Wildland/Urban Interface and Communities at Risk

Joint Fire Modeling Project for Clark 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 value and 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 Clark 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 Clark 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 Clark County, and will be used by regional fire managers to deal with wildfire risk.

Keywords: Fire, Wildfire, GIS, WUI (Wildland/Urban Interface), Clark County, Idaho, BLM

Content:

Introduction:

The Wildland/ Urban Interface 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 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

Geographical Information Systems (GIS). GIS allows for spatial analysis of large geographic areas and is easily integrated with satellite imagery.

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 component model, Ignition Source, takes into account areas that have high potential for lightning and anthropogenic ignition sources (e.g., vehicles' exhaust, sparks from vehicles, drivers improperly disposing of cigarette butts). Finally the Structures at Risk component model takes into account infrastructure density. Each of these component models are weighted and summed to produce the Final Fire Risk Model. The Clark 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) and the city of Lava Hot Springs, Idaho (Jansson *et al*, 2002).

<u>Methods:</u>

Required data sets:

- Digital Elevation Model (DEM) of Clark County
- Landsat 7 ETM+ imagery for Clark County and environs – Path 039, Row 030
- Digital Orthophoto Quarter-Quads (DOQQs) for Clark County

- Digital Raster Graphics (DRGs) for Clark County
- Transportation dataset for Clark County
- Census data for Clark County from the year 2000

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

Landsat 7 ETM+ (Path 039, Row 030), 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 Clark County using ArcInfo Workstation 8.2.

The GIS TReC had approximately 50% of the DOQQs and 100% of the DRGs covering Clark 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 Clark County.

A polygon shapefile containing census data for Clark 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 07-12-2002. 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 equation used to calculated 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.

Creating the Fuel Load Model

Supervised classification of Landsat 7 ETM+ imagery was used for estimating fuel load in Clark County. To estimate fuel load, we used 38 sample points collected by Ben McMahan and Joel Sauder in the summer of 2002 and Landsat 7 ETM+ bands 1, 2, 3, 4, 5, and 7. Each of the sample points were classified, by McMahan, into one of 7 fuel load classes: 0 = 0 tons/acre (No vegetation), 1 = 0.74 tons/acre (Grassland), 2 = 1 ton/acre (Grassland with some Sagebrush), 3 = 2 tons/acre (Low Sagebrush), 4 = 4 tons/acre (Typical Sagebrush), and 6 = >6 tons/acre (Forrest). The fuel model contained data estimating the amount of flammable material (fuel) expressed in tons per acre. A signature file was created for fuel load classes in Idrisi 32→ Image Processing → Signature Development → Makesig. The signature file was then used to make the fuel load model using Idrisi 32→ Hard Classifiers → Maxlikely. To assess overall accuracy of the fuel load model we brought the model into ArcView 3.3 and used an avenue script file that "drilled down" each training site and recorded the underlying grid value to determine model accuracy.

Creating the Slope Model

Using the Clark 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 Clark County, Idaho DEM in ArcMap → Spatial Analyst → Surface Analysis → Aspect.

Output measurement: degree

Output cellsize: 30m

Wildfire risk component models:

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

Creating the wildfire model 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 Clark 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.

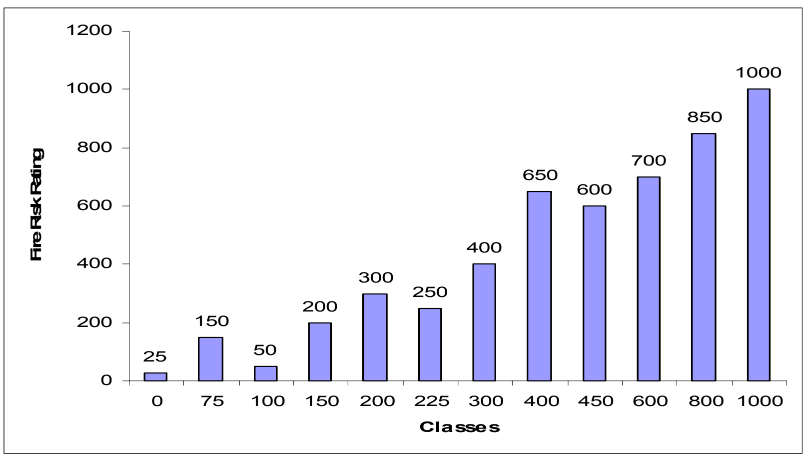


Figure1. Weightings for Fuel Load/ Vegetation Moisture (Jansson et al, 2002).

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).

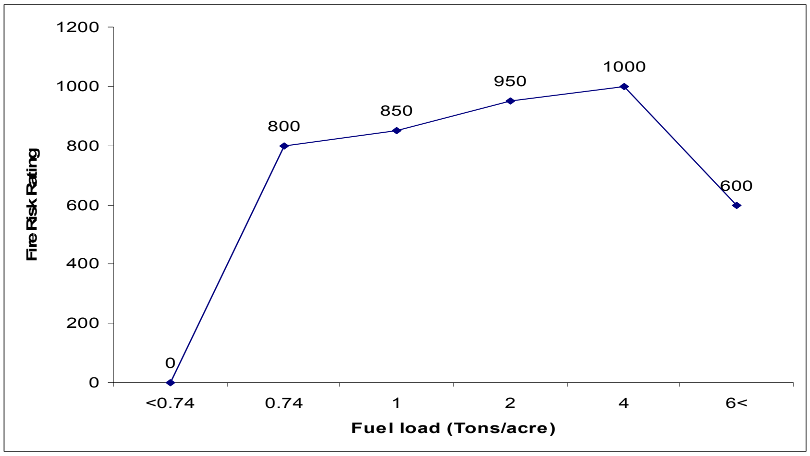


Figure2. Weightings for Fuel Load/ Rate of Spread (Mattsson et al, 2002).

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).

