Wildland/Urban Interface and Communities at Risk

Joint Fire Modeling Project
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) and Communities at Risk (CAR) 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 (BLM) Upper Snake River District (USRD) Geographic Information Systems (GIS) team in cooperation with GIS Training and Research Center (GISTReC) at Idaho State University (ISU) have created a model to predict potential wildfire risk areas for Lava Hot Springs, Idaho and vicinity.

During this project we created maps of wildland/urban interface areas, identified structures encroaching on wildland risk areas, mapped road access and potential response times, predicted suppression methodologies, and identified areas at risk.

This report describes each component of our wildfire risk model and what effect each had on the final wildfire risk model. We hope the information will benefit future users of this model and will help the people in the Lava Hot Springs area better protect themselves against wildfire.

Keywords: Fire, Wildfire, GIS, WUI (Wildland/Urban Interface), Lava Hot Springs

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Introduction: Fire and related agencies first begun to use GIS as a way of sharing and managing information about natural resources. In the mid-1990s the trend culminated and many federal, state, and local wildfire agencies began conducting protection assignments. The California Department of Forestry and Fire Protection published a fire plan. The idea was to train firefighters with experience in the field to use GIS, Amdahl (2001).

This study examined wildland/urban interface (WUI) fire risk for the Town of Lava Hot Springs, Idaho and neighboring areas. It was conducted to produce a WUI risk model using GIS. This is a continuation of the WUI project that began by examining the City of Pocatello. Results can be used by firefighters, homeowners, land managers, and as public information to prevent and manage wildfire. The model predicts wildfire risk in the Lava Hot Springs area. There have been earlier studies but typically, these had a more generalized approach. One example is the Fire Area Simulator Model Development and Evaluation (FARSITE).

<u>Methods:</u> We acquired and assembled the GIS data sets needed for our area of interest (AOI). The area was defined as the area encompassed by the Bancroft, Haystack Mountain, Lava Hot Springs, and Sedgwick Peak 7.5' USGS quadrangles. To utilize the data, we projected and defined each data set as needed.

Required data:

- Vegetation (Idaho GAP and Landsat 7 ETM+ derived NDVI-based classification)
- Geocoded roads
- Wildfire Fuel load model
- Emergency Response Time model (ERT)
- Digital Raster Graphics (DRG)
- Digital Elevation Models (DEM)
- Digital Orthophoto Quarter-Quads (DOQQ)
- Landsat 7 ETM+ imagery
- Fire Station location

To produce one DEM for the AOI, we merged Bancroft, Haystack Mountain, Lava Hot Springs and Sedgwick Peak DEM-quadrangles into one grid using ArcInfo Workstation → GRID → mosaic. Using the spatial extent defined by the footprint of this grid, we created a "cookie cutter", a polygon coverage called aoi_lava. All the data sets listed above were clipped using the "cookie cutter" as needed.

We reclassified vegetation data into three categories (Paved Urban, Fire-Prone Vegetation, and High moisture Vegetation) using ArcMap → Spatial analyst → *reclassify*.

We defined the projection of all data sets as Idaho Transverse Mercator (GCS North American 1927) using Arc Toolbox → define.

Creating NDVI models

We located vegetation of interest with satellite imagery using the Normalized Difference Vegetation Index (NDVI) for Landsat 7. We used Landsat 7 ETM+ imagery dated 08-23-2000. The NDVI uses Red and Near Infrared (NIR) bands. We ratioed these bands following the equation given in figure 1.

$$NDVI = \frac{NIR - red}{NIR + red}$$

Figure 1: How we calculated NDVI.

The NDVI has an interval of –1 to +1, where –1 is no vegetation and +1 is pure photosynthetically active vegetation. Our tests have shown that values > 0.3 reliably indicate photosynthetically active vegetation (Ben McMahan pers. comm.).

We made several raster calculations of the NDVI grid. The first showed all values > 0, the next showed values >0.05, etc (i.e., 0, 0.05, 0.1, 0.15, 0.2, 0.25, 0.3). The calculations were made in ArcMap → Spatial Analyst → Raster Calculator. After making the resulting grids, we compared each of them with the DOQQ's.

GAP verses NDVI

To test the agreement between the GAP and NDVI vegetation models, we multiplied each of the NDVI grid results (described above) with the GAP vegetation grid. The calculations were made in ArcInfo Workstation as a map algebra operation.

The NDVI grid includes both areas with and without vegetation. We needed to determine the NDVI value that approximated a threshold separating between non-vegetation and vegetation areas. We did this by again comparing the DOQQ's with the values within the NDVI grid (in this case -0.35056 - +0.75581). Using the same method, we separated dry vegetation and moist vegetation. We weighted the 3 NDVI classes: No vegetation = 1, Dry vegetation = 2, Moist vegetation = 0.75 in ArcMap → Spatial Analyst → Reclassify. ArcMap's reclassify can not create an outgrid with floating points, so we multiplied the weights with 100 (integer values).

Fuel load model

Supervised classification of Landsat 7 ETM+ imagery was used for estimating fuel load in our area of interest. To estimate fuel load, 128 sample points were gathered on the Snake River Plain. This model experienced some difficulties determining high fuel load areas associated with junipers. A revised fuel load model should correct this problem. The fuel load model was created by Glenn Russell. The model was validated the summer 2002 by Ben McMahan.

The fuel model contained data estimating the amount of flammable material (fuel) expressed in tons per acre. The model contained 7 classes (0-6): 0 = 0 tons/acre (No vegetation), 1 = 0.74 tons/acre (Grassland), 2 = 1 tons/acre (Grassland with some Sagebrush), 3 = 2 tons/acre (Low Sagebrush), 4 = 4 tons/acre (Typical Sagebrush), 5 = 6 tons/acre (Juniper), and 6 = >6 tons/acre (Forrest).

Create wildfire model components

Different analyses were separately treated to learn how each analysis affected fire risk. To be able to merge the models together easily, we reclassified each model into equal risk scales from 0 to 10, where 10 is high risk. We used the same weightings Mattsson and Thoren (2002) did to weight our analyses, except for the fuel load/vegetation moisture model. This is a new component where we developed our own weighting curve (also from 1 to 10). Mattsson and Thoren derived these curves by working with people knowledgeable about fire ecology and suppression methods, topography and vegetation characteristics. These curves were applied in the Lava Hot Springs area as well. After completing the analyses, we examined the impact each fire model component had on the overall fire risk in Lava Hot Springs, Idaho. We weighted the components accordingly.

Fuel load/Vegetation Moisture

To improve the fuel load model and account for moist vegetation, which may be abundant but not readily flammable, we multiplied the fuel model (Table 1) with the NDVI model (Table 2), (Fig. 11 in Results). This calculation was made in ArcMap → Spatial Analyst → Raster Calculator. All classes are shown below (table 3).

Fuel load
0 = 0 tons/acre
1 = 0.74 tons/acre
2 = 1 ton/acre
3 = 2 tons/acre
4 = 4 tons/acre
5 = 6 tons/acre
6 = >6 tons/acre

Table 1

Vegetation
1 = No vegetation
2 = Dry vegetation
0.75 = Moist vegetation

Table 2

Fuel load *	Vegetation =	Class
1	0.75	0.75
1	1	1
2	0.75	1.5
1	2	2
3	0.75	2.25
4	0.75	3
5	0.75	3.75
2	2	4
6	0.75	4.5
5	1	5
3	2	6
4	2	8
5	2	10
6	2	12

Table 3

Weights
1.5
0.5
2
3
2.5
4
5
6.5
6
2
7
8.5
10
10

Table 4

As we did not have a curve for this model, we developed weightings for all classes with Keith T. Weber (Table 4). The weightings are based on worst case scenario and so are conservative. If there could be more than one solution, (e.g., class 2, that can be both 1 tons/acre * 2 (a little fuel and dry vegetation) and 2 tons/acre * 1 (more fuel but no vegetation predicted)) we calculated with the worst scenario. By worst criteria we mean that, if we had class 6 (Table 3), which can be both 3 tons/acre *2 or 6 tons/acre *1, we used 3*2 when we weighted class 6 because 3*2 has a higher fire risk than 6*1 and therefore was the worst case. We did that for all 15 classes, and tried to balance every class to find the correct weights for them (fig 2, table 6 in Appendix B).

