Wildland/Urban Interface and Communities at Risk

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

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Abstract: Wildland/Urban Interface (WUI) fires and Communities at Risk (CAR) projects are high priorities to federal land management agencies. It is important that the federal government help educate homeowners, firefighters, local officials, and land managers regarding the risk of wildland fire. The Bureau of Land Management's (BLM) Upper Snake River District (USRD) Geographic Information Systems (GIS) team and the GIS Training and Research Center (GISTReC) at Idaho State University (ISU), have created a model to predict potential wildfire risk areas for Oneida County, Idaho. During this project models were created of specific individual risks associated with wildfires: topography, vegetation moisture, fuel load, and the number of structures at risk. These models were evaluated together to create a final fire risk model for Oneida County, Idaho. This report describes each of the WUI fire risk components and what effect each has on the final fire risk model. This final model is an accurate depiction of the spatial distribution of wildfire risk in Oneida County and can be used by regional fire managers to manage wildfire risk.

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

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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 valuable tool used by fire managers is Geographic Information Systems (GIS). GIS allows for spatial analysis of large geographic areas and is easily integrated with satellite imagery.

Using both GIS and remote sensing, we created 7 models that describe different aspects 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 model was Fuel Load/ Rate of Spread. This model takes into account how different fuel types spread and affect fire risk. The third model was Fuel Load/ Intensity. This model describes how different fuel load classes release heat energy during a fire and thereby affect their environment. The fourth model, Slope/ Rate of Spread, takes into account how the steepness of a surface affects the rate of spread of a fire. The fifth component model, Slope/ Suppression Difficulty, takes into account how varying slope influences suppression efforts by firefighters and their equipment. The sixth component model, Aspect/ Sun Position, takes into account varying fire risks associated with aspect, especially as it relates to dessication effects. Finally, the Structures at Risk model describes structure density. Each of these component models are weighted and summed to produce the Final Fire Risk Model. The Oneida 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), Clark County, Idaho (Gentry *et al*, 2003), Bannock County, Idaho (Gentry *et al*, 2003), and Power County, Idaho (Gentry *et al*, 2003).

Methods:

Required data sets:

- Digital Elevation Model (DEM) of Oneida County
- Landsat 7 ETM+ imagery for Oneida County and environs – Path 039, Row 030 and Path 039, Row 031.
- Digital Orthophoto Quarter-Quads (DOQQs) for Oneida County
- Digital Raster Graphics (DRGs) for Oneida County
- Transportation dataset for Oneida County
- Census data for Oneida County from the year 2002

Data processing:

We projected all datasets into Idaho Transverse Mercator (GCS North American 1983) as needed using Arc Toolbox → Data Management Tools → Project.

The DEM for Oneida County was downloaded from http://srtm.usgs.gov/data/obtainingdata.html as a single seamless ArcInfo grid with 30m pixels. The Oneida County DEM was then clipped to the footprint of Oneida County using ArcInfo Workstation 8.3.

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 Oneida County using ArcInfo Workstation 8.3.

The GIS TReC owns all of the DOQQs and DRGs covering Oneida County. These datasets were used for visual purposes only and were already projected into IDTM, though they needed to be reprojected from IDTM 27 to IDTM 83.

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 Oneida County.

A polygon shapefile containing census block data for Oneida County was downloaded from http://arcdata.esri.com/data/tiger2000/tiger_download.cfm and data from the ESRI Data & Maps Media Kit, 2003 (Disc 3; "blockpop.shp") were used to define structure density.

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 05-28-2003. 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.

The NDVI for the area covered by the Landsat imagery used was created in Idrisi. The values obtained from the imagery were stretched from 0-255 to accurately represent the value range from -1 to +1. 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 Oneida County. To estimate fuel load, we used a total of 464 sample points collected in the summer of 2003 in southeastern Idaho, primarily within the Big Desert region of the Snake River plain and Oneida County. Forty-one of these points were collected by Chad Gentry, with the remaining 423 points being collected by Chris Moller and Luke Sander. Each of the sample points was classified into one of 4 fuel load classes: 0 = 0 tons/acre (No vegetation), <2 tons/acre (Grassland with some Sagebrush), 2-6 tons/acre (Low and Typical Sagebrush), and = >6 tons/acre (Forest).

Using Idrisi, we created signature files for the field training sites using an NDVI model produced from Landsat 7 ETM+ imagery (Idrisi 32→ Image Processing → Signature Development → MAKESIG. The signature files were then used to create a fuel load model using Idrisi 32→ Hard Classifiers → MAXLIKE. We validated the predictions of this model using techniques described in the next section "Fuel load Model Validation".

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 results of these tests are reported in the text. 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 Oneida 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 Oneida 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 Position
- Structures at Risk

Creating the wildfire risk 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 Oneida County, Idaho.

<u>Fuel load/ Vegetation Moisture</u>

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.

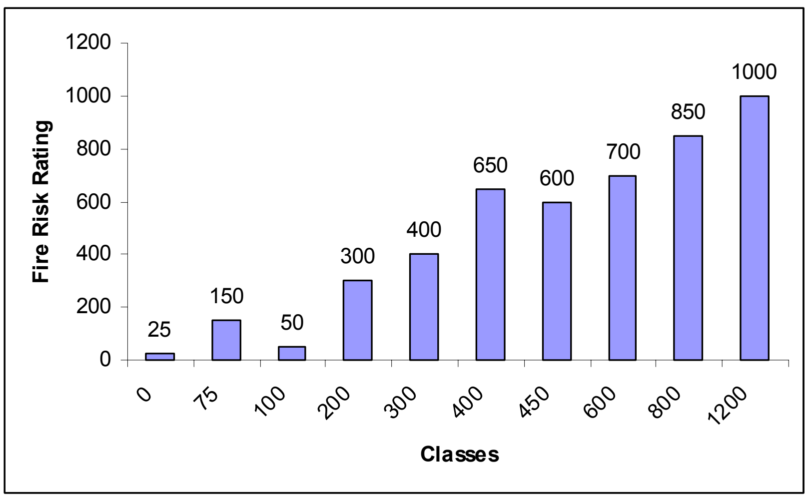


Figure 1. Weightings for Fuel Load/ Vegetation Moisture (Jansson et al, 2002).

<u>Fuel load/ Rate of Spread</u>

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

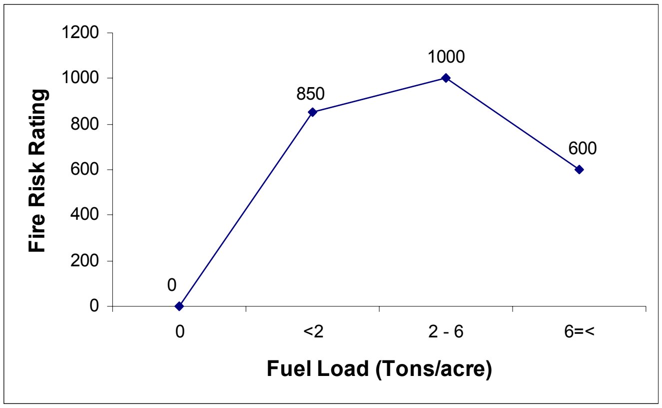


Figure 2. Weightings for Fuel Load/ Rate of Spread (Mattsson et al, 2002).

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).

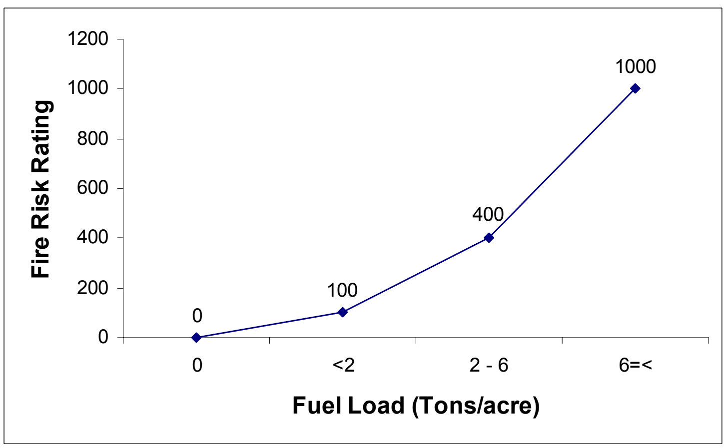


Figure 3. This chart describes all weightings for Fuel Load/ Intensity (Mattsson et al, 2002).