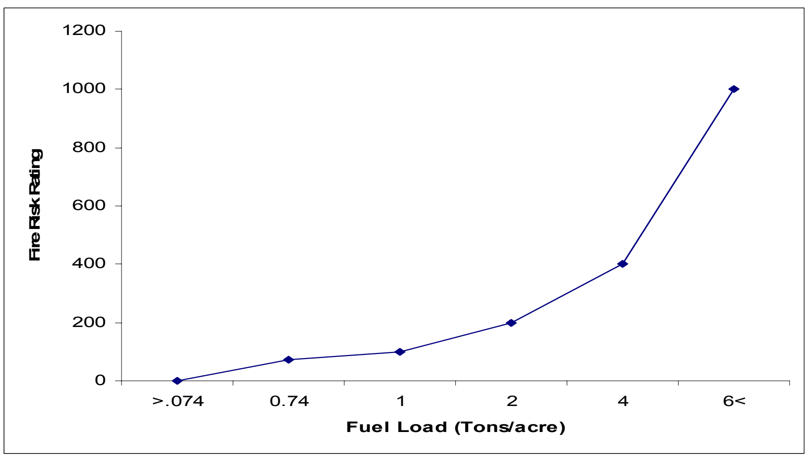


Figure 3. This chart describes all weightings for Fuel Load/ Intensity (Mattsson et al, 2002).

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).

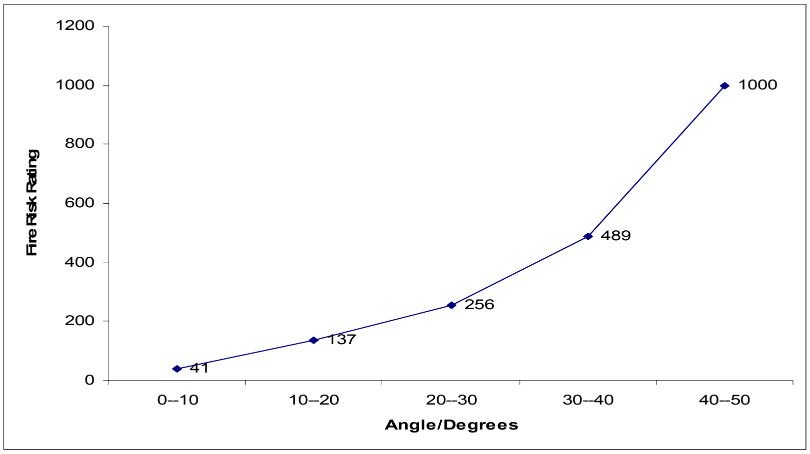


Figure 4. Weightings describe how spread rate increase with angle of slope. The weight proportion is essentislly exponential with slope angle (Mattsson et al., 2002).

Slope/ Suppression Difficulties

For the Slope/Suppression Difficulties model, we used the original slope grid once again, but applied weighting data for Slope/ Suppression Difficulties following Mattsson *et al.* (2002) (table B-6 in Appendix B). ArcMap → Spatial Analyst → Reclassify, shown in (fig 5).

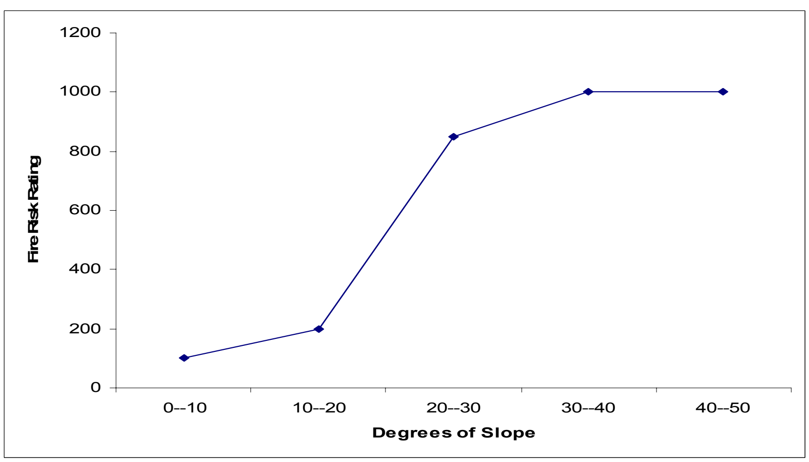


Figure 5. Weightings for slope/suppression difficulties describe how suppression difficulties are affected by the angle of slope (Mattsson et al, 2002).

Aspect/ Sun position

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

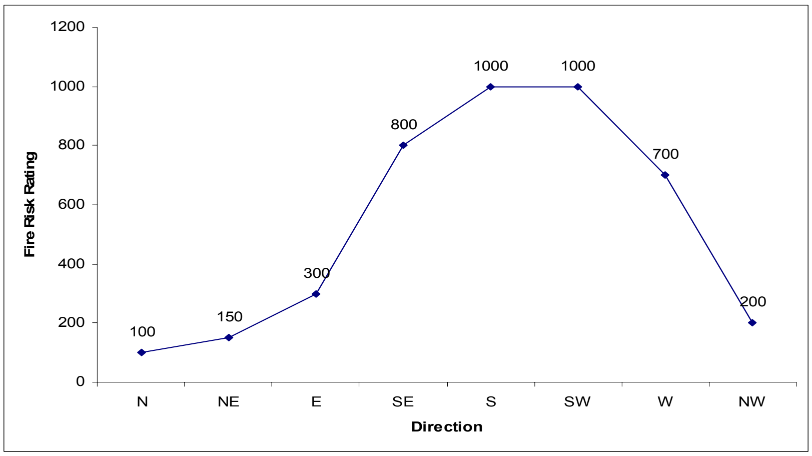


Figure 6. Weightings for Aspect/Sun position describe how the sun desiccates the ground at different aspects (Mattsson et al, 2002).

