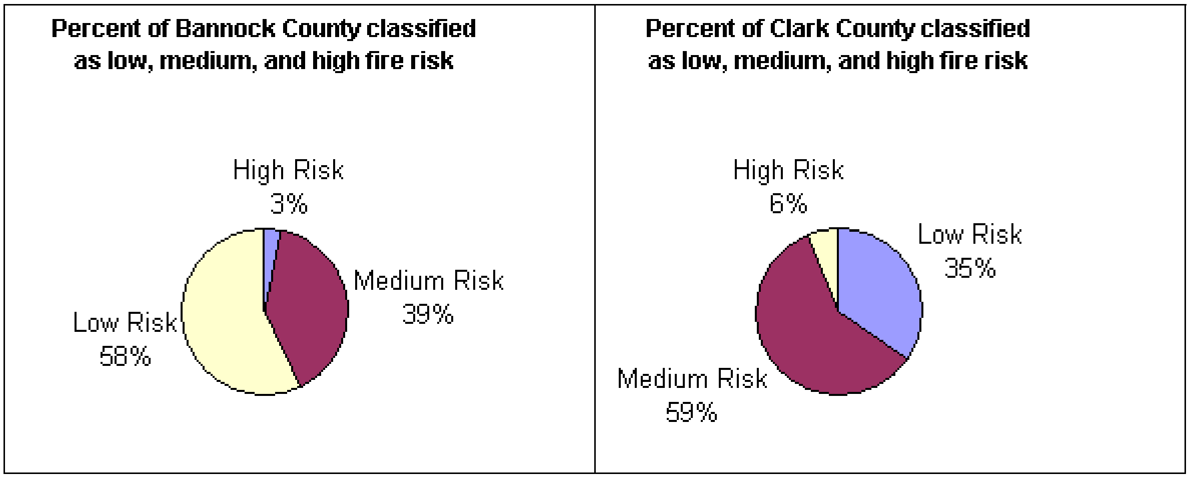


Figure 8. Comparison of fire risk model classification (low, medium, and high fire risk) for both Bannock and Clark County, Idaho .

We also compared the WUI fire risk model for the city of Pocatello, Idaho *(Mattsson et al, 2002)* against the city of Pocatello within the Bannock County WUI risk model. Table 1 shows the error matrix results.

Table1: Error matrix for WUI project comparison.

		Bannock County WUI project (acres)				
		Low Fire Risk	Medium Fire Risk	High Fire Risk	Total	% Agree
Pocatello WUI Project (acres)	Low Fire Risk	9529.4	1261.6	30.7	10821.7	88.06%
	Medium Fire Risk	12703.6	2936.7	48.5	15688.8	18.72%
	High Fire Risk	4847.9	1335.0	82.1	6265.0	1.31%
	Total	27080.9	5533.3	161.3	32775.7	
	% Agree	35.19%	53.07%	50.90%		
					Overall Agreement	38.29%

The NDVI grid used to generate the fuel load model is shown in figure 9. Our 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 7 ETM+ satellite imagery. Table 2 shows the error matrix validation for the fuel load model. Table 3 shows the kappa statistics for the fuel load model.

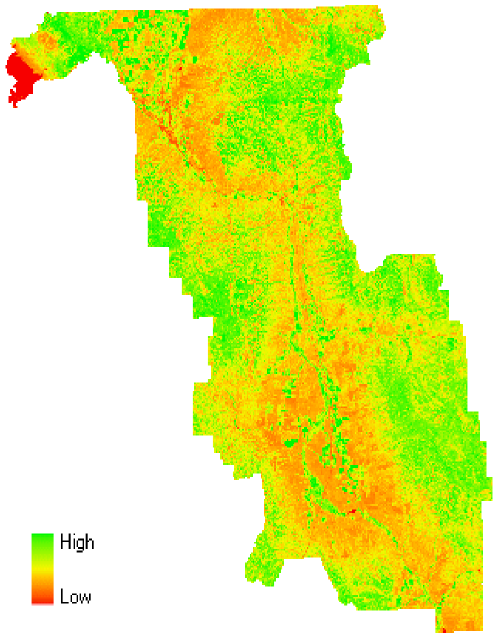


Figure 9. The NDVI has an interval of –1 to +1, where –1 is no vegetation and +1 is pure vegetation.