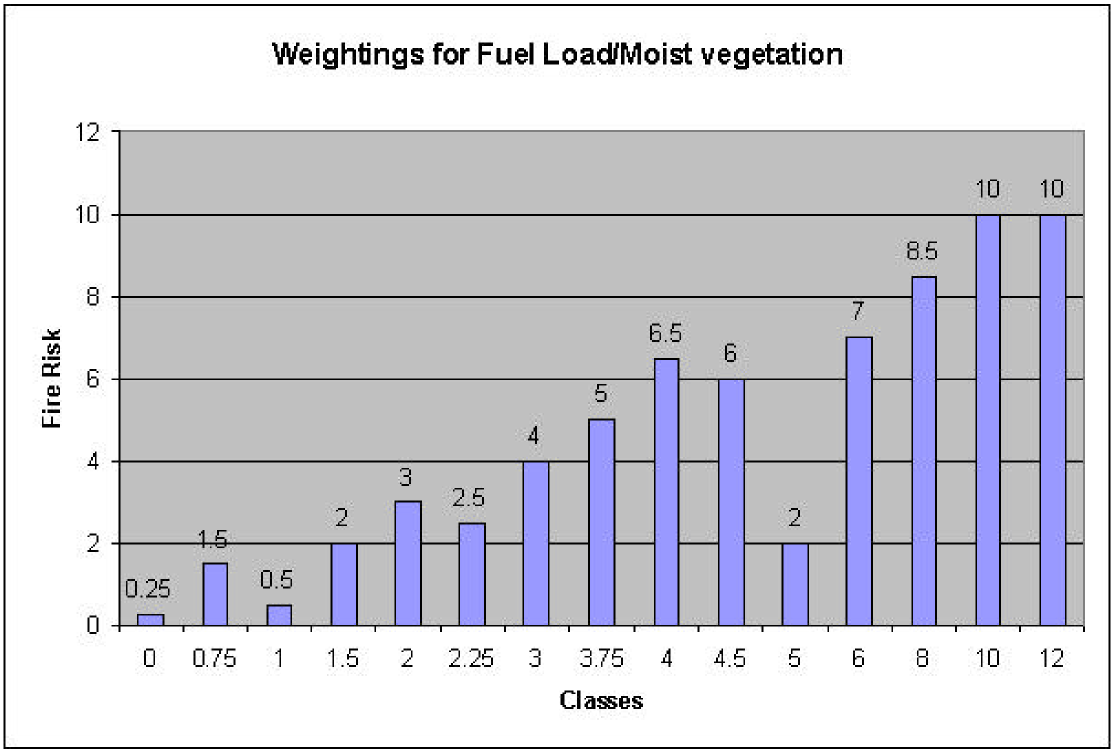


Figure 2. This chart describes all weightings for fuel load/moist vegetation.

Fuel load/Rate of Spread

How fast a fire will spread depends on the amount of continuous fuels and other factors. The lower fuel load classes were considered to be the primary carrier of fire (e.g. grasser), and have the fastest spread rate. The higher fuel load classes will not burn as quickly because as moisture content increases, spread rate is reduced. We reclassified the Fuel load model following Mattsson and Thoren, 2002 (table 7 in Appendix B), using ArcMap → Spatial Analyst → Reclassify (fig 3).

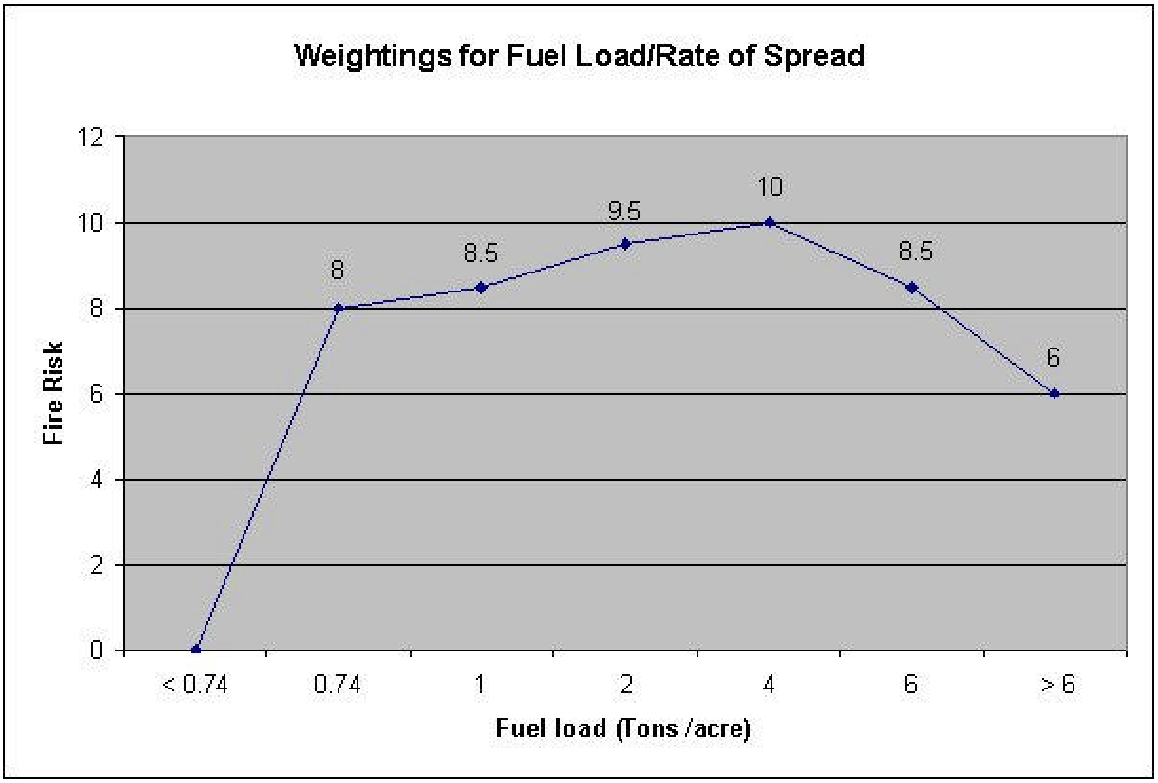


Figure 3. Weightings for Fuel load/Rate of Spread describe how the fuel load affects the fire spread rate.

Fuel load/Intensity

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. Intensity depends on fuel load and other factors such as wind and ground conditions at the time of the fire. We reclassified the Fuel load model using values following Mattsson and Thoren (table 8 in Appendix B) using ArcMap → Spatial Analyst → Reclassify (Fig 4).