Ignition Source

The Ignition Source model was created using both anthropogenic ignition sources (e.g., vehicles' exhaust, sparks from vehicles, drivers improperly disposing of cigarette butts) and lightning ignition sources. For anthropogenic ignition sources, we used Idaho roads and railroads shapefiles from the GISTReC websites → Spatial Library. The shapefiles were clipped to the extent of Clark County and a 30 meter buffer was applied to all roads and a 60 meter buffer applied to railroads using ArcMap→ GeoProcessing Wizard. Areas within these buffers were considered higher risk than areas outside the buffers. For the lightning ignition sources we used the Clark County DEM. Risk weightings were applied using Weber *et al.* (2003). Mountains were classified as everything >700 m above minimum relative elevation. To accomplish the delineations of mountains we used ArcMap → Spatial Analyst → Raster Calculator. Mountains were given the highest fire risk (400) for lightning ignition sources. To delineate foothills (intermediate risk) and lowlands (low risk) we created a polygon shapefile of the mountains and, using ArcMap → Spatial Analyst → Distance, we delineated foothills as anything within 10 km of mountains. Risk of lightning strike in these areas approaches highest risk (400) with proximity to mountains, with areas most distal from mountains receiving values of 100. Lowlands were considered any areas >10km from mountains, and are classified as low risk (100). Next, the buffered transportation shapefiles, for roads and for railroads, were converted to grids and reclassified accordingly – between 0 and 400 for the railroads and between 0 and 200 for the roads. Finally, using ArcMap → Spatial Analyst → Raster Calculator, all three grids were added together.

Structures at Risk

We used census data for Clark 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 decided how important each component was to the overall fire risk model with expert input from Judd (2003). 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%
- Slope/ Rate of Spread 15%
- Fuel load/ Vegetation Moisture 10%
- Slope/ Suppression Difficulties 10%
- Ignition Source 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:

The NDVI grid used to generate the fuel load model is shown in figure 7. Our reclassified NDVI grid estimating the position of wet vegetation, dry vegetation and no vegetation is shown in Figure 8. Figure 9 displays the Fuel Load model derived from the NDVI model.

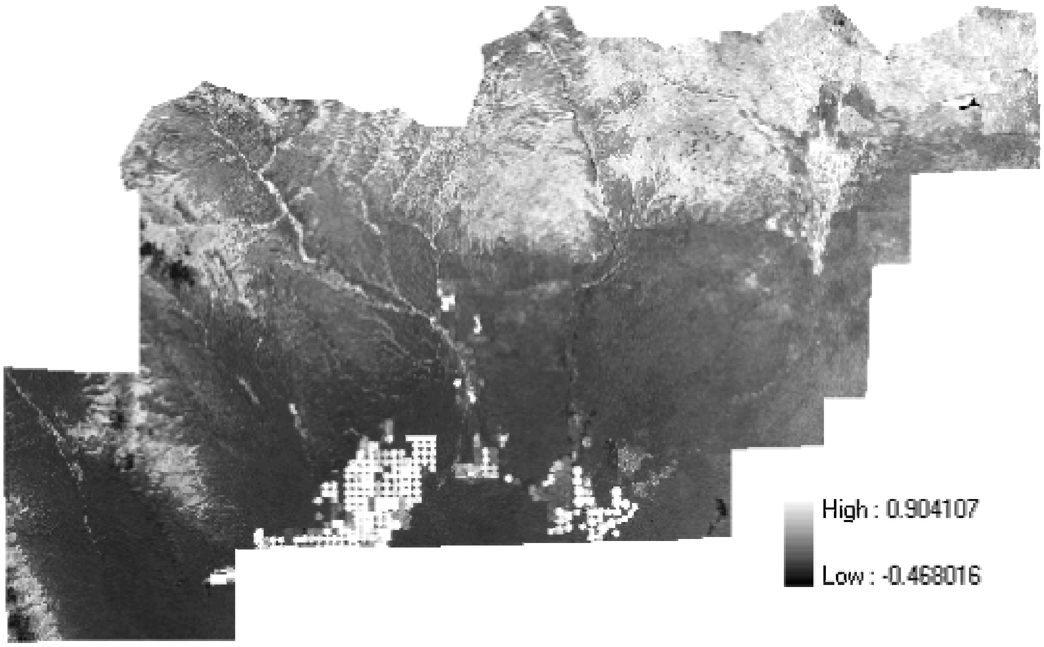


Figure 7. The NDVI has an interval of –1 to +1, where –1 is no vegetation and +1 is pure vegetation.

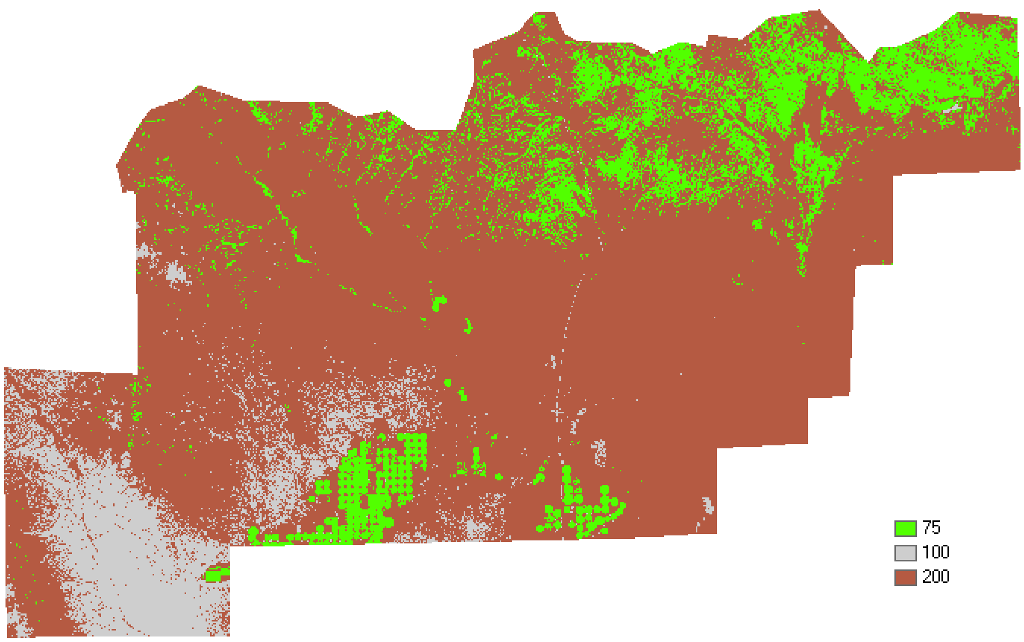


Figure 8 The results of the reclassification of NDVI into no vegetation (100), dry vegetation (200) and wet vegetation (75).