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).

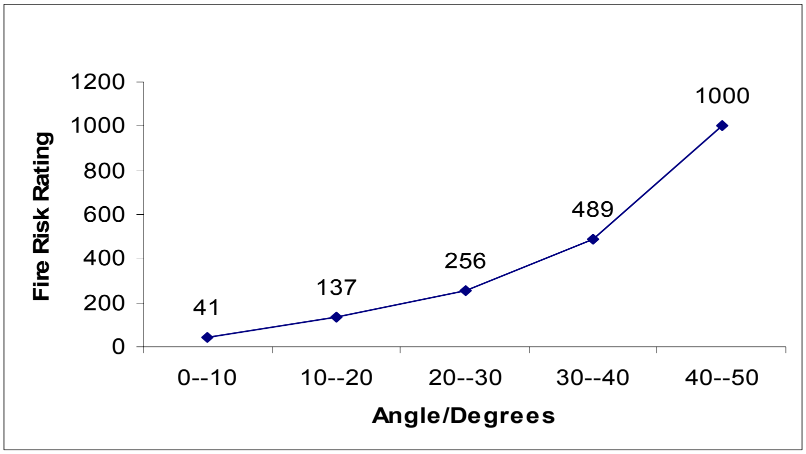


Figure 4. Weightings describe how spread rate increase with angle of slope. The weight proportion is essentially exponential with slope angle (Mattsson et al., 2002).

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).

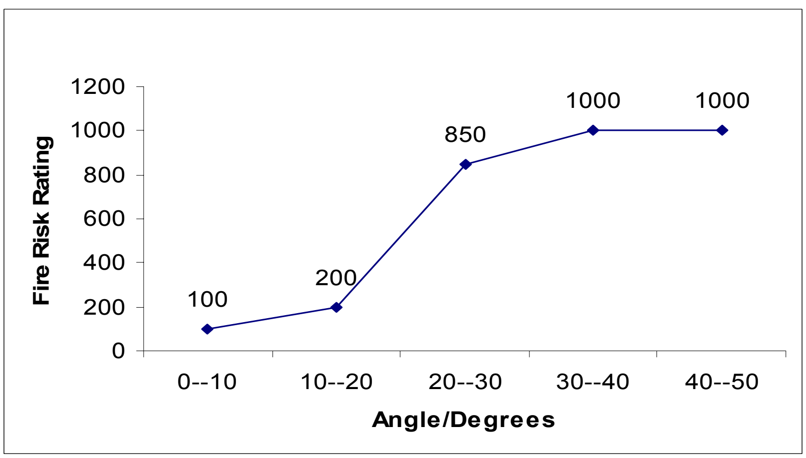


Figure 5. Weightings for slope/suppression difficulties describe how suppression difficulties are affected by the angle of slope (Mattsson et al, 2002).

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).

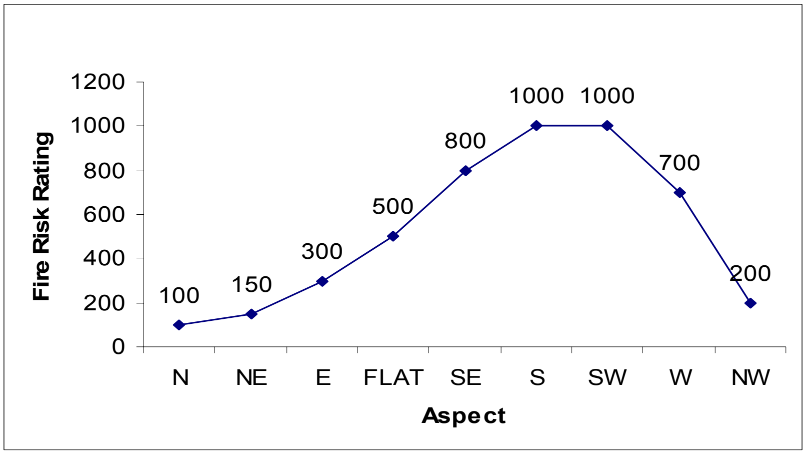


Figure 6. Weightings for Aspect/Sun position describe how the sun desiccates the ground at different aspects (Mattsson et al, 2002).

Structures at Risk

We used census block data for Oneida 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 ESRI Data & Maps Media Kit, 2003. 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:

- Structures at Risk 22%
- Fuel load/ Rate of Spread 17%
- Fuel load/ Intensity 17%
- Fuel load/ Vegetation Moisture 11%
- Slope/ Rate of Spread 17%
- Slope/ Suppression Difficulties 11%
- 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 Clark County, Bannock County, Power County, and Oneida County, Idaho. Figure 8 shows portions of each county classified as low, medium, and high risk relative to individual areas. We did this by reclassifying the final fire risk model into three distinct classes (0-333 = low risk; 333-666 = medium risk; 666-1000 = high risk). Comparison between total acres classified as low, medium, and high fire risk is shown in table 1. Figure 9 describes the fuel load distribution for each county. Table 2 show total acres of BLM Land classified as low, medium, and high fire risk.