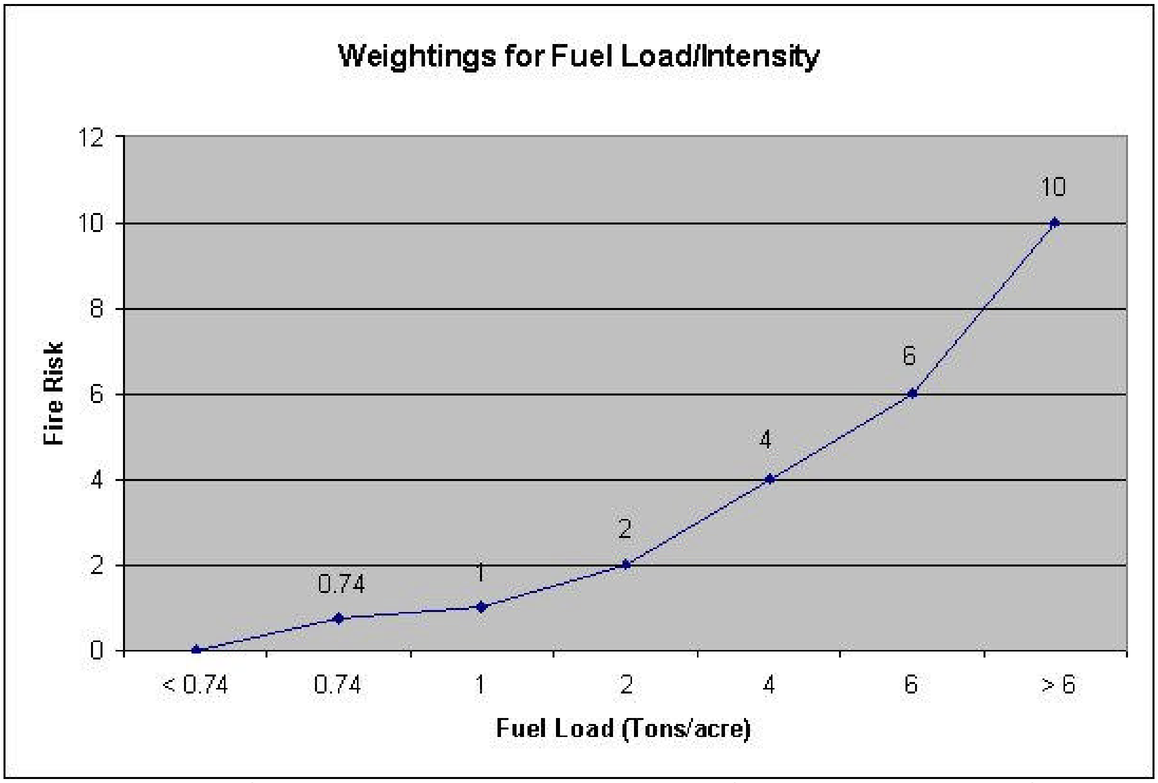


Figure 4. Weightings for the Fuel load/Intensity describes how the fire intensity depend on the fuel load.

Slope

Slope is a matter of degree and stability of surface. The extent and intensity of a wildfire depends on the topography of the land it is burning up. When fire moves across flat land it moves more slowly then fire on a mountainside. However, the fire moves much faster up hill then down hill, so you can say, the steeper the slope, the faster the fire, Amdahl (2001).

Using the merged DEM-quadrangles aoi_lavadem, we made a slope grid that calculated how steep the surface is using ArcMap → Spatial Analyst → Surface Analysis → Slope.

Output measurement: degree
Z-factor: 1
Output cellsize: 30

Slope/Rate of Spread

To make the Slope/Rate of Spread model, we weighted the result of the slope model (aoi_lavaslope) by using weightings for slope/rate of spread from table 9 in Appendix B (Mattsson and Thoren, 2002) in ArcMap → Spatial Analyst → Reclassify. As the reclassified grid must be integer, we multiplied all weights by100 (we did this with all fire model components). Slope/Rate of Spread shows spread rate that is dependent on slope (i.e., the steeper the terrain is, the higher the fire risk is (fig 5)).

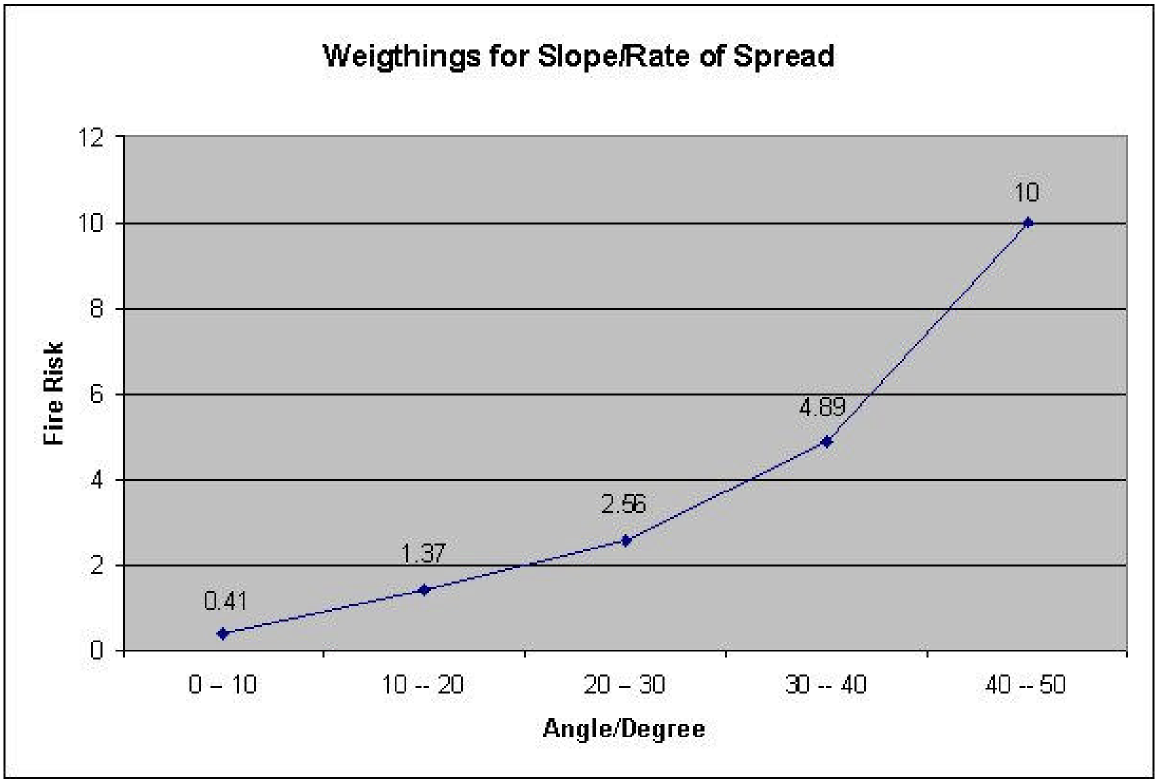


Figure 5. Weightings describe how spread rate increase by the angle of slope. The weight proportion is assumed to be exponentially with slope angle.

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 and Thoren, 2002 (table 10 in Appendix B). ArcMap → Spatial Analyst → Reclassify (fig 6). Slope/Suppression Difficulties shows how difficult it is for firefighters to fight fire based on slope. If firefighters cannot reach the fire, it will keep burning even though it may be a low risk area according to other criteria.