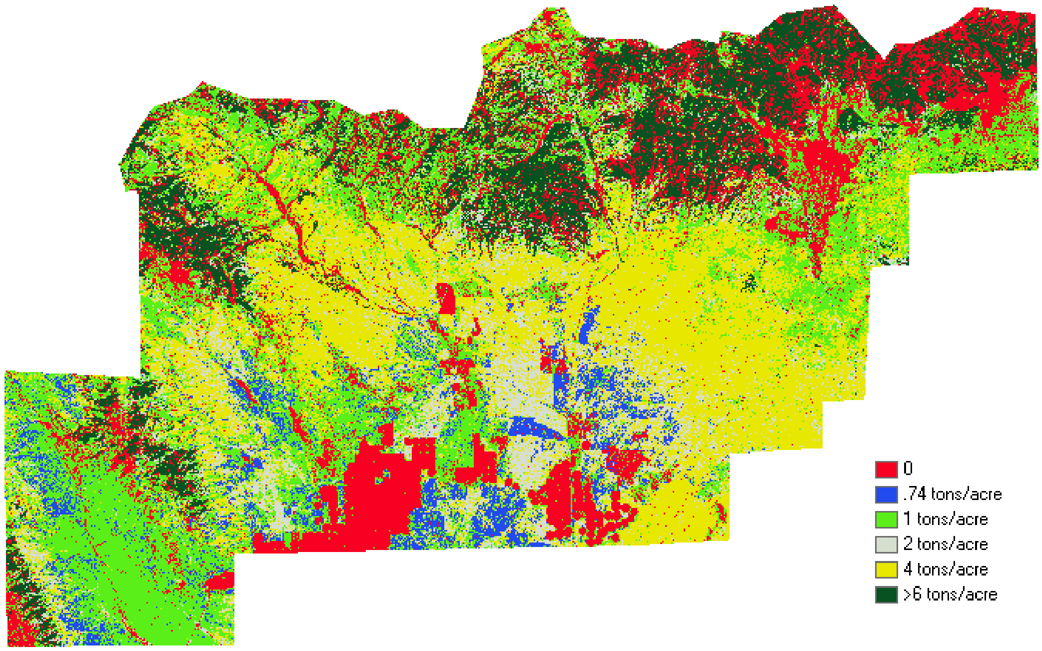


Figure 9 The fuel load model and the distribution of different fuel load classes for Clark County, ID.

An error matrix of the comparison between training sites and the fuel load model is reported in table 1. The absolute accuracy of the model is 79%.

Table1: Error matrix for the fuel load model.

	Measured in the Field							
Model Predicted		0 tons/acre	.74 tons/acre	1 tons/acre	2 tons/acre	4 tons/acre	>6 tons/acre	Model accuracy
	0 tons/acre	0	0	0	0	0	1	0%
	.74 tons/acre	0	8	0	0	0	0	100%
	1 tons/acre	0	0	6	1	1	0	75%
	2 tons/acre	0	0	1	3	2	0	50%
	4 tons/acre	0	0	0	2	11	0	85%
	>6 tons/acre	0	0	0	0	0	2	100%
	Field Accuracy	0%	100%	86%	50%	79%	66%	**79%**

The three component models involving the fuel load model are shown in figures 10, 11, and 12. Figure 10 is the vegetation moisture model, and one would expect, the areas with irrigated agriculture contain the lowest-risk values in the study area. The effect of fuel load on fire's spread rate is reported in figure 11, where the grasses on the margins of the Snake River Plain have been classified with highest risk. Finally, figure 12 is the intensity model. Conifers in the highlands, especially in the northeastern section of the county, comprise the highest risks for the most intense fires.

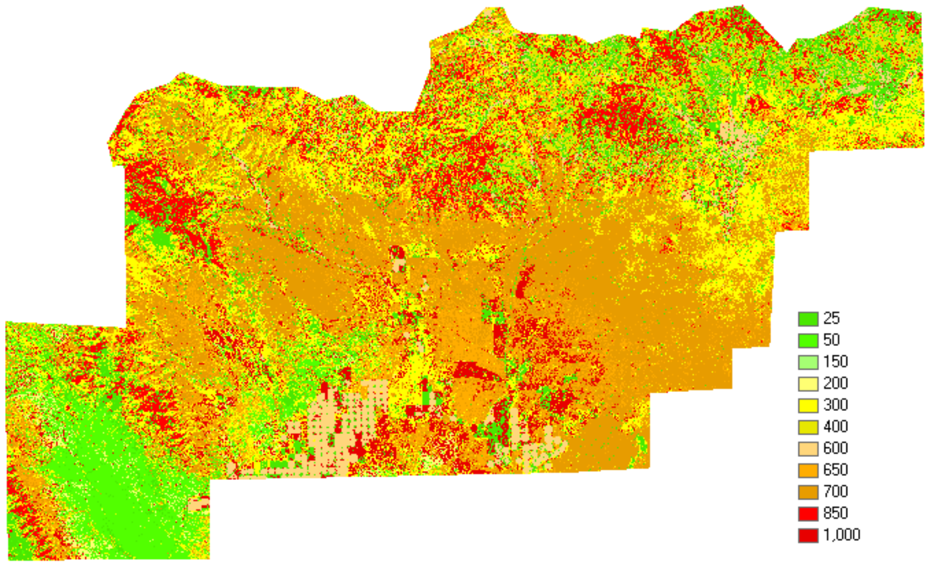


Figure 10 The Fuel Load/ Vegetation Moisture model. This model expresses how vegetation moisture and the combination of different fuel load classes affect fire risk. This model was given an overall weighting of 10% of the final model.