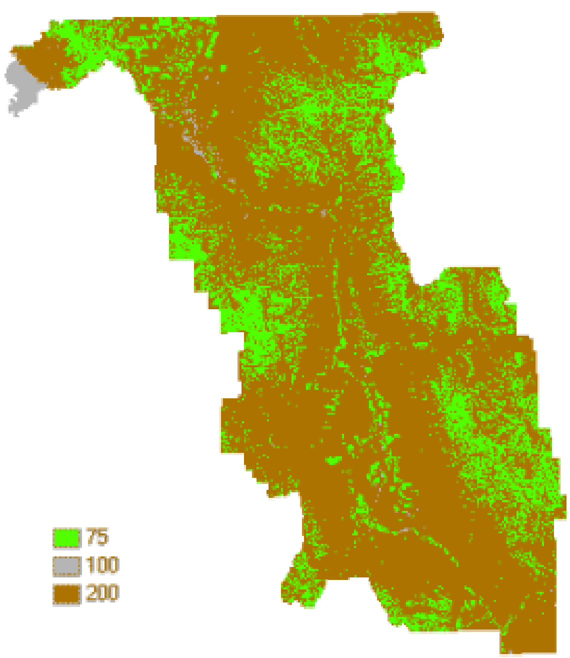


Figure 10. The results of the reclassification of NDVI into no vegetation (100), dry vegetation (200) and wet vegetation (75).

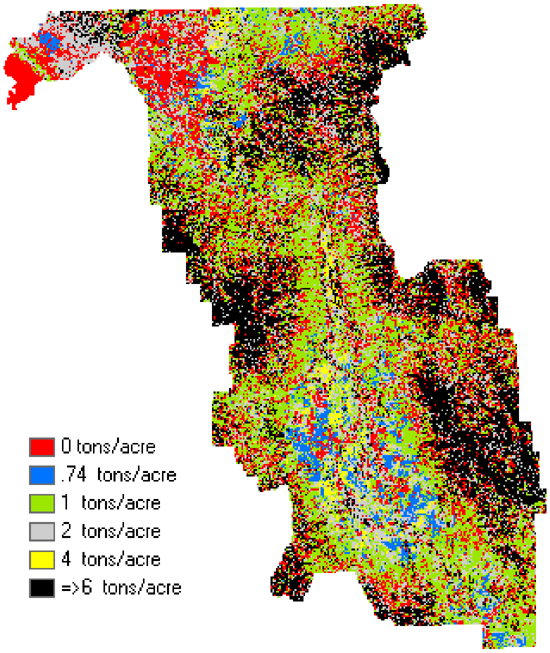


Figure 11. The fuel load model and the distribution of different fuel load classes for Bannock County, ID.

Table2: Error matrix for the fuel load model.

		Field Measurement of Fuel Load (Tons/Acre)						
		0.74	**1**	**2**	**4**	**>6**	**Total**	**Acc %**
Modeled Fuel Load (Tons/Acre)	**0.74**	33	11	5	6	1	56	58.93%
	1	15	23	21	10	2	71	32.39%
	2	17	25	42	27	5	116	36.21%
	4	7	12	37	59	8	123	47.97%
	>6	0	4	2	1	5	12	41.67%
	Total	72	75	107	103	21	378	
	Acc %	45.83%	30.67%	39.25%	57.28%	23.81%	Standard/ Expanded	42.86%
							USFS/ Anderson	66.67%
							Fuzzy Set Theory	81.22%

Table3: Kappa Statistics for the fuel load model.

PC	PO	KAPPA	LO-95% CI	HI-95% CI	SE	Z
0.242784	0.428571	0.245356	0.178126	0.312585	0.029124	8.424444

The three component models derived from the fuel load model are shown in figures 12, 13, and 14. Figure 12 is the vegetation moisture model, irrigated and riparian areas contain the lowest risk values, while the grasses and shrubs along the I-15 corridor contain the highest values. The high risk areas are due to the low moisture content associated with sage brush steppe that dominates the area. The effect of fuel load on fire's spread rate is reported in figure 13. Mountainous areas, with larger fuel loads, contain the lowest values, where grasses and shrubs along the I-15 corridor have been classified with highest risk. The high risk areas are due to the high concentration of 4 tons/acre fuels. Finally, figure 14 is the intensity model. Conifers in the highlands, especially in the east and west sections of the county, comprise the highest risks for the most intense fires.