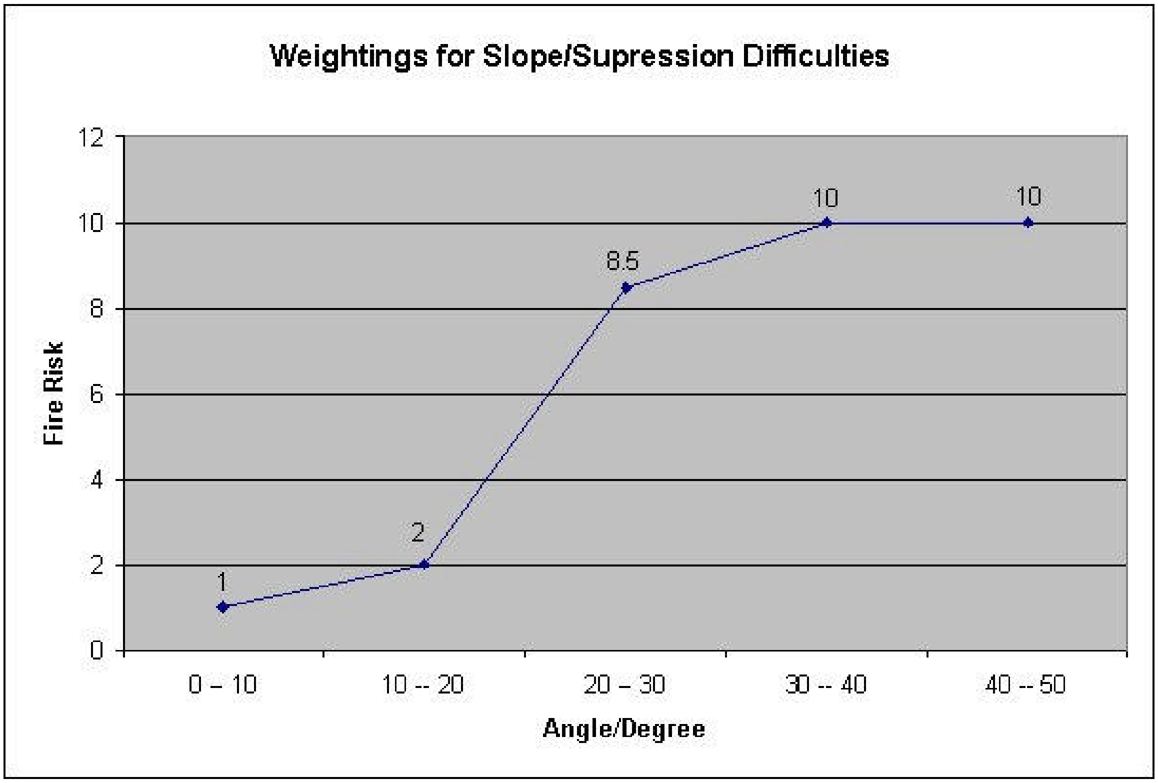


Figure 6. Weightings for slope/suppression difficulties describe how suppression difficulties are affected by the angle of slope.

Aspect

Aspect shows what direction the surface faces. We made the aspect model from aoi_lavadem in ArcMap → Spatial Analyst → Surface Analysis → Aspect.

Output cellsize: 30

Aspect/Sun position and daily temperature

Aspect/Sun position and daily temperature illustrates the direction the slope is facing and where the sun affects the ground/vegetation most. The sun is predicted to desiccate the ground/vegetation more on the southerly aspects than others. We reclassed the aspect grid (aoi_lavaasp) in ArcMap → Spatial Analyst → Reclassify (fig 7 and table 11 in Appendix B).

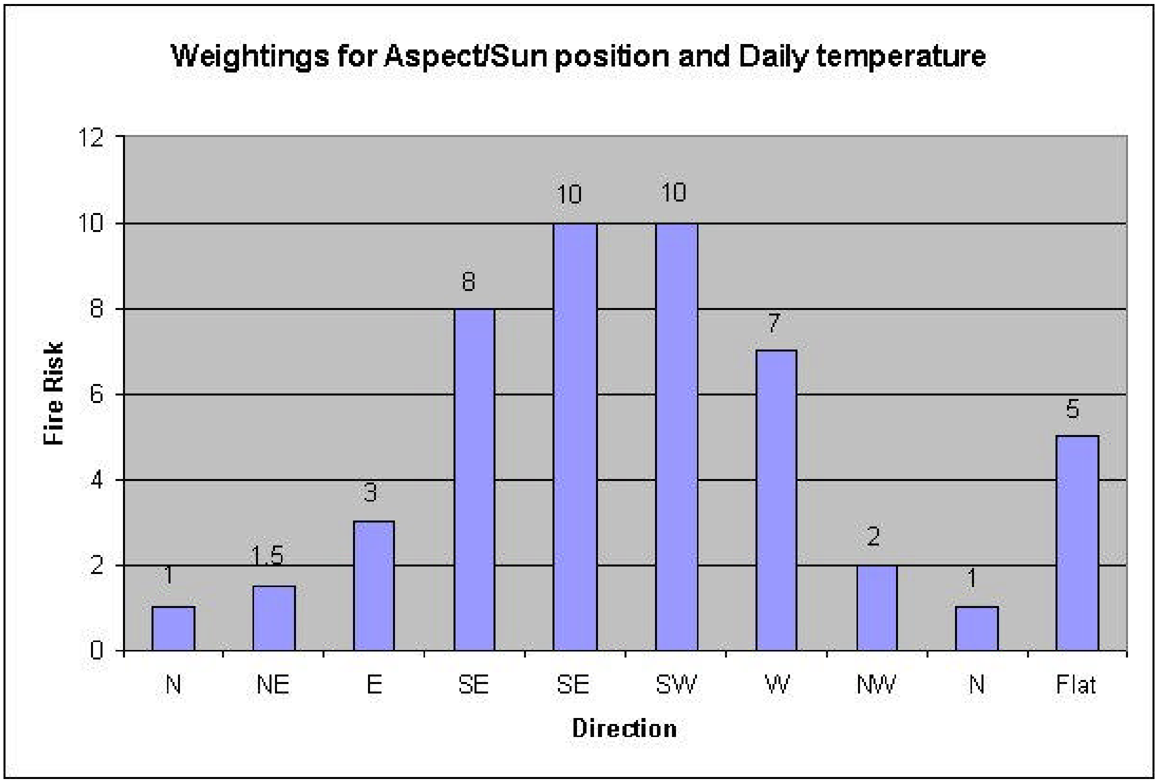


Figure 7. Weightings for Aspect/Sun position and daily temperature describe how the sun desiccates the ground more in south facing aspects and therefore get higher risk.

Response Time

The fire station in Lava Hot Springs is a volunteer fire station. Because it is a volunteer fire station, it is unstaffed. Thus it will take a while for the firefighters to respond to an emergency. According to Lava Hot Springs fire chief Joel Price it will take the firefighters 1 – 2 minutes to arrive at the station and up to five minutes to respond.

The weightings for the response time model Mattsson and Thoren, 2002 (table 12 in Appendix B) are based on the time frame from when a house catches fire until it flashes over (fig. 8). The weightings describe how the fire risk due to delayed travel time for the firefighters influences the risk. Because it takes the firefighters 5 minutes to respond, the entire Lava Hot Springs area has a response time risk of 10. Since the entire area of interest is in the highest risk, there are no variations in the response time model. Therefore we did not need it for the final model, but have made a response time model for cartographic purposes.

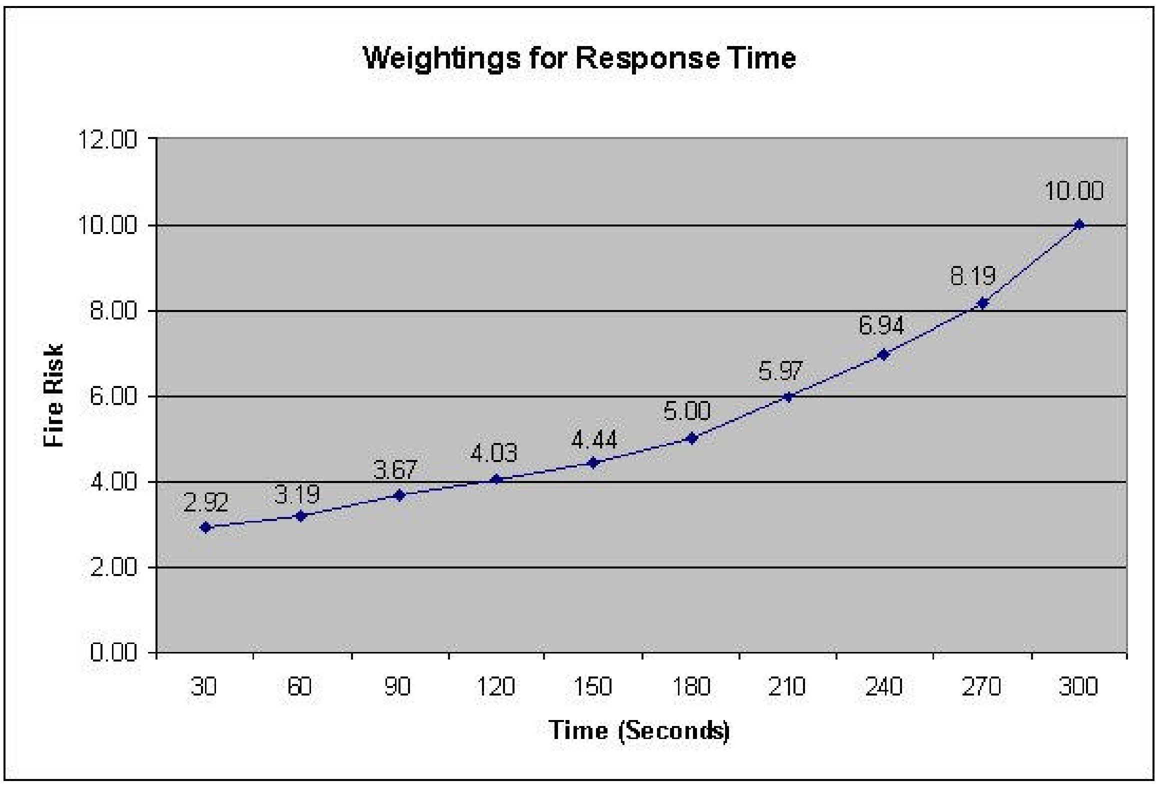


Figure 8. The weightings describe how the fire risk due to delayed travel time for the firefighters influences the risk.