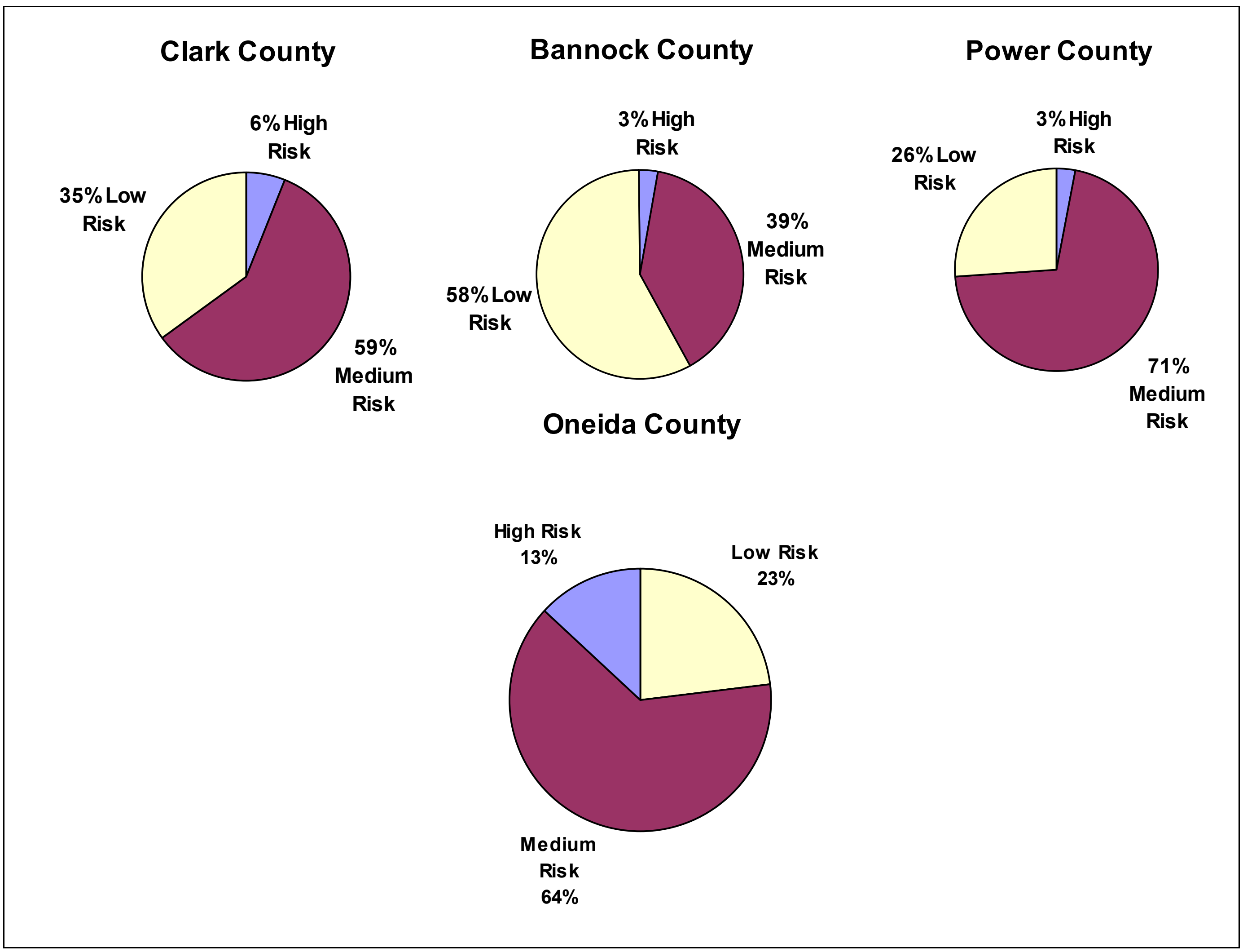


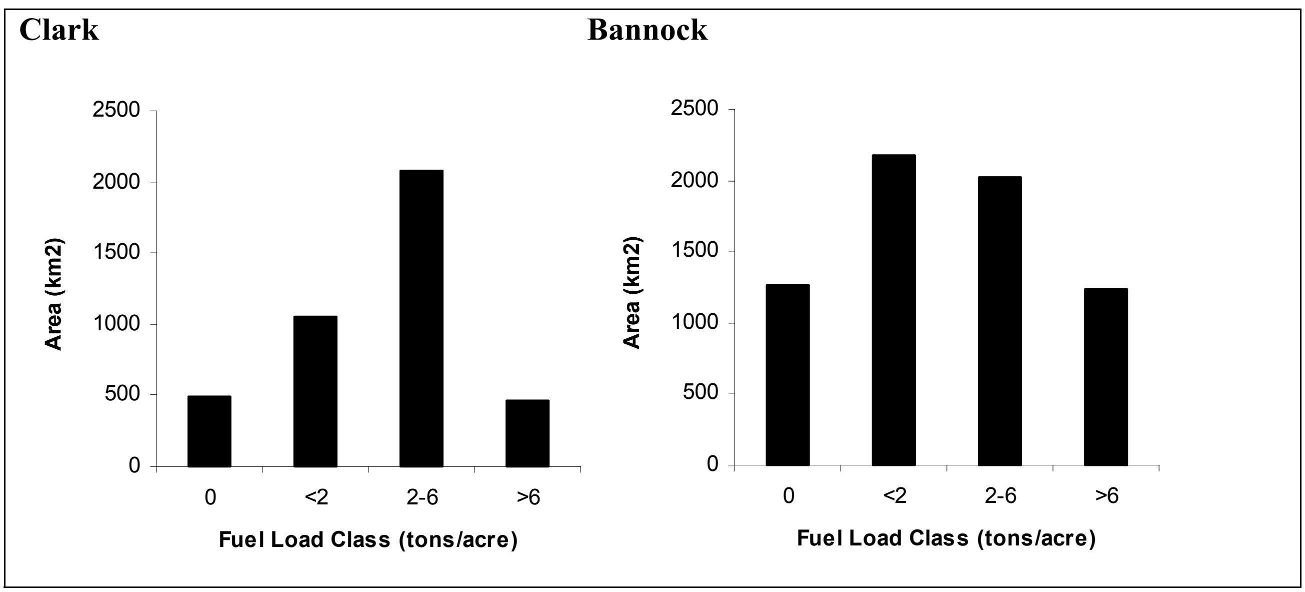
Figure 8. Percent of Clark County, Bannock County, Power County and Oneida County considered low, medium, and high fire risk.

Table 1. Total acres classified as low, medium, and high fire risk for Clark, Bannock, Power, and Oneida County.

Total Acres Classified as low, medium, and high fire risk				
	Clark County	**Bannock County**	**Power County**	**Oneida County**
Low	395,360	413,146	233,958	175,761
Medium	666,464	277,805	638,886	495,089
High	67,776	21,370	26,996	97,599
Total	**1,129,600**	**712,321**	**899,840**	**768,449**

Table 2. BLM land area classified as low, medium, and high fire risk.

BLM Land Classified as low, medium, and high fire risk			
	Km^2	**Acres**	**Percent**
Low	343.5	84,880	31%
Medium	763.6	188,689	69%
High	.5	124	--
Total	**1,107.6**	**273,693**	



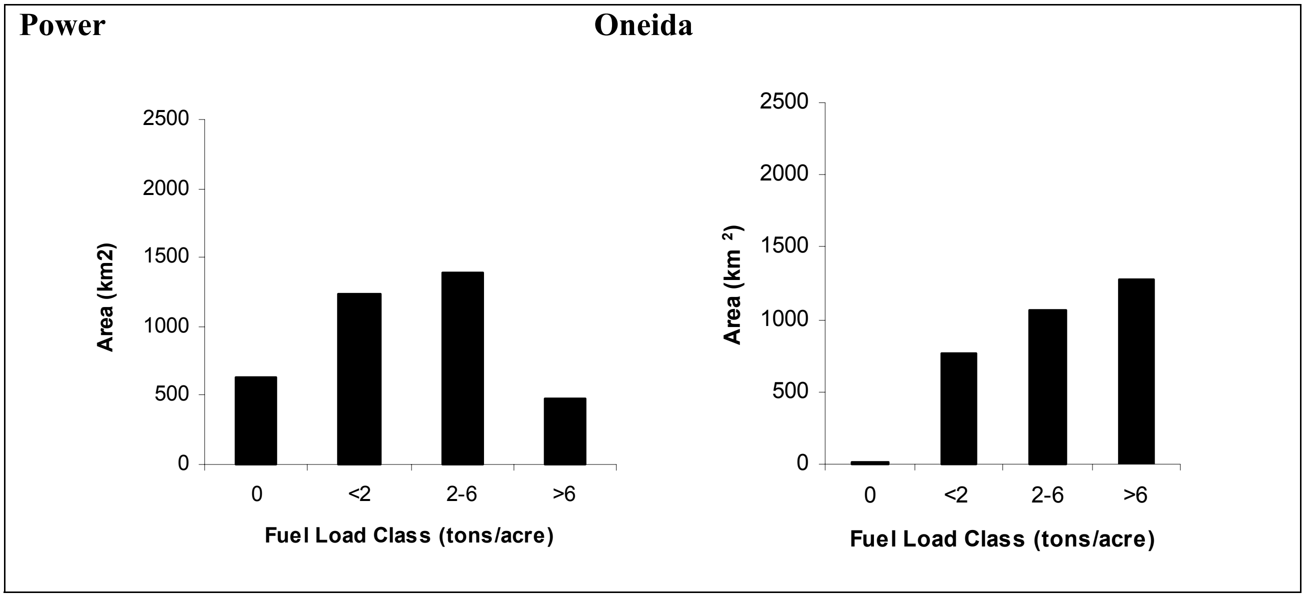


Figure 9. Comparison of fuel load distribution for Clark County (A), Bannock County (B), Power County (C), and Oneida County (D).

The NDVI grid used to generate the fuel load model is shown in figure 10. Our reclassified NDVI grid estimating the location of wet vegetation, dry vegetation and no vegetation is shown in Figure 11. Figure 12 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.