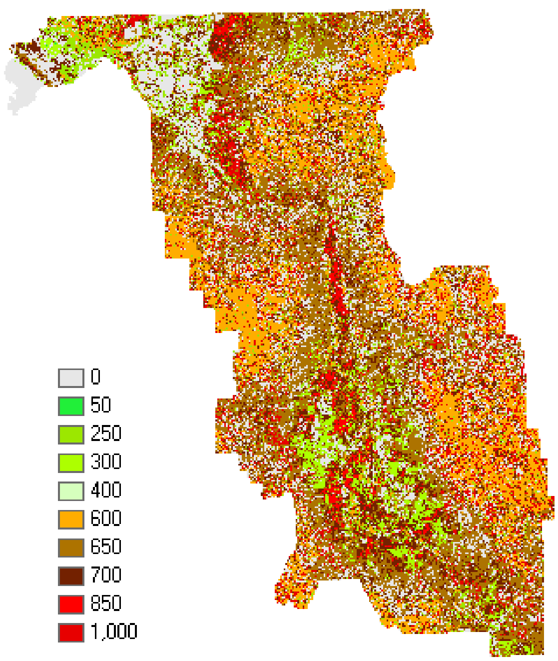


Figure 12. The Fuel Load/ Vegetation Moisture model. This model expresses how vegetation moisture and the combination of different fuel load classes affect fire risk. This model was given an overall weighting of 10% of the final model.

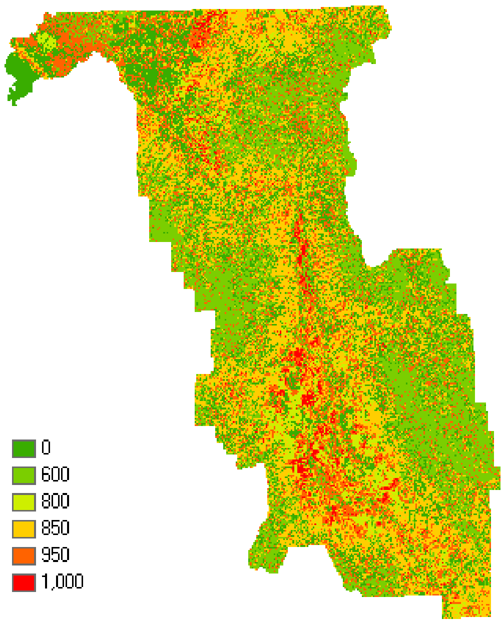


Figure 13. The Fuel Load/ Rate of Spread model. This model expresses the fire risk associated with the spread rate of different fuel load classes. This model was given an overall weighting of 15% of the final model.

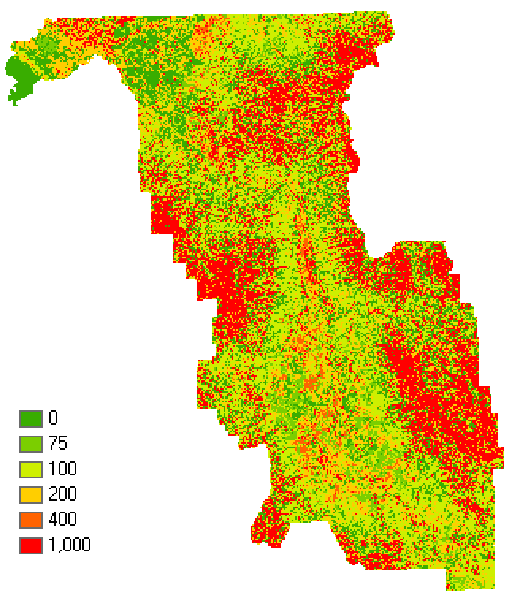


Figure 14. The Fuel Load/ Intensity model. This model expresses the fire risk associated with the amount of heat energy (intensity) each fuel load class gives off. This model was given an overall weighting of 15% of the final model.

The next three figures (15-17) are the component models generated using the Bannock County DEM. Figure 15 assesses the risk of fires spreading quickly due to steep slopes. Here, the highlands in the eastern and western portions of the county received the highest values and the bottom land, with shallow slopes, along the I-15 corridor received a much lower risk. 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. Once again, the steeper terrain in the north is weighted the highest risk. Figure 17 is the Aspect/ Sun Position component model, south and southwest aspects contain the highest fire risk, due the intense sunlight and prevailing wind exposure. North facing slopes, which are sheltered from intense sunlight and prevailing wind through much of the day, contain the lowest fire risk.