WUI fire risk model

After estimating the different fire model components, we decided how important each component was to the overall fire risk model. Beginning with the highest, we distributed the components as follows:

- Fuel load/Rate of Spread 25% (of total fire risk model)
- Fuel load/Vegetation Moisture 23%
- Fuel load/Intensity 20%
- Slope/Suppression Difficulties 17%
- Slope/Rate of Spread 10%
- Aspect/Sun position and Daily temperature 5%

After this, we added the individual components together in ArcMap → Spatial Analyst → Raster Calculator, to produce a final WUI fire risk model.

Adding fires occurring after 1999

After merging all the fire model components together we realized that our risk model did not include any fires occuring after 1999. Such recent fires drastically change an areas risk to subsequent fires. The Bureau of Land Management (BLM) and ISU GIS TreC had data describing fires from 1939 to 2000. We selected the wildfires from 2000 using ArcMap → Select Features, and then converted the resulting features to a grid by using ArcMap → Spatial Analyst → Convert → Features to Raster.

Field: fire_freq
Output cellsize: 30

To get the wildfires for 2001, we again used a BLM wildfire coverage. We followed the same procedures as for the 2000 fires.

Field: wildfire-ID
Output cellsize: 30

Using the two recent wildfire grids (2000 and 2001), we added them together into a grid called aoi_f00-01 where No Data was zero and fire pixels had a value of one. We reclassified it twice. First we produced a grid where we assigned fire pixels from both 2000 and 2001 the value zero and No Data the value of one in ArcMap → Spatial Analyst → Reclassify. Then, when we multiplied that mask grid with the complete fire risk model in ArcMap → Spatial Analyst → Raster Calculator, the new fires received a value of zero and all other data remained the same. The resulting grid was called “reset”. In the second reclassification, we gave the fire pixels a value of one and No Data pixels a value of zero. We used ArcMap → Spatial Analyst → Reclassify to accomplish this. We added this grid to reset in ArcMap → Spatial Analyst → Raster Calculator. The result is that new fires received a value of one “unclassified” and all other data did not change. The final fire risk model was called “aoi_wui”.

Results: All results are presented with the same approach as in Methods.

GAP verses NDVI

To determine if the area was correctly classified by the GAP vegetation model, we compared the GAP vegetation grid (aoi_lavaveg) with DOQQ (fig. 9). We found there is vegetation in the area where the GAP vegetation grid (aoi_lavaveg) says it is "paved urban".

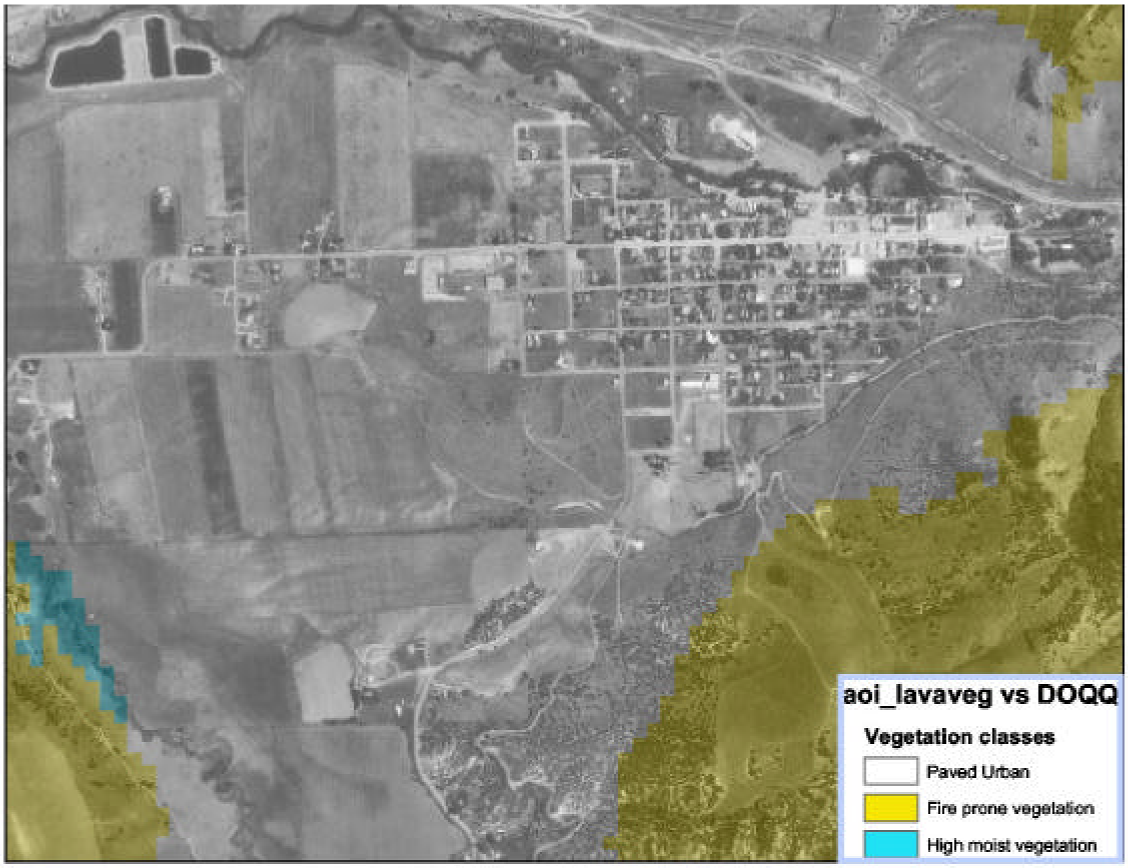


Figure 9. Overlay of aoi_lavaveg and the DOQQ's. This layout is made in ArcMap.

According to the GAP vegetation model (aoi_lavaveg) (fig. 9), the entire area around Lava Hot Springs is "paved urban". The NDVI (fig. 10) shows that it is not just "paved urban", but also a good deal of vegetation. Since we had to choose one of these two grids for our vegetation model, we compared them as follows.

The resulting NDVI grid (fig. 10) is a measure of the amount and vigor of vegetation.