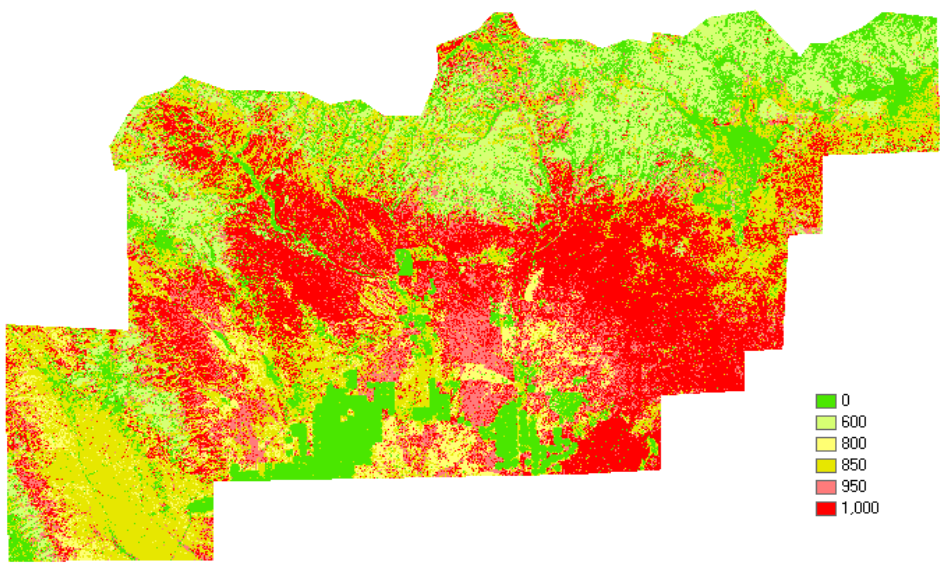


Figure 11 The Fuel Load/ Rate of Spread model. This model expresses the fire risk associated with the spread rate of different fuel load classes. This model was given an overall weighting of 15% of the final model.

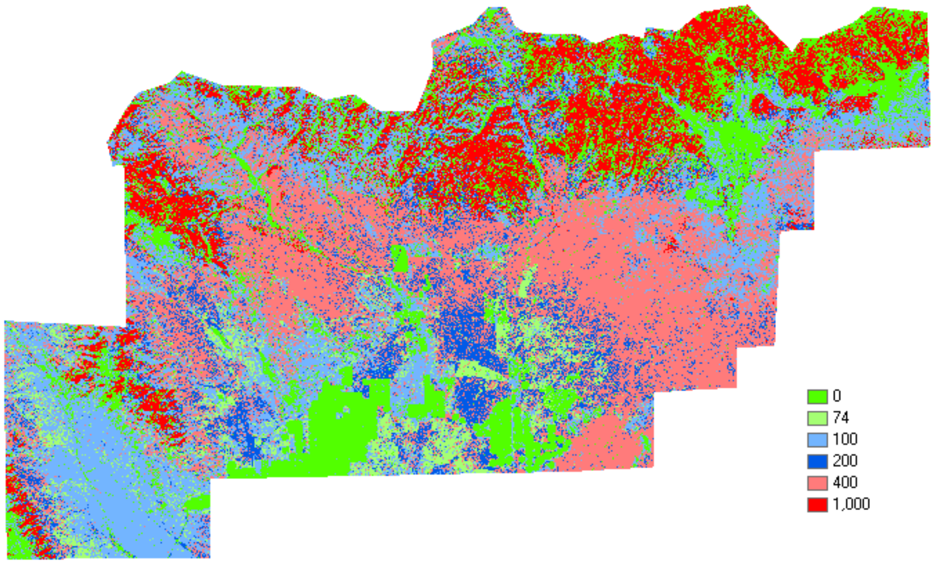


Figure 12 The Fuel Load/ Intensity model. This model expresses the fire risk associated with the amount of heat energy (intensity) each fuel load class gives off. This model was given an overall weighting of 15% of the final model.

The next three figures, numbered 13 through 15, are the component models generated using the Clark County DEM. Figure 13 assesses the risk of fires spreading quickly due to steep slopes. Here, the highlands in the northern portion of the county received high values and the Snake River Plain in the south received much lower risk. Next is the suppression difficulty model (figure 14), 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 and highest risk. Figure 15 is the Aspect/ Sun Position component model.

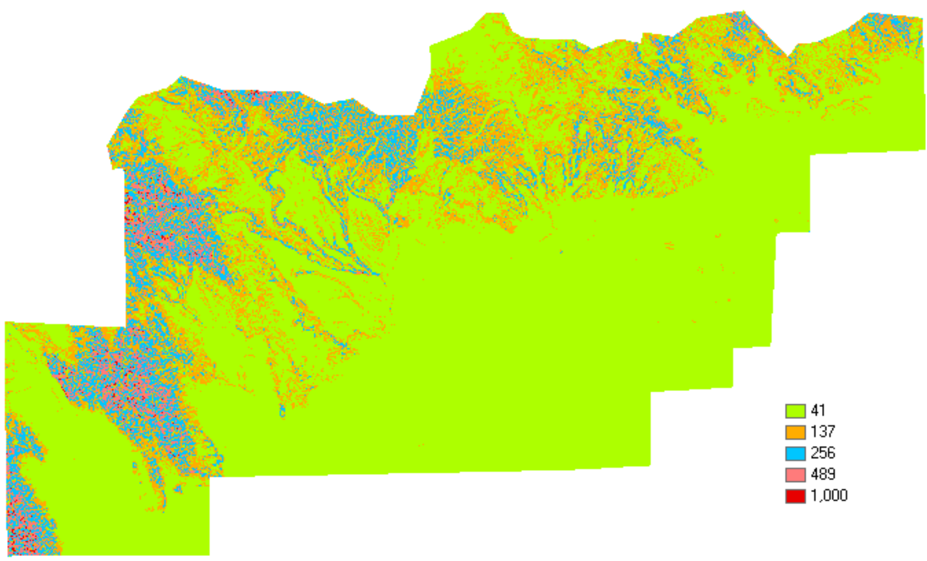


Figure 13 The Slope/ Rate of spread model. This model expresses how different angles of slope affect the spread rate of fire. Steeper slops are given the highest fire risk. This model was given an overall weighting of 15% of the final model.