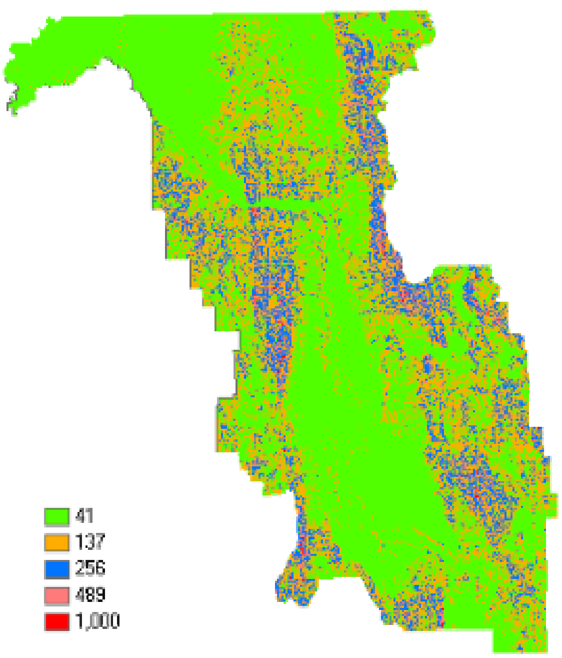


Figure 15. The Slope/ Rate of spread model. This model expresses how different angles of slope affect the spread rate of fire. Steeper slops are given the highest fire risk. This model was given an overall weighting of 10% of the final model.

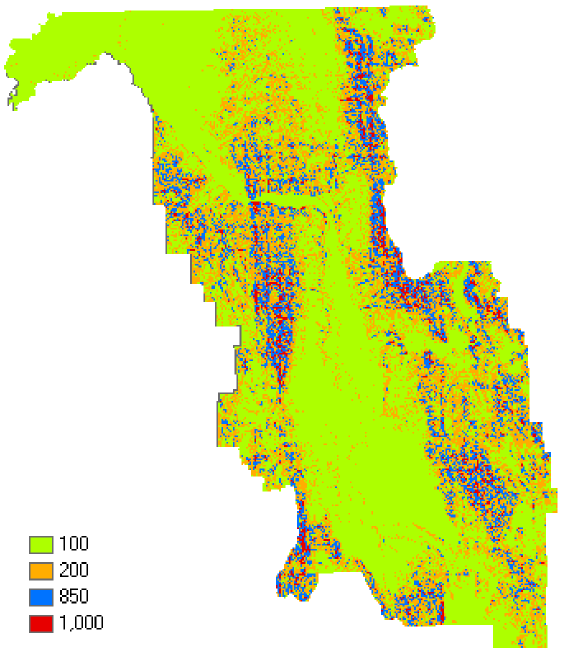


Figure 16. The Slope/ Suppression Difficulty model. This model expresses how different slope angles suppression efforts of firefighters. This model was given an overall weighting of 10% of the final model.

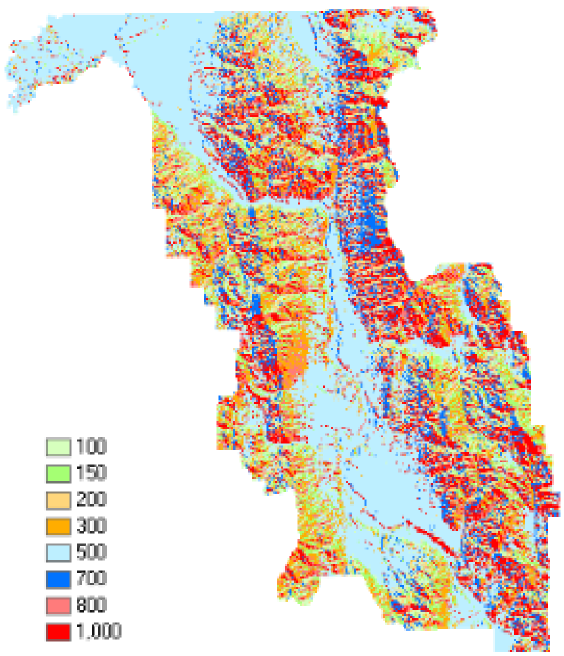


Figure 17. The Aspect/ Sun Position model. This model expresses how different aspects affect fire risk. Southern aspects have the highest fire risk. This model was given an overall weighting of 5% of the final model.

The Structures at Risk component model is shown in figure 18. Here the population centers of Bannock County; Pocatello, Chubbuck, McCammon, Arimo, Lava Hot Springs, Downey and Malad contain the highest structure density and the highest fire risk. Figure 19 show the Response Time component model. Pocatello is the only city within Bannock County that has a full time fire department and that can maintain the 300 second (5 minute) criteria. The rest of the towns and cities within Bannock County are limited to volunteer fire departments, which put them over the criteria and give them the highest risk.