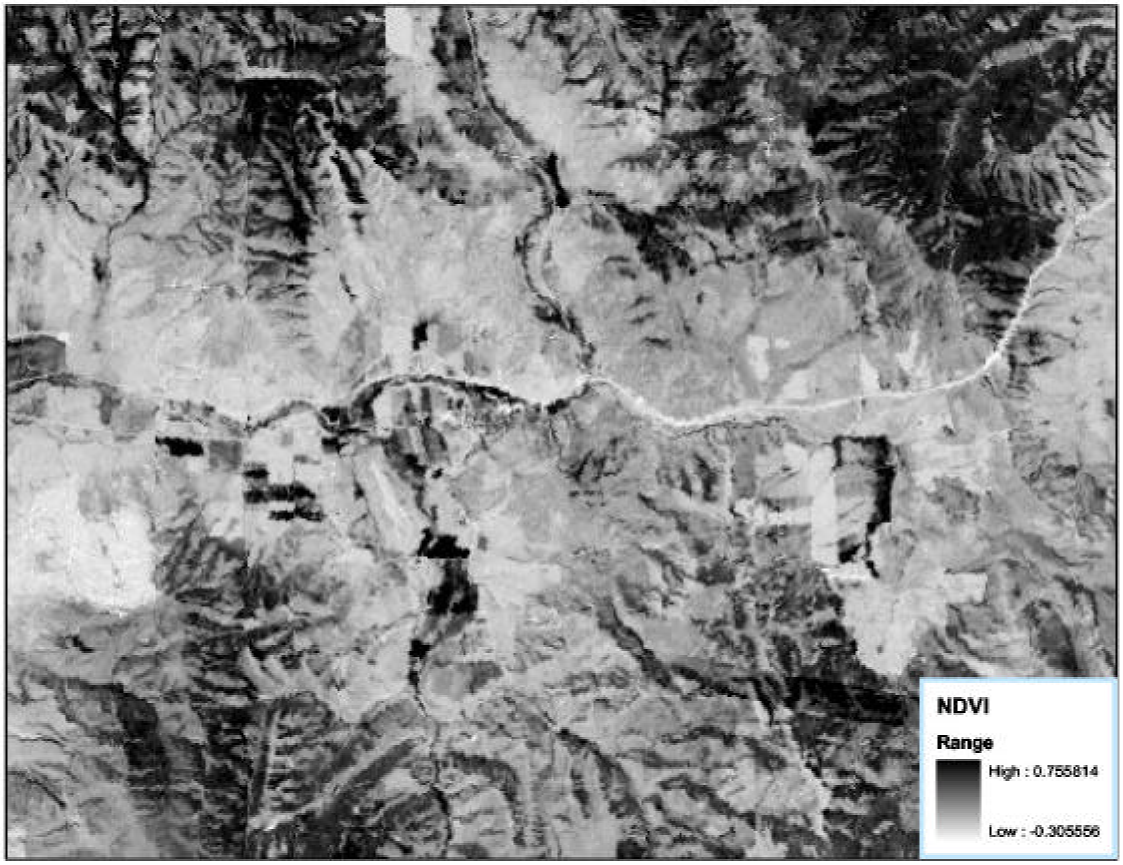


Figure 10. The NDVI has an interval of –1 to +1, where –1 is no vegetation and +1 is pure vegetation. This layout was made in ArcMap.

The NDVI based model predicts vegetation more accurately than the GAP model, compared with the DOQQ's.

Comparing the values within the NDVI and the DOQQ's, we found that all values <0.01 represented no vegetation. Values between 0.10 and 0.17 represent dry vegetation and values >0.17 represent moist vegetation.

We next created a new grid from the NDVI grid where we gave all values <0.01 (no vegetation) the value of 100, all values between 0.01 and 0.17 (dry vegetation) the value of 200 and all values >0.17 (moist vegetation) the value of 75. This grid was called aoi_vegmodel.

Fuel load/Vegetation moisture

We merged the reclassified NDVI (aoi_vegmodel) and the fuel model (aoi_lavafuel) (table 5), and completed one of the necessary analyses required to fully implement our model. The result was a grid with 15 classes (0, 0.75, 1, 1.5, 2, 2.25, 3, 3.75, 4, 4.5, 6, 8, 10, 12). Areas with value 0 have a low fire risk (no vegetation and 0 tons of fuel/acre) and areas with value 12 have a high fire risk (dry vegetation and >6 tons of fuel/acre).

Vegetation Moisture model				Fuel load model				Result		
100	200	75		1	4	6		100	800	450
100	200	200	*	0	4	6	=	0	800	1200
75	200	100		3	6	5		225	1200	500

Table 5. This is an example of what happens when you multiply the Vegetation Moisture model (built using NDVI index) with the fuel load model.

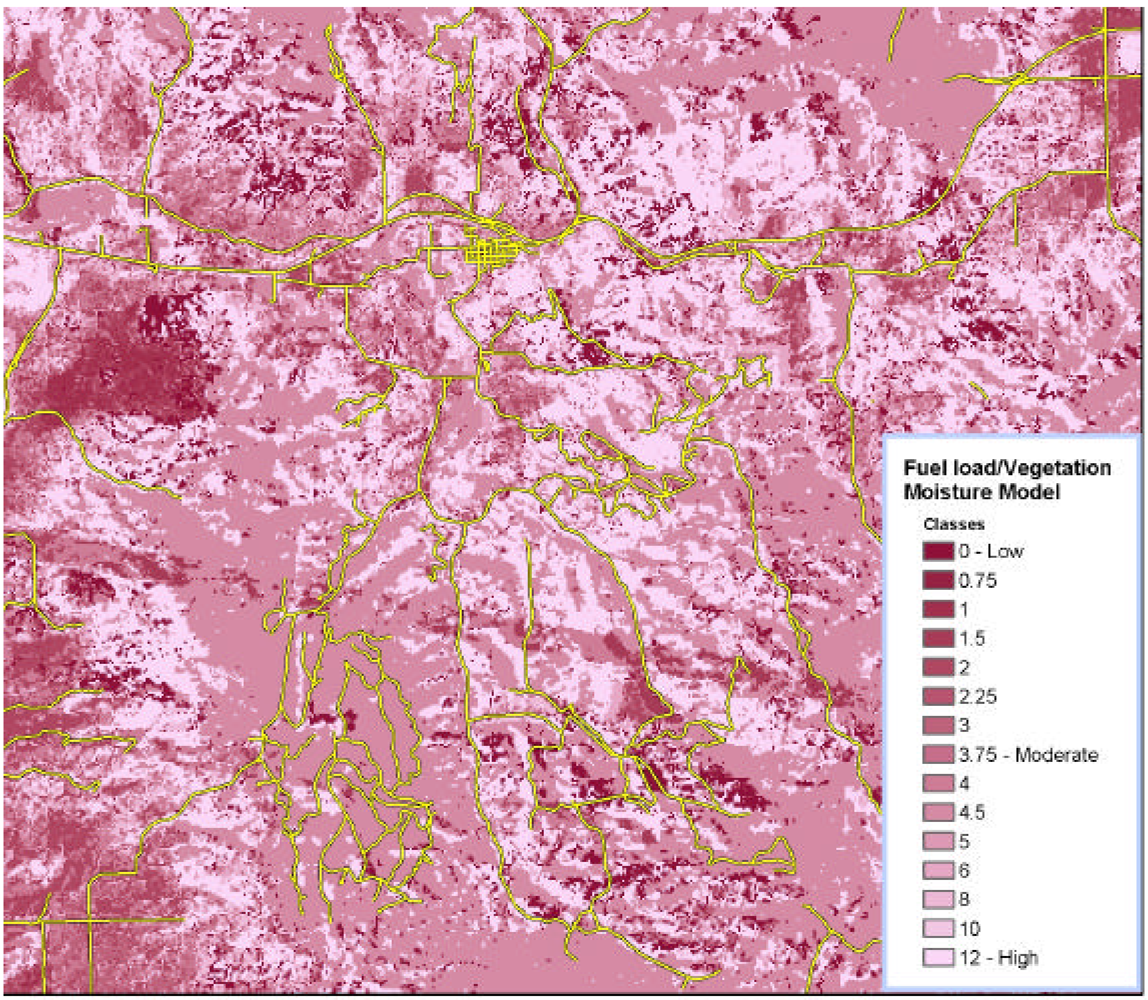


Figure 11. This is our modified fuel load/vegetation moisture model (ndvi_fuelmod).

Since there were no previous weightings for the fuel load/vegetation moisture model, we developed our own weightings. Figure 2 in Methods shows how we weighted each class. We also created a map (fig 12) that shows how fuel load/vegetation moisture model affects fire risk in our study area using weights in figure 2.