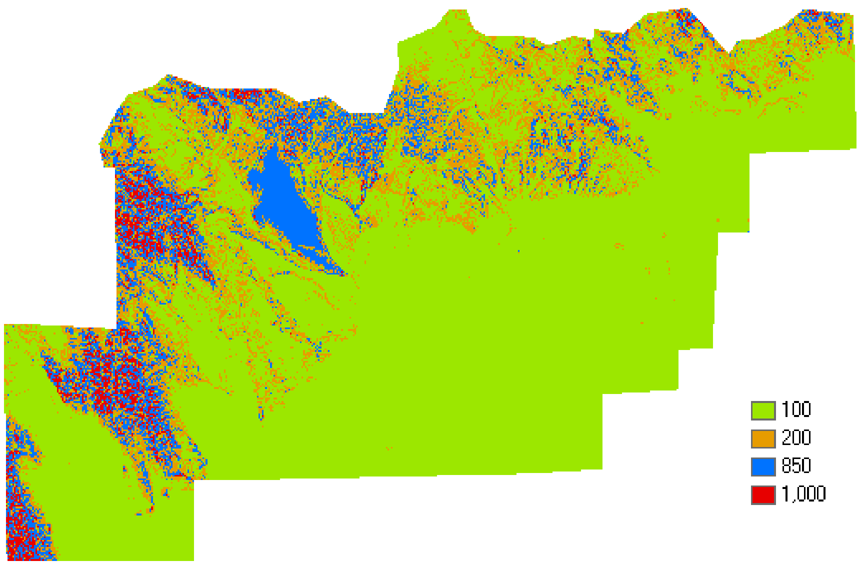


Figure 14 The Slope/ Suppression Difficulty model. This model expresses how different slope angles suppression efforts of firefighters. This model was given an overall weighting of 10% of the final model.

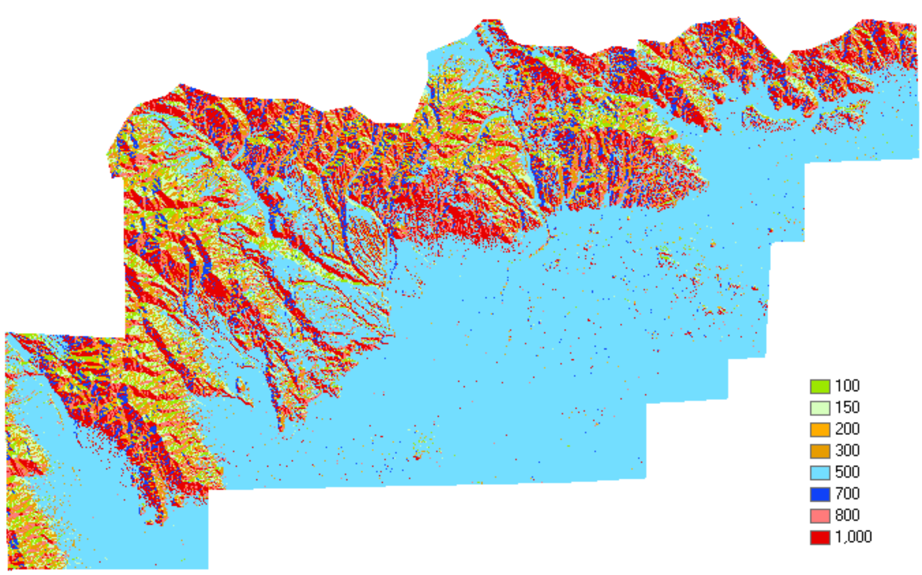


Figure 15 The Aspect/ Sun Position model. This model expresses how different aspects affect fire risk. Southern aspects have the highest fire risk. This model was given an overall weighting of 5% of the final model.

The Ignition Source component model is shown in figure 16. The lightning strike model dominates this model, with the highlands containing the great bulk of the high risk. The

Structures at Risk component model is shown in Figure 17. Here, of course, the population centers of Clark County; Dubois, Kilgore, and Spencer; contain the highest structure density and the highest fire risk.

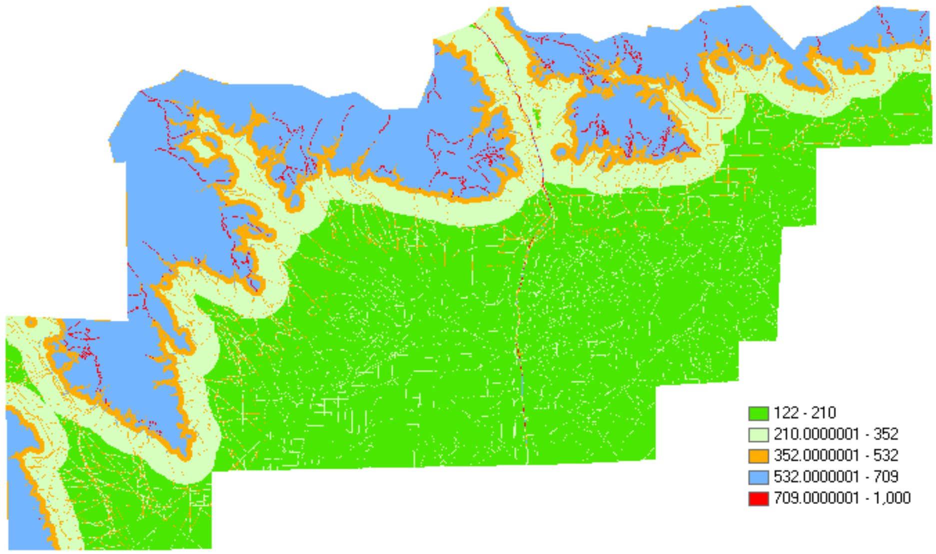


Figure 16 The Ignition Source model. This model expresses areas that are high risk due to lightning and anthropogenic sources and is given an overall weighting of 10% of the final model.