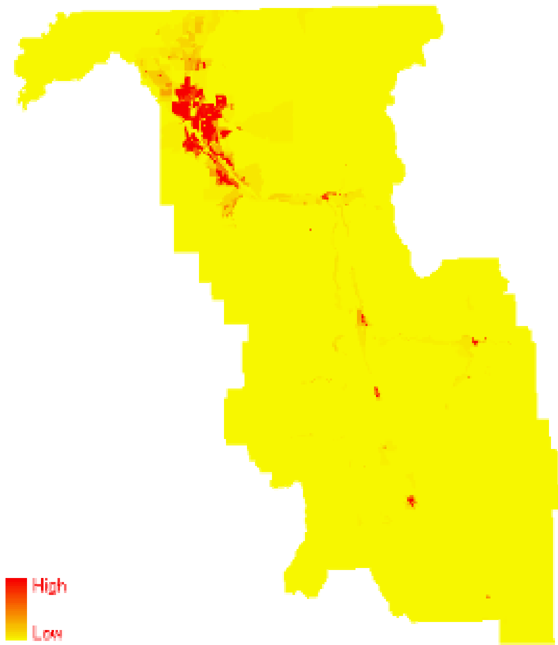


Figure 18. The Structures at Risk model. This model expresses areas that are high risk due to high structure density and is given an overall weighting of 20% of the final model.

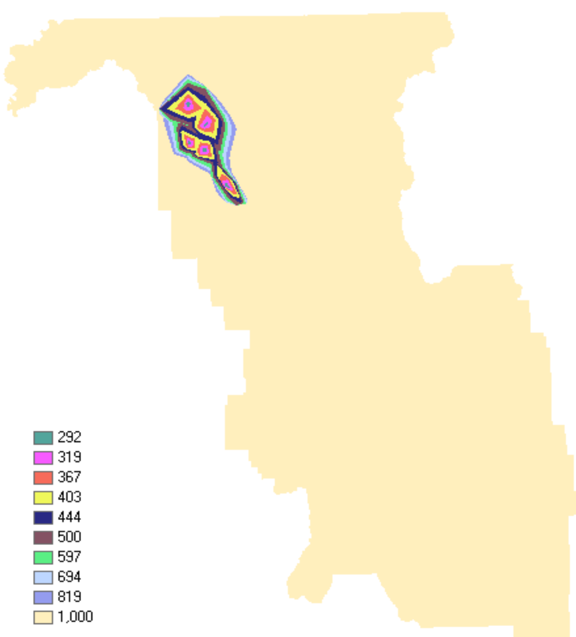


Figure 19. The Response Time model. This model expresses how quickly fire fighters can respond to a fire. The overall weighting for this model is 15% of the final model.

The Final Fire Risk Model is shown in figure 20.

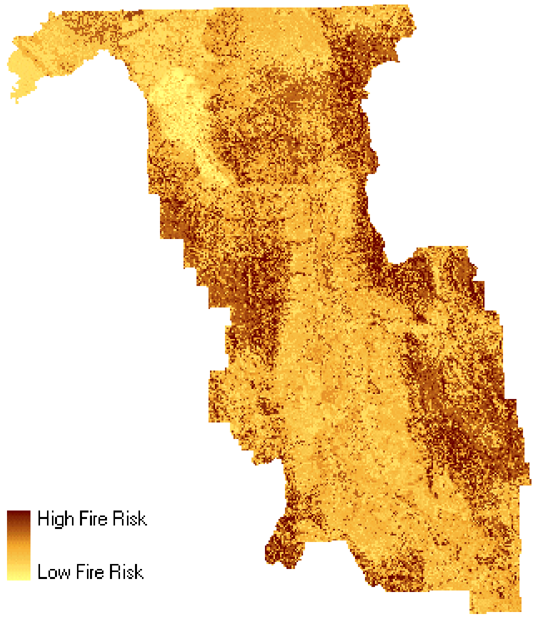


Figure 20. The Final Fire Risk Model for Bannock County, Idaho. Fire risk is shown on a graduated symbology.

Discussion:

Bannock and Clark County are considered high desert sage brush steppe ecosystems. Comparison between fire risk models for Bannock County and Clark County, Idaho, reveals a similarity in high fire risk classification. The high fire risk classification for both counties is consistently 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. Bannock County did show distinct differences in medium and low fire risk classification. This is due to the distribution of different landscapes among the two. Clark County consists of mostly low elevation with the mountainous areas along the northern perimeter, while Bannock County has more variation in elevation and has mountainous areas throughout.