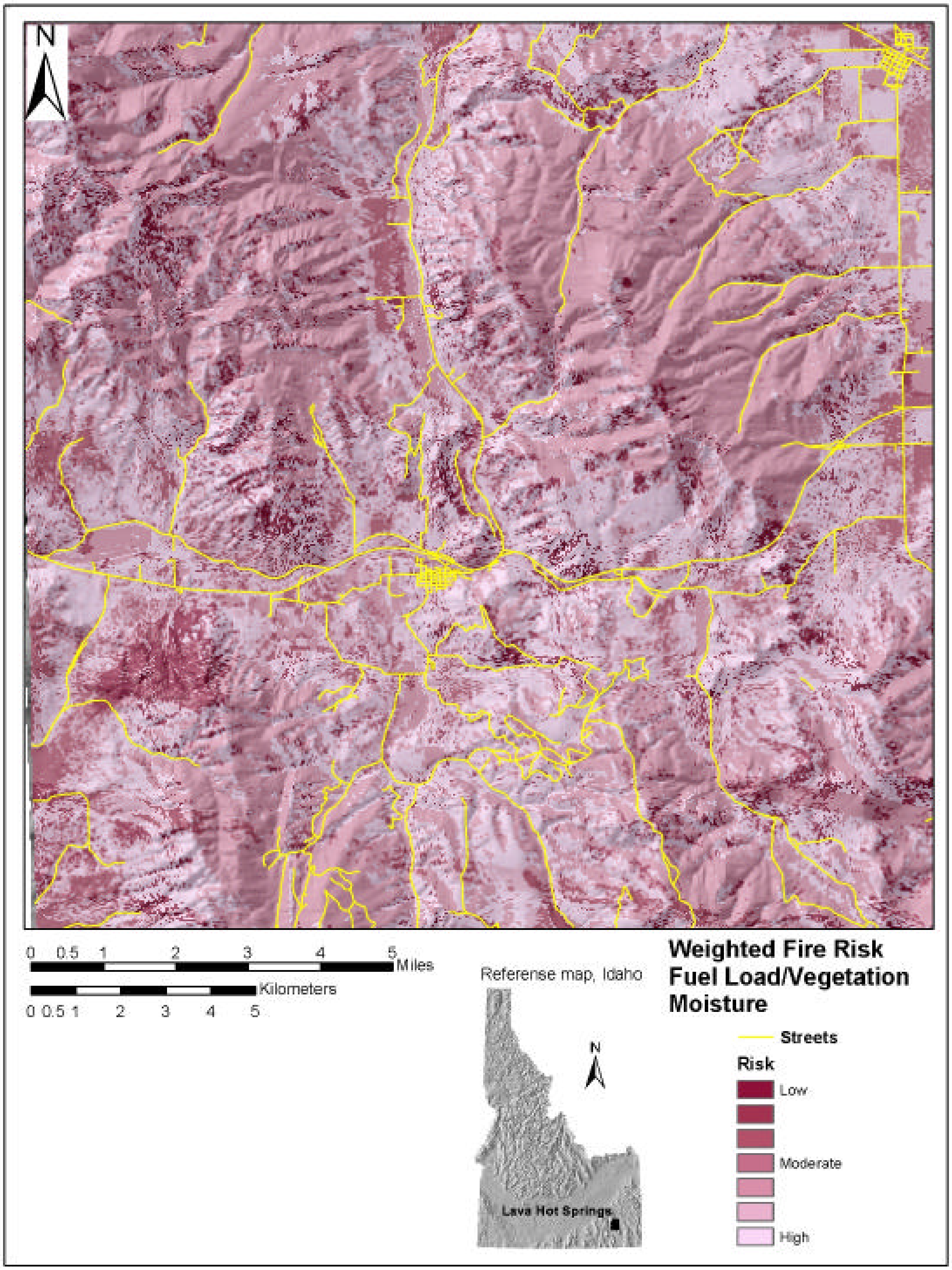


Figure 12. This map shows how fuel load/vegetation moisture model affects fire risk.

Remaining fire risk model components

We created a map (fig 13) that shows how the fuel load affects the fire spread rate in our study area.

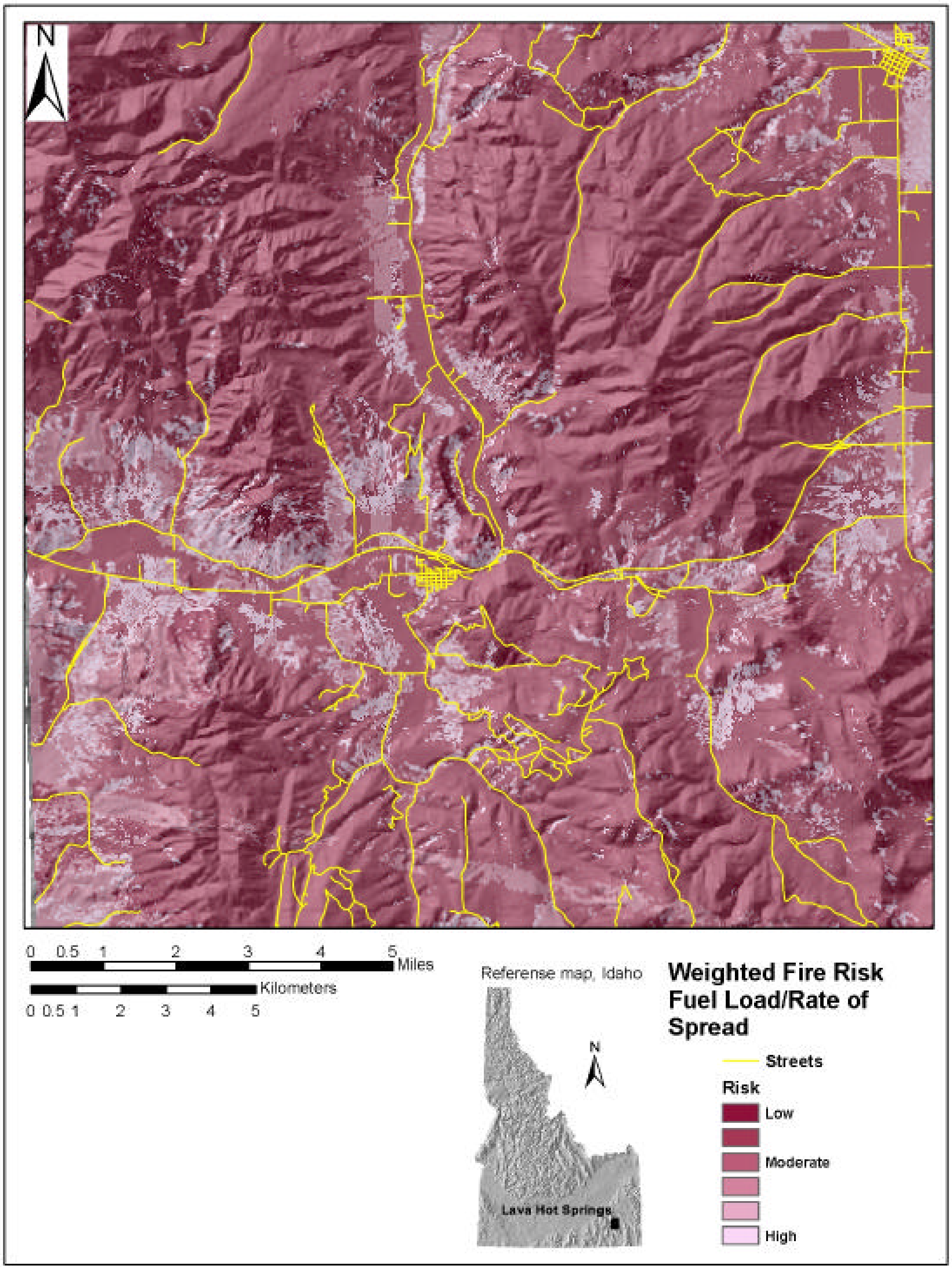


Figure 13. This map shows how the rate of spread of fire is affected by fuel load.

We created a map (fig 14) that shows how the intensity of a fire is affected by the fuel load in our study area.