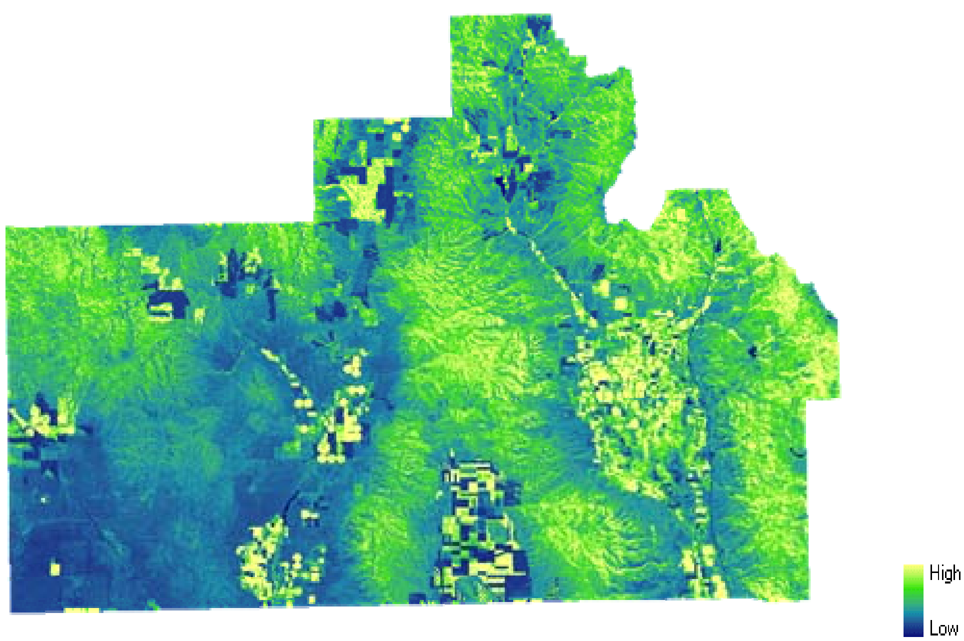


Figure 10. The NDVI has an interval of –1 to +1, where –1 is no vegetation and +1 is pure vegetation.

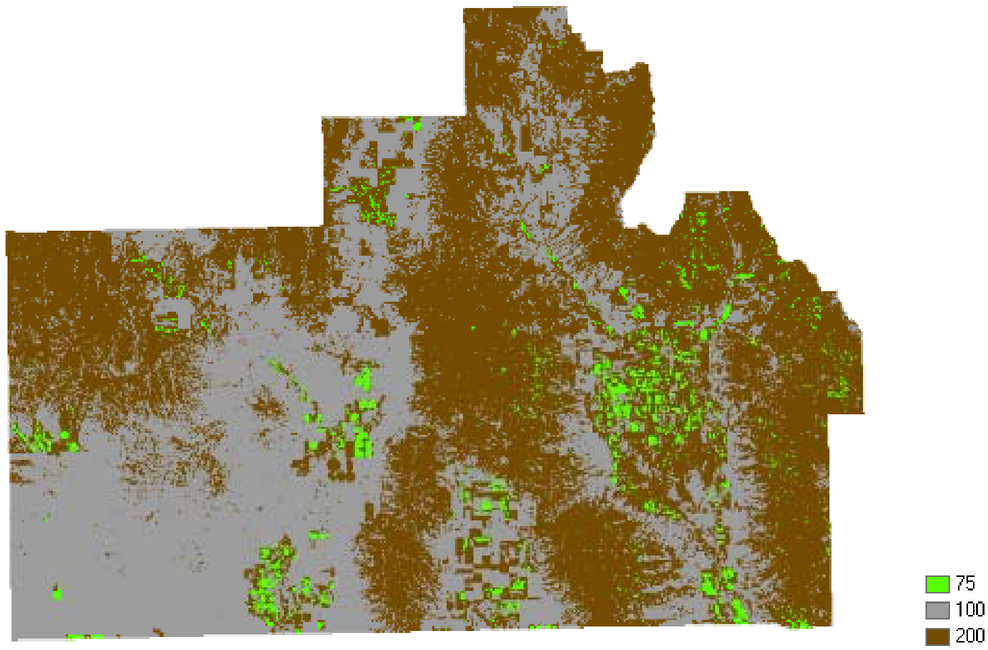


Figure 11. The results of the reclassification of NDVI into no vegetation (100), dry vegetation (200) and wet vegetation (75).

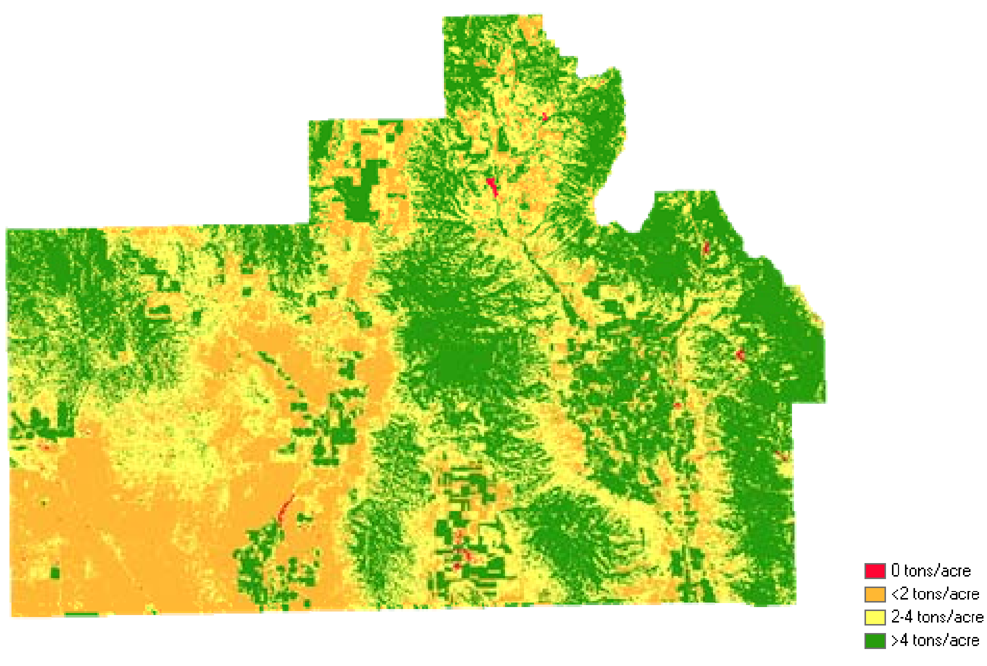


Figure 12. The fuel load model and the distribution of different fuel load classes for Oneida County, ID.

Table 3. Error matrix for the fuel load model.

	Field Measurement of Fuel Load (Tons/Acre)						
		0	< 2	2 - 4	> 6	Total	Acc %
Modeled Fuel Load (Tons/Acre)	0	216	25	1	1	243	88.89%
	< 2	16	4	6	0	26	15.38%
	2 - 4	1	4	59	0	64	92.19%
	> 6	1	0	0	130	131	99.24%
	Total	234	33	66	131	464	
	Acc %	92.31%	12.12%	89.39%	99.24%	Overall Accuracy	88.15%

Table 4. Kappa Statistics for the fuel load model.

PC	PO	KAPPA	LO-95%CI	HI-95%CI	SE	Z
0.367424	0.881466	0.812616	0.765172	0.86006	3.538089	22.967654

The three component models derived from the fuel load model are shown in figures 13, 14, and 15. Figure 13 is the vegetation moisture model, irrigated and riparian areas contain the lowest risk values, while the grasses, shrubs, and mountainous areas throughout Oneida County contain the highest values. The high risk 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 14. Mountainous areas, with larger fuel loads, contain the lowest values, where grasses and shrubs in the southwestern portion of Oneida County contain the highest values. The high risk areas are due to the high concentration of 2-4 tons/acre fuels. Finally, figure 15 is the intensity model. Conifers in the highlands, especially in the eastern and northwestern part of the county, comprise the highest risks for the most intense fires.