Comparing the city of Pocatello using both the Bannock County WUI and the city of Pocatello WUI project (Mattsson *et al* 2002) showed a 38.22% overall similarity. Many factors may influence the differences between these models. Factors, such as difference in georectification, different Landsat ETM+ satellite imagery dates (August 7, 2001 and July 28, 2002), different fuel load models used, and different component model weightings. To make any assumption based on the differences between the two models without fully understanding each project would be based on biased opinions.

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 overall accuracy of the 2003 fuel load model was quantified using all three methodologies described above (standard/expanded, clumped, and fuzzy set). These results emphasize the difficulties associated with using multispectral remote sensing imagery to delineate vegetation types with extremely similar spectral signatures.

The Structures at Risk component was weighted most heavily (20%). This is due to the nature of this project; we were most interested in quantifying risk for the Wildland/ Urban Interface. This model allowed us to emphasize the interface areas. Areas of high structure density received the highest fire risk values and areas of low or no structure got the lowest fire risk values.

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 4 tons/acre received the highest fire risk value, because of its high load of fine, low-standing fuels. Fuel Load class >6 tons/acre received the lowest fire risk 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 moves up a mountainside (Amdahl, 2001). The steeper angles in this model have the highest fire risk values, because fire increases exponentially with slope. Correspondingly, shallower angles have lower fire risk 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 risk value. Areas that had wet vegetation and lower fuel load had the lowest fire risk values.

The Fuel Load/ Intensity component takes into account how intense a fire of different fuel load classes affects fire risk. 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 risk 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 risk 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 risk values and shallow slopes received the lowest fire risk values.

The Response Time component describes how delayed travel time, by fire fighters, influences fire risk. The criteria for this model, was established by fire managers and knowledgeable persons, during Pocatello WUI project. The criteria is based on a 300 seconds (5 minute) flash over (fig. 21). Pocatello is the only city within Bannock County that has a full time fire department. The rest of the towns and cites have volunteer fire department, which put them over the five minute criteria.

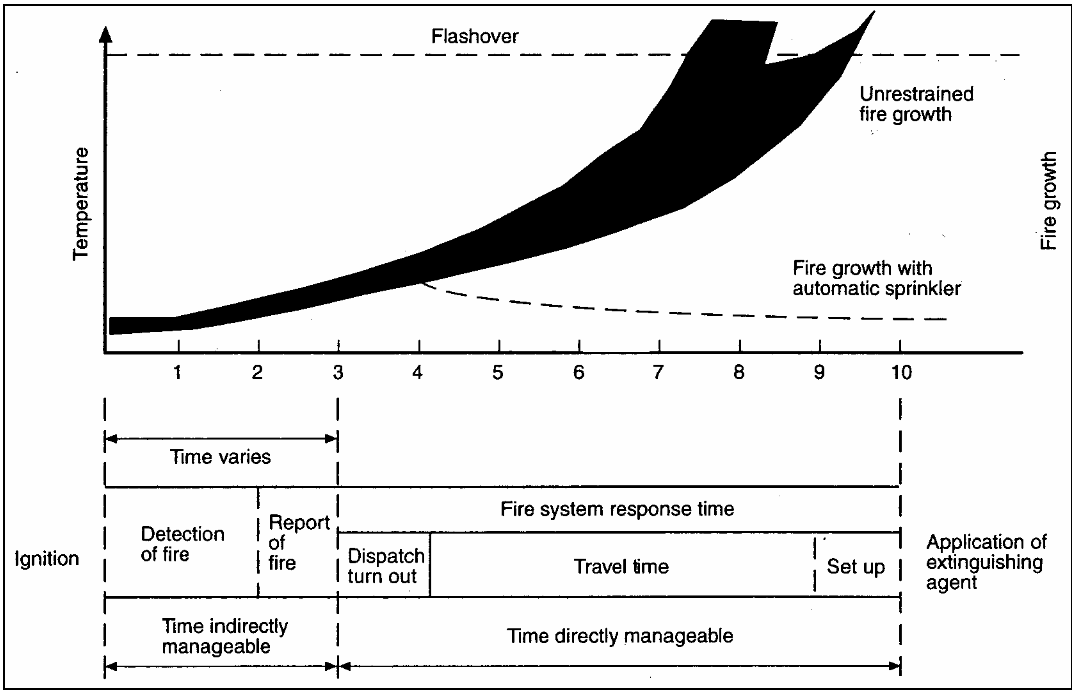


Figure 21. This chart shows how fire grows during the time when emergency vehicles travel to the fire (Mattsson et al, 2002).