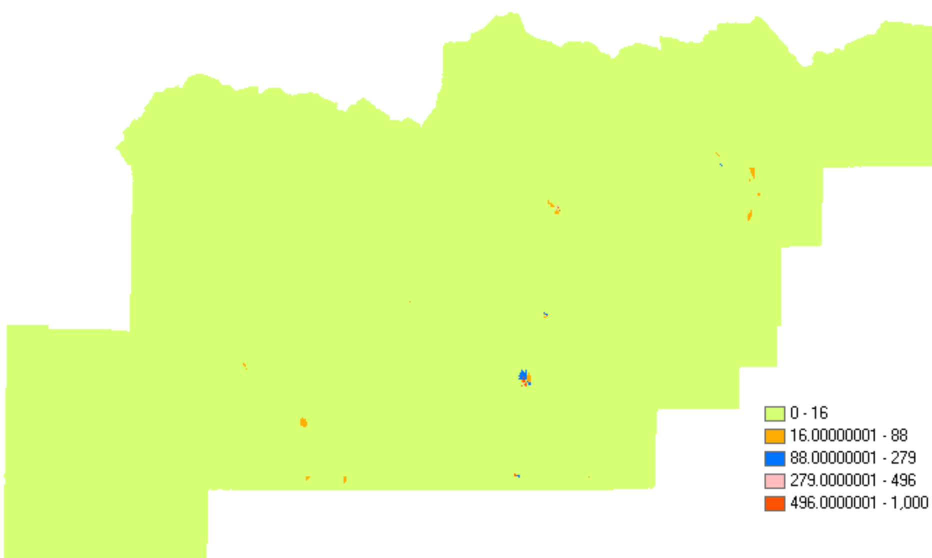


Figure 17 The Structures at Risk model. This model expresses areas that are high risk due to high structure density and is given an overall weighting of 20% of the final model.

The Final Fire Risk Model is shown in figure 18. In a 5km buffer around Dubois, the lowest risk was classified as 35, with a maximum possible risk value of 1000. The highest risk value in that buffer was an intermediate value of 550. Roughly 75% of all pixels within 5km of Dubois were rated with a value above 250. A portion of this area is taken up by irrigated agriculture, but the great majority (approximately 75%) is sagebrush steppe and grassland with some human development.

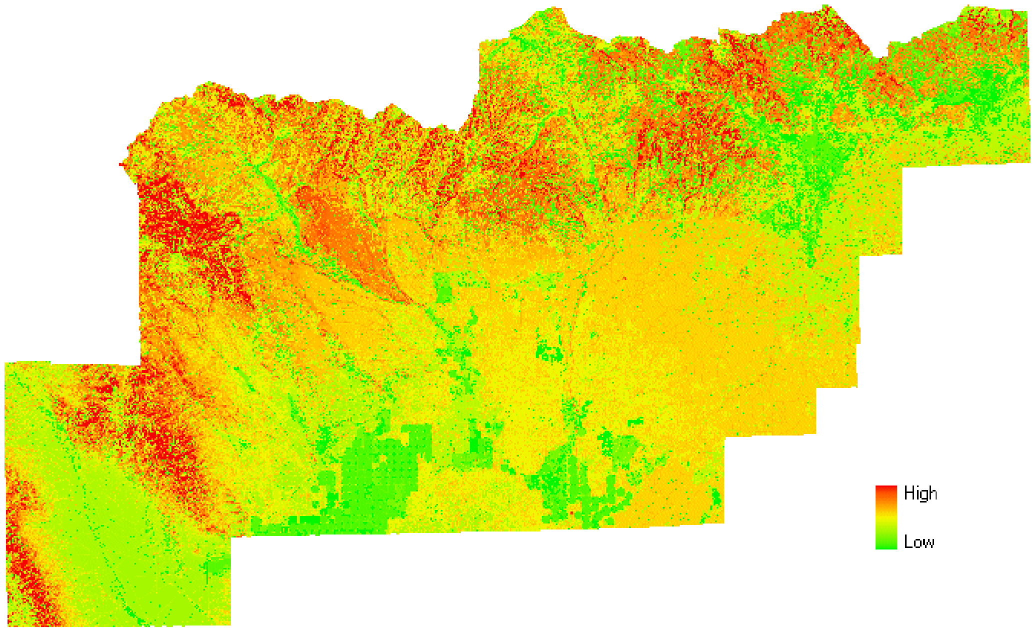


Figure 18 The Final Fire Risk Model for Clark County, Idaho. Fire risk is shown on a gradient scale.

Discussion:

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). 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. We found our threshold values to be different from Mattson *et al.,* (2002). We believe this is most likely due to the difference in climate. Our area consisted mostly of xeric rangelands.

Overall accuracy of our fuel load model was 79%. The Fuel Load model had the greatest misclassification between fuel load classes with 2 tons/acre and 4 tons/per acre. This is most likely due to the similarity of these fuel load classes (e.g., both classes contain mainly grasses and sage in slightly differing proportions).

The Structures at Risk component was weighted most heavily (20%). This is due to the nature of this project; we were most interested in the Wildland/ Urban Interface. This model allowed us to emphasize these 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 Ignition Source component takes into account how different ignition sources affect fire risk. This model used both natural (lightning) and anthropogenic sources. Mountainous areas, railroads, and roadways were given the highest fire risk value, while lower elevation and roadless areas received the lowest fire risk 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 risk 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, and Mac Murdock. 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 we and others (Judd, 2003) felt were more important.

The date (July 12, 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.

Jansson, C., Pettersson, O., Weber K.T., and Burkhardt F. 2002. Wildland/Urban Interface and Communities at Risk: Lava Hot Springs, Idaho

Judd, F. 2003. Personal communication via email

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.

Weber K.T., McMahon B. J., Russell G., and Johnson P. 2003. Modeling Lightning as an Ignition Source of Rangeland Wildfire in Southeastern Idaho.

Acknowledgements:

On March 14, and March 31, 2003 we had a presentation of our project for people that have good knowledge about this subject. We discussed the weightings of the wildfire model components and accepted the weightings described in this report. We also decided to added two new component models; Ignition Source model and Structure's at Risk model.