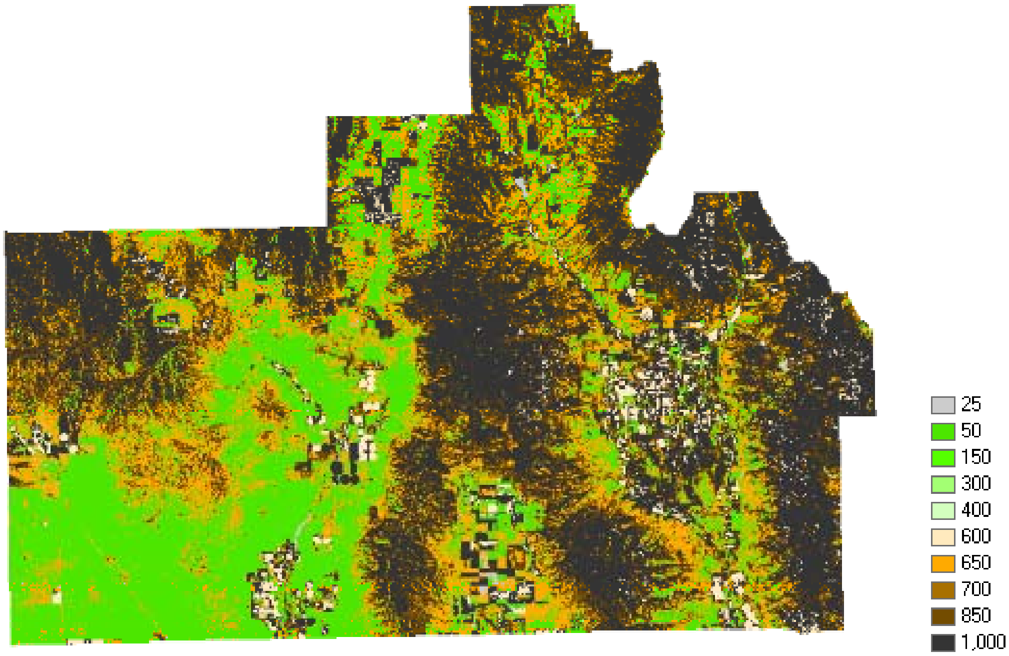


Figure 13. The Fuel Load/ Vegetation Moisture model. This model expresses how vegetation moisture and the combination of different fuel load classes affect fire risk. This model was given an overall weighting of 11% of the final model.

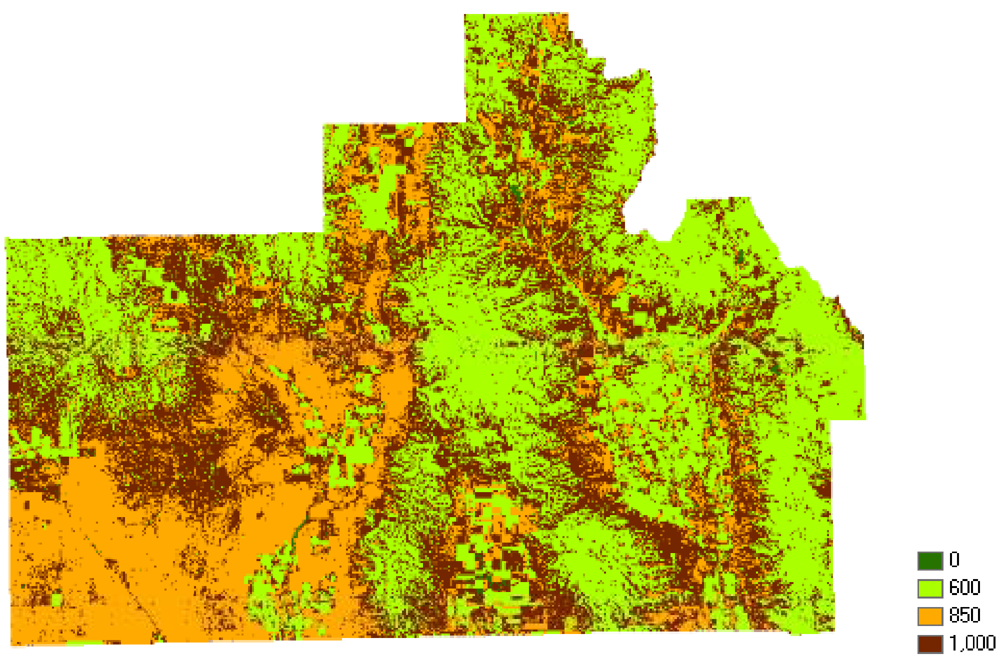


Figure 14. The Fuel Load/ Rate of Spread model. This model expresses the fire risk associated with the spread rate of different fuel load classes. This model was given an overall weighting of 17% of the final model.

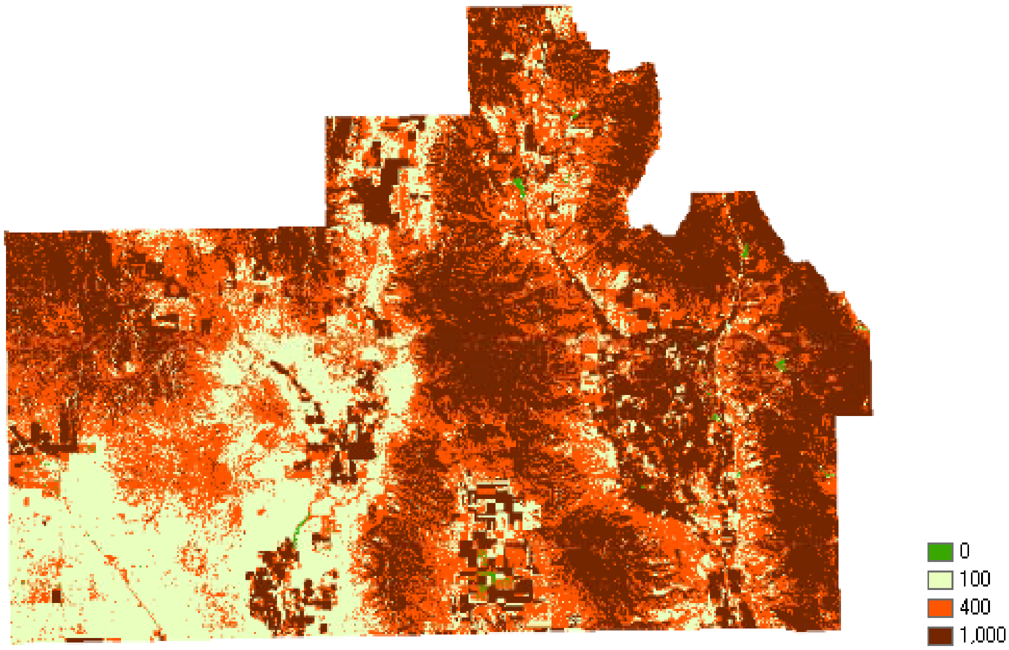


Figure 15. The Fuel Load/ Intensity model. This model expresses the fire risk associated with the amount of heat energy (intensity) each fuel load class gives off. This model was given an overall weighting of 17% of the final model.

Figures 16-18 are the component models generated using the Oneida County DEM. Figure 16 assesses the risk of fires spreading quickly due to steep slopes. Here, the highlands throughout the county received the highest values and the bottom land running southwest to northeast in the western portion of the county and from southeast to northwest in the eastern portion of the county, with shallow slopes, received the lowest values. Next is the suppression difficulty model (figure 17), where steeper slopes pose increasingly greater problems to fire fighters attempting to access fires in order to suppress them. The steeper terrain in the south, east, and extreme northeast is weighted the highest risk. Figure 18 is the Aspect/ Sun Position component model, south and southwest aspects contain the highest fire risk, 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 risk.