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 risk values and northern aspects received the lowest.

Assessments of error and bias:

The first part of our project was completed using ArcGIS 8.2. ArcGIS 8.3 was installed during the project. Although this should not cause any difficulty with the methods described above, it has been noted within the text.

All estimations in this report are made based upon our knowledge of the criteria and the expert knowledge of Keith T. Weber, Felicia Burkhardt, and Fred Judd. 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 risk 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 us and Fred Judd (pers.comm.) felt were more important.

The date (July 28, 2002) during which the Landsat 7 ETM+ data was gathered plays a significant role in the outcome of the Fuel Load-based components of the final model.

References cited:

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.

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

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

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.

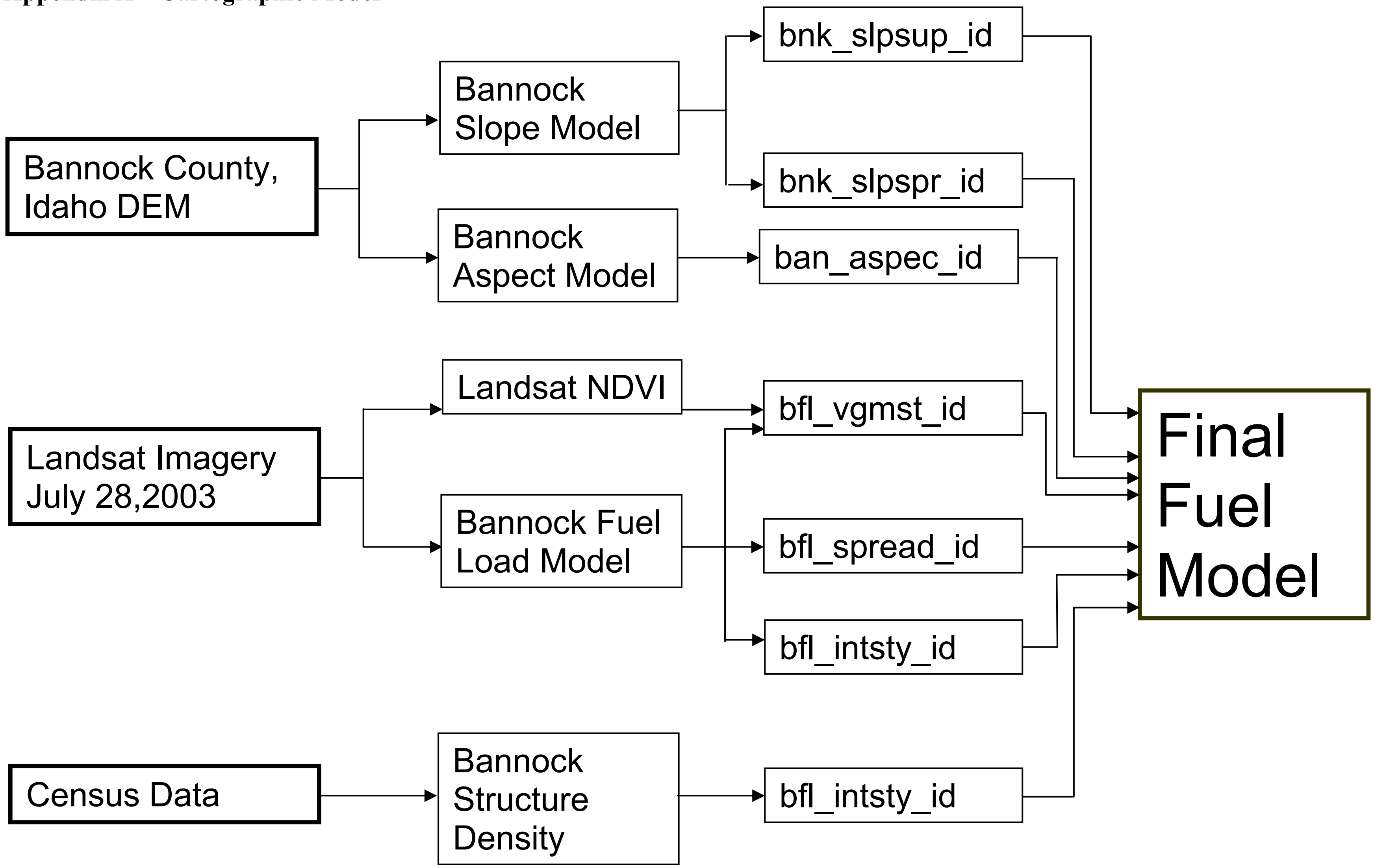
Acknowledgements:

On July 9, 2003, we had a presentation of our project and discussed the project as a whole. We decided to make maps of each of the component models and break them down into the seven Rural Fire Districts for Bannock County.