These people were attending:

Felicia Burkhardt: GIS Coordinator, USRD BLM

Fred Judd: Fire Mitigation and Education Officer, USDR BLM

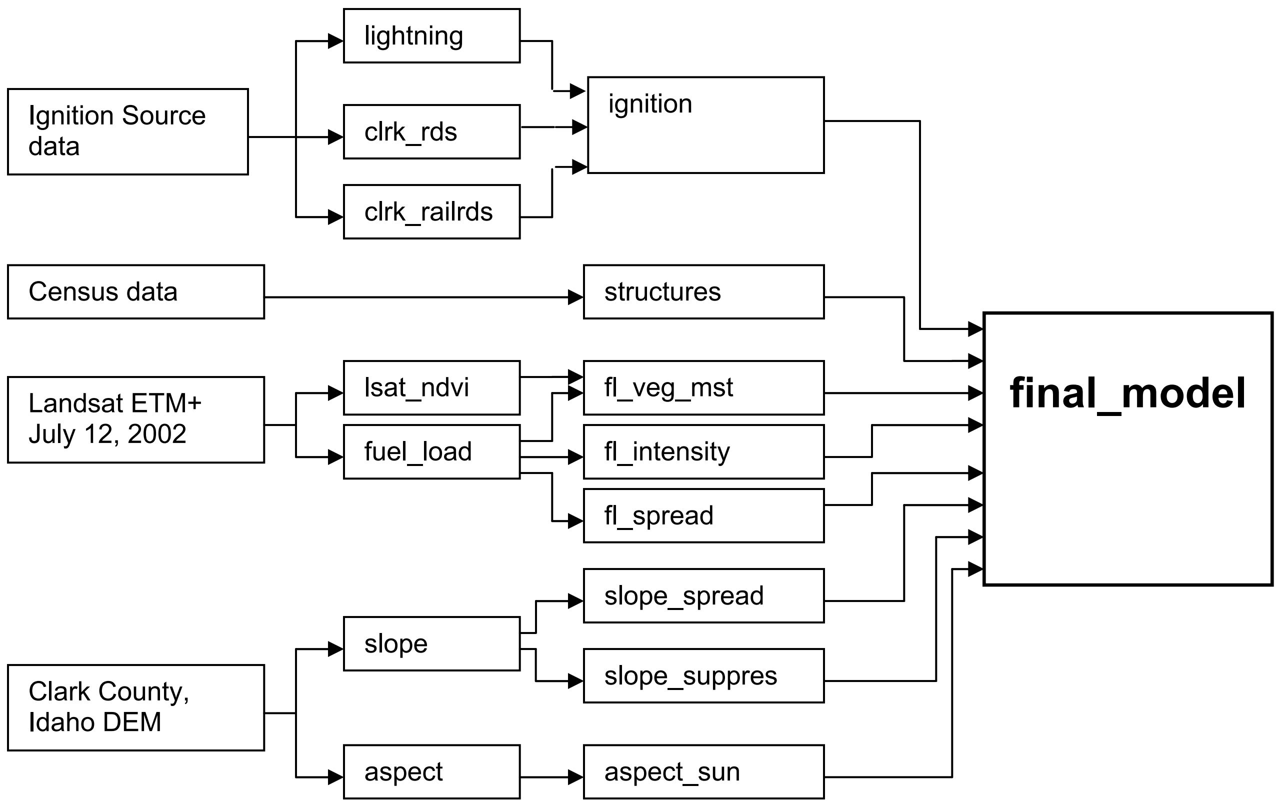
Mac Murdoch: Fire Fire risk assessment contractor for Clark County, ID

Keith T. Weber: GIS Director, Idaho State University (ISU), GIS Training and Research Center

Chad Gentry: GIS Intern, ISU, GIS Training and Research Center

Dan Narsavage: 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

Appendix C – Data dictionary

Data	File name	Full path to dataset	Description	Format
County bound	clark_bound	\\Alpine\Data\urbint\Clark\all_datasets	Boundary of clark county	polygon coverage
Roads	clark_roads.shp	\\Alpine\Data\urbint\Clark\all_datasets	Roads in Clark County	line shapefile
Census data	census.shp	\\Alpine\Data\urbint\Clark\all_datasets	Census tracts with population and structures data	polygon shapefile
Bands used for NDVI	lsat_band3	\\Alpine\Data\urbint\Clark\all_datasets	Landsat Band 3 for Clark County	Grid - 28.5m pixels
	lsat_band4	\\Alpine\Data\urbint\Clark\all_datasets	Landsat Band 4 for Clark County	Grid - 28.5m pixels
	lsat_NDVI	\\Alpine\Data\urbint\Clark\all_datasets	Landsat NDVI model for all of Clark County	Grid - 28.5m pixels
Fuel Load	fuel_load	\\Alpine\Data\urbint\Clark\all_datasets	Reclassified NDVI modeling fuel load in tons/acre	Grid - 28.5m pixels
Terrain models	dem	\\Alpine\Data\urbint\Clark\all_datasets	Digital Elevation Model of Clark County	Grid - 30m pixels
	aspect	\\Alpine\Data\urbint\Clark\all_datasets	Aspect model - Clark Cty	Grid - 30m pixels
	slope	\\Alpine\Data\urbint\Clark\all_datasets	Slope model - Clark Cty	Grid - 30m pixels
Component models	aspect_sun	\\Alpine\Data\urbint\Clark\all_datasets	Risk increases near S & W aspects	Grid - 30m pixels
	slope_spread	\\Alpine\Data\urbint\Clark\all_datasets	Risk increases with steepness	Grid - 30m pixels
	slope_suppres	\\Alpine\Data\urbint\Clark\all_datasets	Risk increases with steepness	Grid - 30m pixels
	fl_spread	\\Alpine\Data\urbint\Clark\all_datasets	Highest risk in grasses	Grid - 26m pixels
	fl_intensity	\\Alpine\Data\urbint\Clark\all_datasets	Risk increases with tons/acre	Grid - 26m pixels
	fl_vegmst	\\Alpine\Data\urbint\Clark\all_datasets	Risk increases with drier vegetation	Grid - 26m pixels
	structures	\\Alpine\Data\urbint\Clark\all_datasets	Risk increases with structure density	Grid - 30m pixels
	ignition	\\Alpine\Data\urbint\Clark\all_datasets	Risk increases with elevation and proximity to roads	Grid - 30m pixels
Final Model	final_model	\\Alpine\Data\urbint\Clark\all_datasets	Final risk model - 30m pixels - ArcInfo Grid	Grid - 30m pixels
Reports	Clark_WUI_Final_Report	\\Alpine\Data\urbint\Clark\reports	Report covering methods, results, & conclusions of WUI modeling	Word Document
	NDVI_White_Paper_Report	\\Alpine\Data\urbint\Clark\reports	Report covering methods, results, & conclusions of NDVI comparison	Word Document