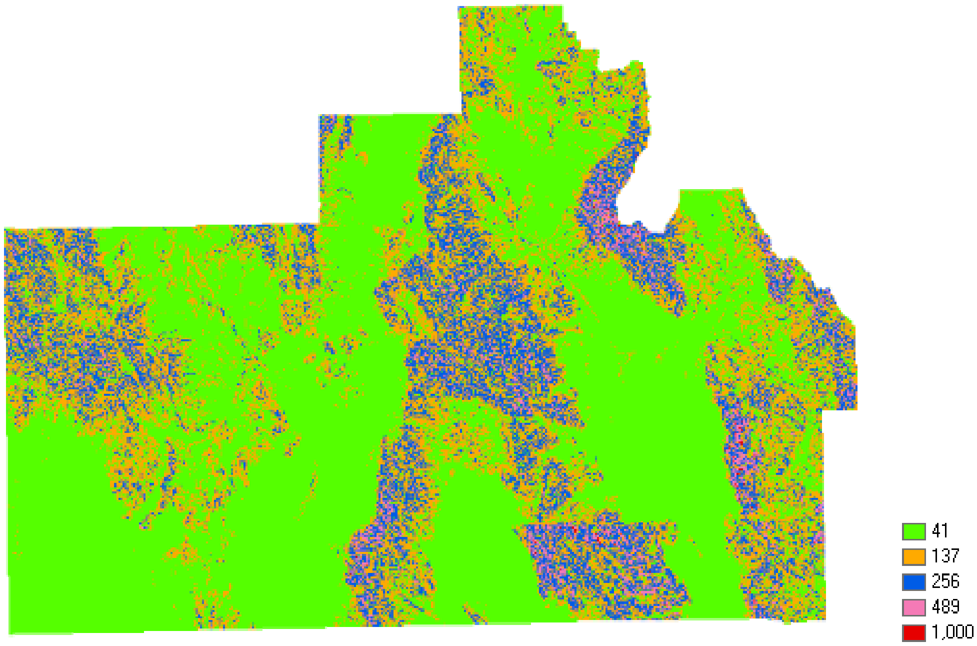


Figure 16. The Slope/ Rate of spread model. This model expresses how different angles of slope affect the spread rate of fire. Steeper slops are given the highest fire risk. This model was given an overall weighting of 17% of the final model.

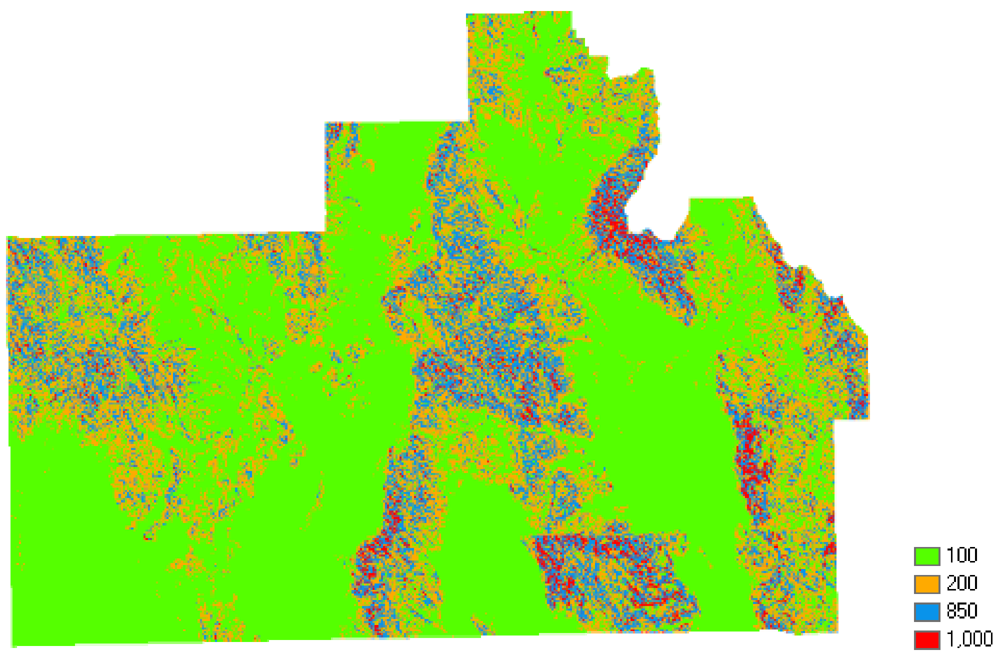


Figure 17. The Slope/ Suppression Difficulty model. This model expresses how different slope angles affect suppression efforts of firefighters. This model was given an overall weighting of 11% of the final model.

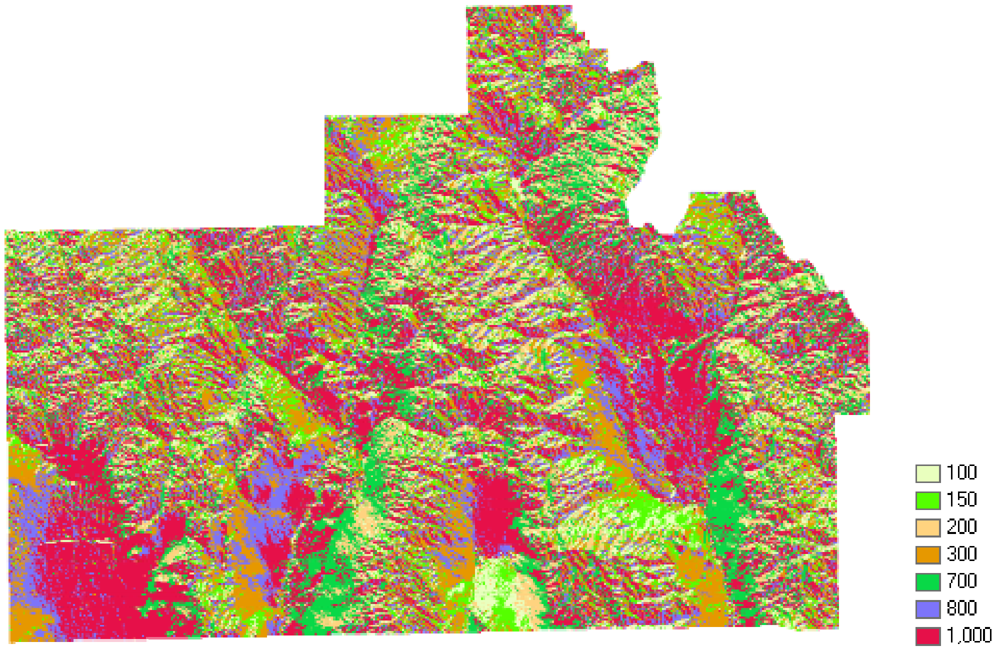


Figure 18. The Aspect/ Sun Position model. This model expresses how different aspects affect fire risk. Southern aspects have the highest fire risk. This model was given an overall weighting of 5% of the final model.

The Structures at Risk component model is shown in figure 19. Here, the population centers of Malad City, Samaria, and Holbrook (concentrations of bright red running across the middle of the county right to left) contain the highest structure density and the highest fire risk.

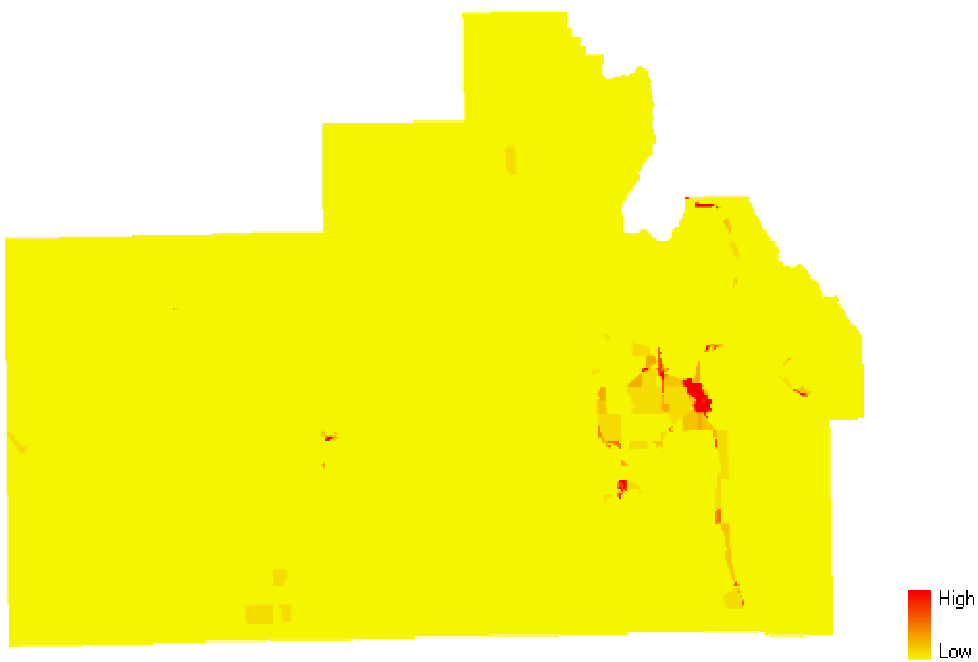


Figure 19. The Structures at Risk model. This model expresses areas that are high risk due to high structure density and is given an overall weighting of 22% of the final model.