These people were attending:

Zac Muirbrook: GIS Tech, USRD BLM
Gary Moore: Bannock County Sheriff's Dept., Emergency Services
Dennis Hill: GIS Coordinator, Pocatello
Keith T. Weber: GIS Director, Idaho State University (ISU), GIS Training and Research Center
Chad Gentry: GIS Intern, ISU, GIS Training and Research Center

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 = 0.74 tons/acre	200 = Dry Vegetation
2 = 1 tons/acre	75 = Moist Vegetation
3 = 2 tons/acre	
4 = 4 tons/acre	
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	75	75	150
1	100	100	50
2	75	150	200
1	200	200	300
3	75	225	250
4	75	300	400
2	200	400	650
6	75	450	600
3	200	600	700
4	200	800	850
6	200	1200	1000

Table B-3: Weighting data for Fuel Load/ Rate of Spread. Compare with figure 2.

Classes (Tons/acres)	Weights
< 0.74	0
0.74	800
1	850
2	950
4	1000
>6	600

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

Classes (Tons/acres)	Weights
< 0.74	0
0.74	74
1	100
2	200
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

Table B-8: Weighting data for Response Time. Compare with figure 7.

Time (Seconds)	Weights
30	292
60	319
90	367
120	403
150	444
180	500
210	597
240	694
270	819
300	1000

Appendix C – Data dictionary

Data		File name		Full path to dataset		Description		Format
County bound		banock_idtm.shp		\\Alpine\Data\urbint\Bannock\all_datasets		Boundary of Bannock county		polygon coverage
Roads		Roads_streets.shp		\\Alpine\Data\urbint\Bannock\all_datasets		Roads and streets in Bannock County		line shapefile
Bands used for NDVI		B3mrger30r31		\\Alpine\Data\urbint\Bannock\all_datasets		Landsat Band 3 for Bannock County		Grid - 28.5m pixels
		b4mrger30r31		\\Alpine\Data\urbint\Bannock\all_datasets		Landsat Band 4 for Bannock County		Grid - 28.5m pixels
		pow_ban_ndvi		\\Alpine\Data\urbint\Bannock\all_datasets		Landsat NDVI model for all of Bannock and Power County		Grid - 28.5m pixels
Fuel Load		fuelload_id		\\Alpine\Data\urbint\Bannock\all_datasets		Fuel Load model for Bannock County. Classes are .74 tons/acre, 1 tons/acre, 2 tons/acre, 4 tons/acre, and =>6 tons/acre		Grid - 28.5m pixels
DEM		powban_dem		\\Alpine\Data\urbint\Bannock\all_datasets		Digital Elevation Model of Bannock County		Grid - 30m pixels
Component models		ban_aspec_id		\\Alpine\Data\urbint\Bannock\all_datasets		Risk associated with aspect angle **i.e**. North, East,…….		Grid - 30m pixels
		bnk_slpspr_id		\\Alpine\Data\urbint\Bannock\all_datasets		Risk associated with how fire spreads with angel of slope.		Grid - 30m pixels
		bnk_slpsup_id		\\Alpine\Data\urbint\Bannock\all_datasets		Risk associated with how Suppression efforts are affected by angle of slope.		Grid - 30m pixels
		bfl_spread_id		\\Alpine\Data\urbint\Bannock\all_datasets		Risk associated with how quick different fuel load classes spread during a fire.		Grid - 26m pixels
		bfl_intsty_id		\\Alpine\Data\urbint\Bannock\all_datasets		Risk associated with how intense (release heat energy) different fuel load classes burn.		Grid - 26m pixels
		bfl_vgmst_id		\\Alpine\Data\urbint\Bannock\all_datasets		Risk associated with vegetation moisture.		Grid - 26m pixels
		bnk_densty_id		\\Alpine\Data\urbint\Bannock\all_datasets		Risk associated with structure density.		Grid - 30m pixels
Final Model		fin_fire_mdl		\\Alpine\Data\urbint\Bannock\all_datasets		Final risk model - 30m pixels - ArcInfo Grid		Grid - 30m pixels
Reports		Bannock_WUI_Final_Report		\\Alpine\Data\urbint\Bannock\reports		Report covering methods, results, & conclusions of WUI modeling		Word Document