The Final Fire Risk Model for Oneida County is shown in Figure 20 and the fire risk model with BLM lands superimposed is in Figure 21. Figure 22 shows Oneida County's fire history from 1939 – 2002, superimposed.

Figure 20. The Final Fire Risk Model for Oneida County, Idaho. Fire risk is shown using graduated symbology.

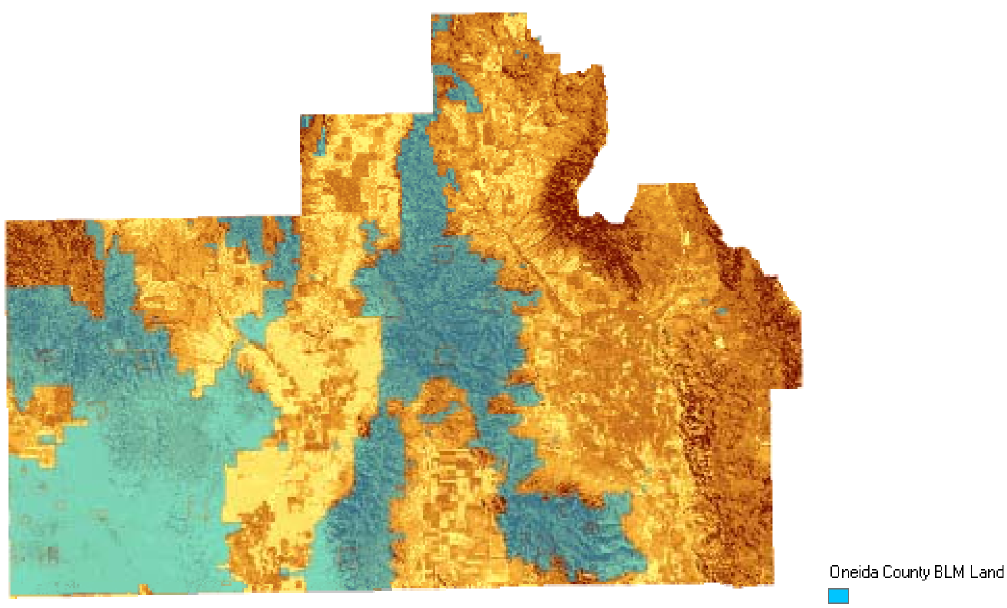


Figure 21. BLM lands within Oneida County.

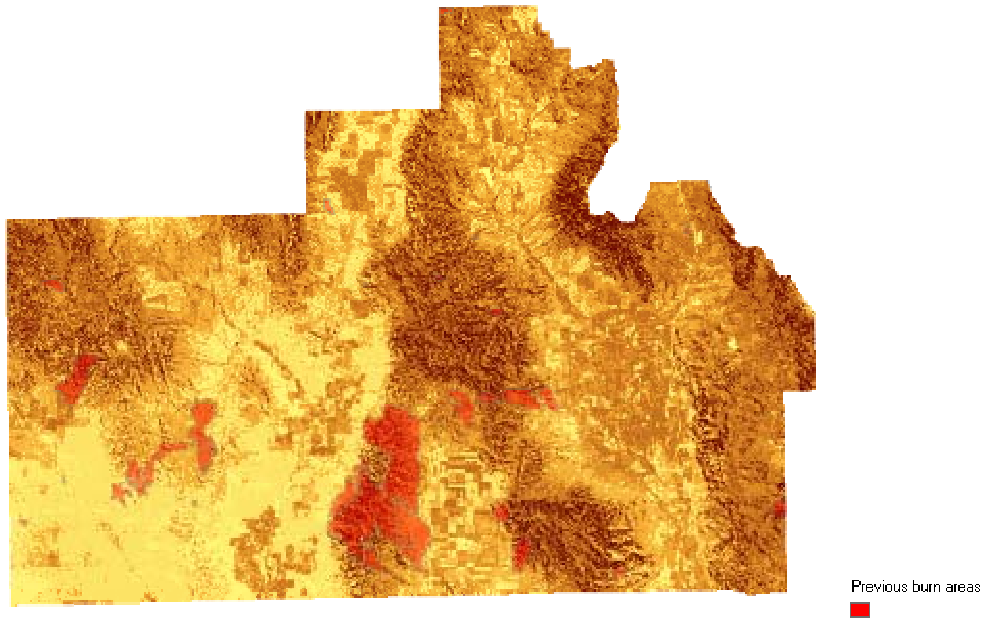


Figure 22. Fire history for Oneida County, 1939-2002

Discussion:

Clark, Bannock, Power, and Oneida Counties are considered high desert sagebrush steppe ecosystems. Clark County has the largest area, with 1,765 square miles (1,129,600 acres). Power County is the second largest with 1,406 square miles (899,840 acres), followed by Oneida County with 1,200 square miles (768,000 acres). Bannock County, the smallest of the four modeled counties, has an area of 1,113 square miles (712,321 acres). Oneida County has the highest total acres classified as high fire risk with 97,599 acres. Clark County has the second-highest total acres classified as high fire risk, with 67,776 acres, followed by Power County with 26,996 acres and Bannock with 21,370 acres. The high fire risk classification for all four counties is concentrated in the mountainous areas. This is due to the influence of the topography component models Aspect/ Sun Position, Slope/ Suppression Difficulty, and Slope/ Rate of Spread, as well as the fuel load >6 tons/acre. Clark County and Power County had the highest medium risk classification, followed by Oneida and Bannock County (495,089 and 277,805 respectively). The southern portion of Clark County and the northern portion of Power County are located within the Snake River Plain which consists of primarily < 2 and 2-6 tons/acre fuels.

NDVI values vary with absorption of red light by plant chlorophyll and the reflection of infrared radiation by water-filled leaf cells. It is correlated with Intercepted Photo-synthetically Active

Radiation (IPAR) (Land Management Monitoring, 2003). In most cases (but not all) IPAR and hence NDVI is correlated with photosynthesis. Because photosynthesis occurs in the green parts of plant material the NDVI is normally used to estimate green vegetation. The NDVI is a nonlinear function which varies between -1 and +1 but is undefined when RED and NIR are zero (Land Management Monitoring, 2003). Early in this project we determined thresholds for no-vegetation, dry-vegetation, and moist vegetation using NDVI. We chose the value 0.15 as a threshold between no vegetation and general vegetation based on where and how well the NDVI values matched a DOQQ. We chose the second threshold (separating dry vegetation from moisture vegetation) using similar methods. The NDVI value of 0.6 was the threshold limit between dry vegetation and moist vegetation.

The Structures at Risk component was weighted most heavily (22%). 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 Structures at Risk component shows that of all four counties, Bannock, by far, has the largest population with 75,323, while Power County has a population of 7,468. Oneida County's population is 4,131, and Clark County has 971 (U.S. Census Bureau Quick Facts 2003). Though each county has a relatively large area (Clark- 1,765 sq. miles; Power- 1,406 sq. miles; Oneida- 1,200 sq. miles; Bannock- 1,113 sq. miles), the structure density component model for Bannock County shows the highest risk to structure (U.S. Census Bureau Quick Facts 2003) because of the number of urban areas within the county.

The Fuel Load/ Rate of Spread takes into account how fast a fire will spread depending on different fuel load classes. The lower fuel load classes were considered to be the primary carrier of fire (e.g. grasses) and have the fastest spread rate. Fuel Load class 2-6 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 moving 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 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, 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 we and Fred Judd (pers.comm.) felt were more important.

Lastly, the date (May 28, 2003) on which the Landsat 7 ETM+ data was acquired plays a significant role in the outcome of the Fuel Load-based components of the final model.

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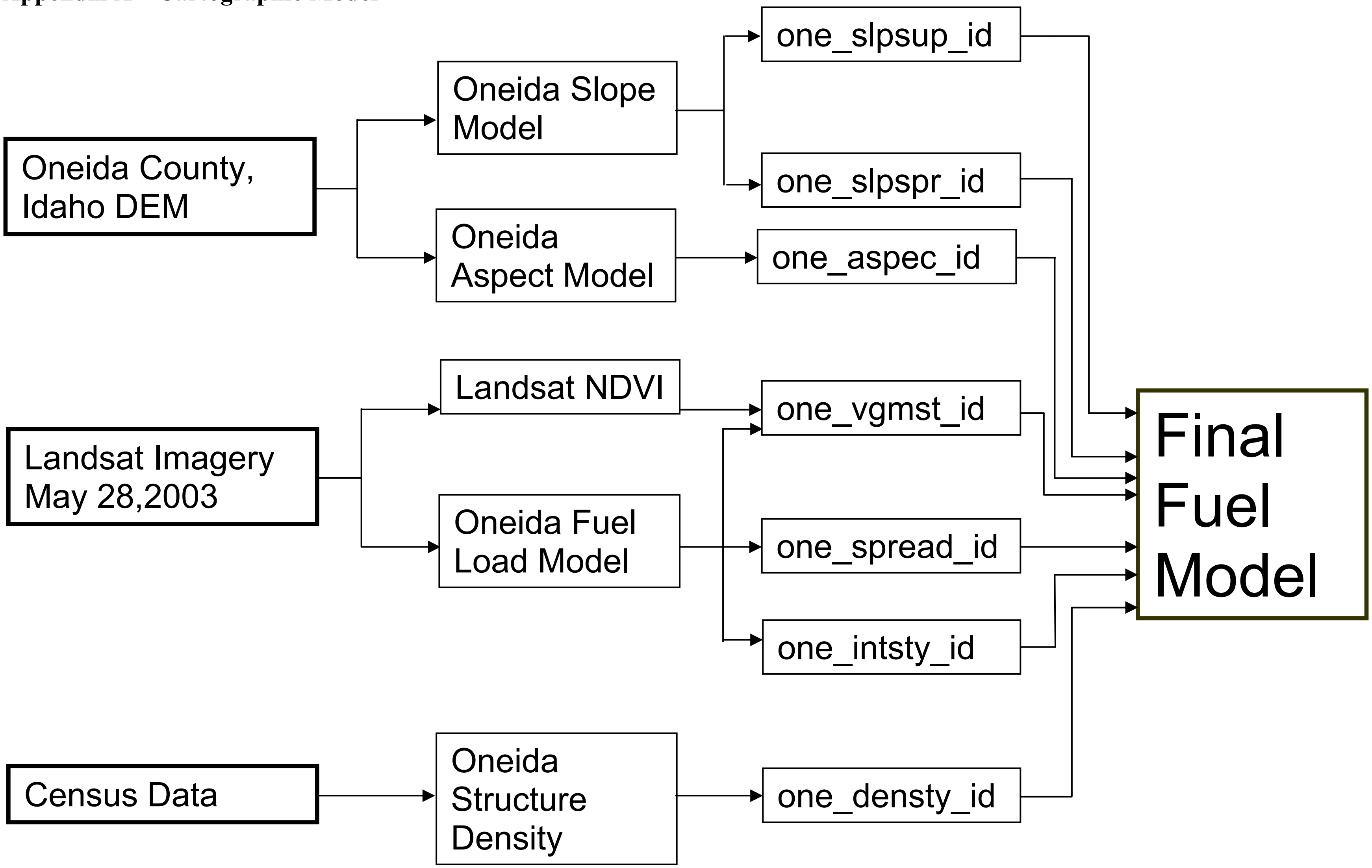
Acknowledgements:

On February 13, 2003 and April 15, 2003, we had meetings with Keith T. Weber to discuss our progress. We also discussed the possibility of adding a component model that would reflect fire season duration within Oneida County (this idea was first suggested in October and November, 2003's meetings with regional fire managers and the GIS Training and Research Center's staff involved with the project). Due to time constraints, however, this model was abandoned until future WUI model compilations.

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 = <2 tons/acre	200 = Dry Vegetation
4 = 2-6 tons/acre	75 = Moist Vegetation
6 = >6 tons/acre	

Table B-2: Weighting data for Fuel Load/ Vegetation Moisture component model (Jansson et al. 2002). Compare with figure 1.

Fuel Load *	Vegetation =	Class	Weights
1	75	75	150
1	100	100	50
1	75	75	150
1	200	200	300
4	75	300	400
4	75	300	400
1	200	200	300
6	75	450	600
4	200	800	850
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	0
1	850
4	1000
6	600

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

Classes (Tons/acres)	Weights
0	0
1	100
4	400
6	1000

Table B-5: Weighting data for Slope/ Rate of Spread. Compare with figure 4.

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

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

Angle/degree Intervals	Weights
0--10	100
10--20	200
20--30	850
30--40	1000
40--50	1000

Table B-7: Weighting data for Aspect/ Sun Position. Compare with figure 6.

Degree Interval	Aspect	Weight
337.5--22.5	N	100
22.5--67.5	NE	150
67.5--112.5	E	300
112.5--157.5	SE	800
157.5--202.5	S	1000
202.5--247.5	SW	1000
247.5--292.5	W	700
292.5--337.5	NW	200

Appendix C – Data dictionary

Data		File name		Full path to dataset		Description		Format
County bound		Oneida_83.shp		\\Alpine\Data\urbint\Oneida\Final_products		Boundary of Oneida county		polygon coverage
Roads		One_rds83.shp		\\Alpine\Data\urbint\Oneida\Final_products		Roads and streets in Oneida County		line shapefile
Bands used for NDVI		B3mrger30r31		\\Alpine\Data\urbint\Oneida\Final_products		Landsat Band 3 for Oneida County		Grid - 28.5m pixels
		b4mrger30r31		\\Alpine\Data\urbint\Oneida\Final_products		Landsat Band 4 for Oneida County		Grid - 28.5m pixels
		one_ndvi		\\Alpine\Data\urbint\Oneida\Final_products		Landsat NDVI model for Oneida County		Grid - 28.5m pixels
Fuel Load		fl_mdl_oneida		\\Alpine\Data\urbint\Oneida\Final_products		Fuel Load model for Oneida County. Classes are <2 tons/acre, 2-4 tons/acre, and 4> tons/acre		Grid - 28.5m pixels
DEM		one_dem		\\Alpine\Data\urbint\Oneida\Final_products		Digital Elevation Model of Oneida County		Grid - 30m pixels
Component models		one_aspec_id		\\Alpine\Data\urbint\Oneida\Final_products		Risk associated with aspect angle **i.e**. North, East,…….		Grid - 30m pixels
		one _slpspr_id		\\Alpine\Data\urbint\Oneida\Final_products		Risk associated with how fire spreads with angle of slope.		Grid - 30m pixels
		one _slpsup_id		\\Alpine\Data\urbint\Oneida\Final_products		Risk associated with how suppression efforts are affected by angle of slope.		Grid - 30m pixels
		one_spread_id		\\Alpine\Data\urbint\Oneida\Final_products		Risk associated with how quickly different fuel load classes spread during a fire.		Grid - 26m pixels
		one _intsty_id		\\Alpine\Data\urbint\Oneida\Final_products		Risk associated with how intense (release of heat energy) different fuel load classes burn.		Grid - 26m pixels
		one _vgmst_id		\\Alpine\Data\urbint\Oneida\Final_products		Risk associated with vegetation moisture.		Grid - 26m pixels
		one_densty_id		\\Alpine\Data\urbint\Oneida\Final_products		Risk associated with structure density.		Grid - 30m pixels
Final Model		one_final		\\Alpine\Data\urbint\Oneida\Final_products		Final risk model - 30m pixels - ArcInfo Grid		Grid - 30m pixels
Reports		Oneida_WUI_Report		\\Alpine\Data\urbint\Oneida\Final_products		Report covering methods, results, & conclusions of WUI modeling		Word Document