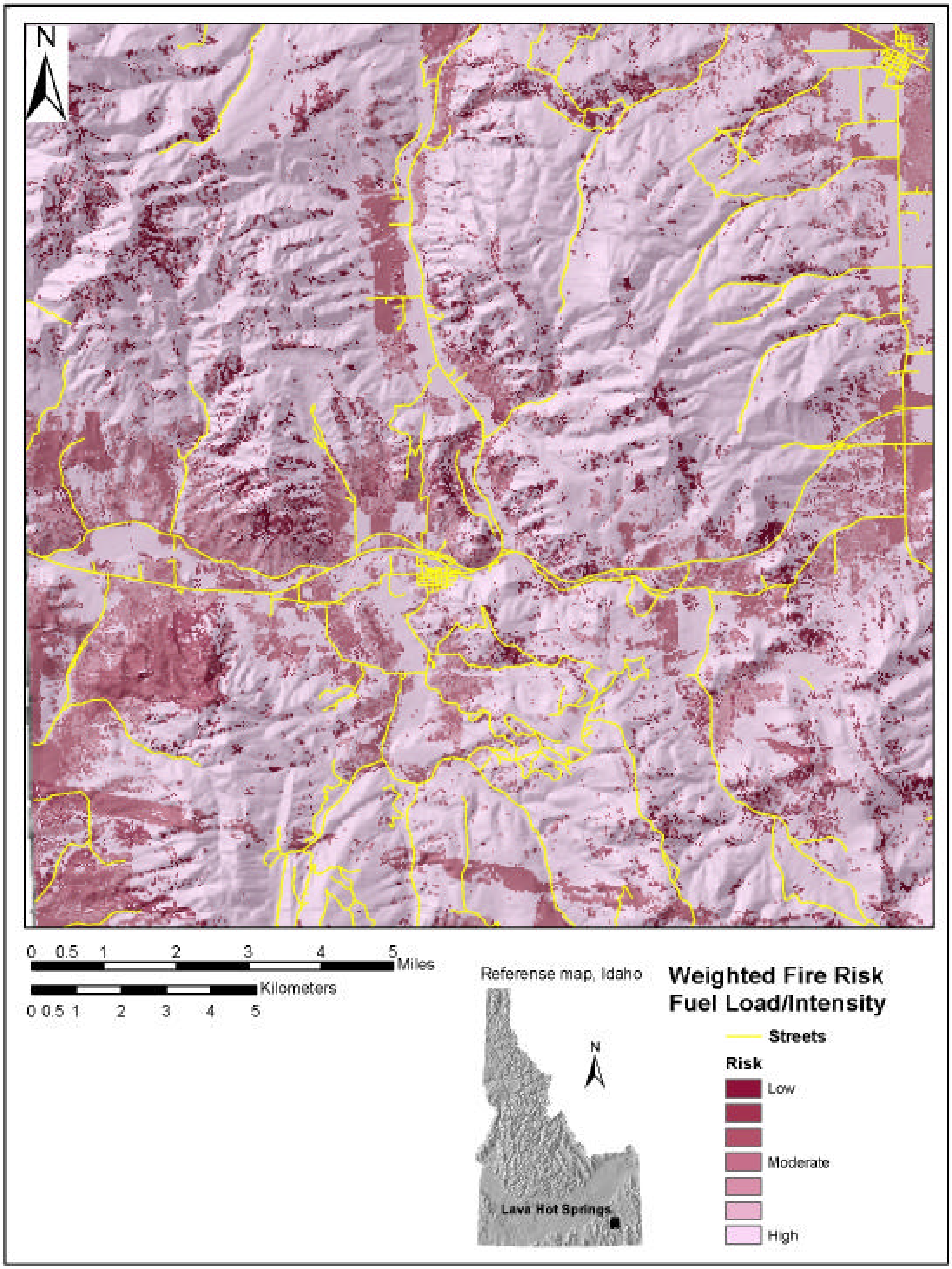


Figure 14. This map shows how the fire intensity is affected by the fuel load.

We created a map (fig 15) that shows how rate of spread increases in areas with a steeper slope and therefore these areas have a higher fire risk.

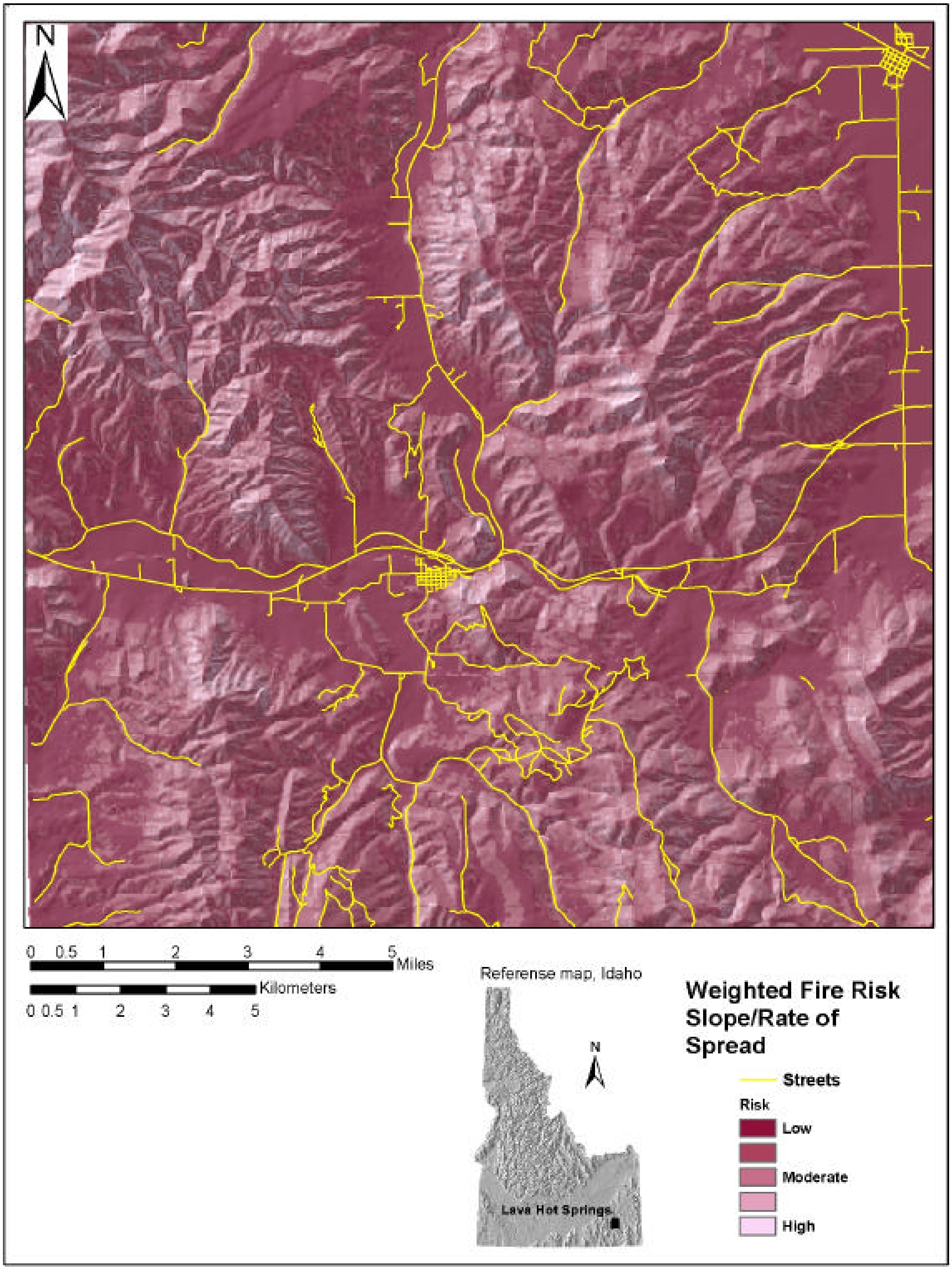


Figure 15. This map shows rate of spread depending on slope. The steeper the terrain is, the higher will the fire risk be.

We created a map (fig 16) that shows how suppression difficulties, depending on slope, affects the fire risk in our study area.

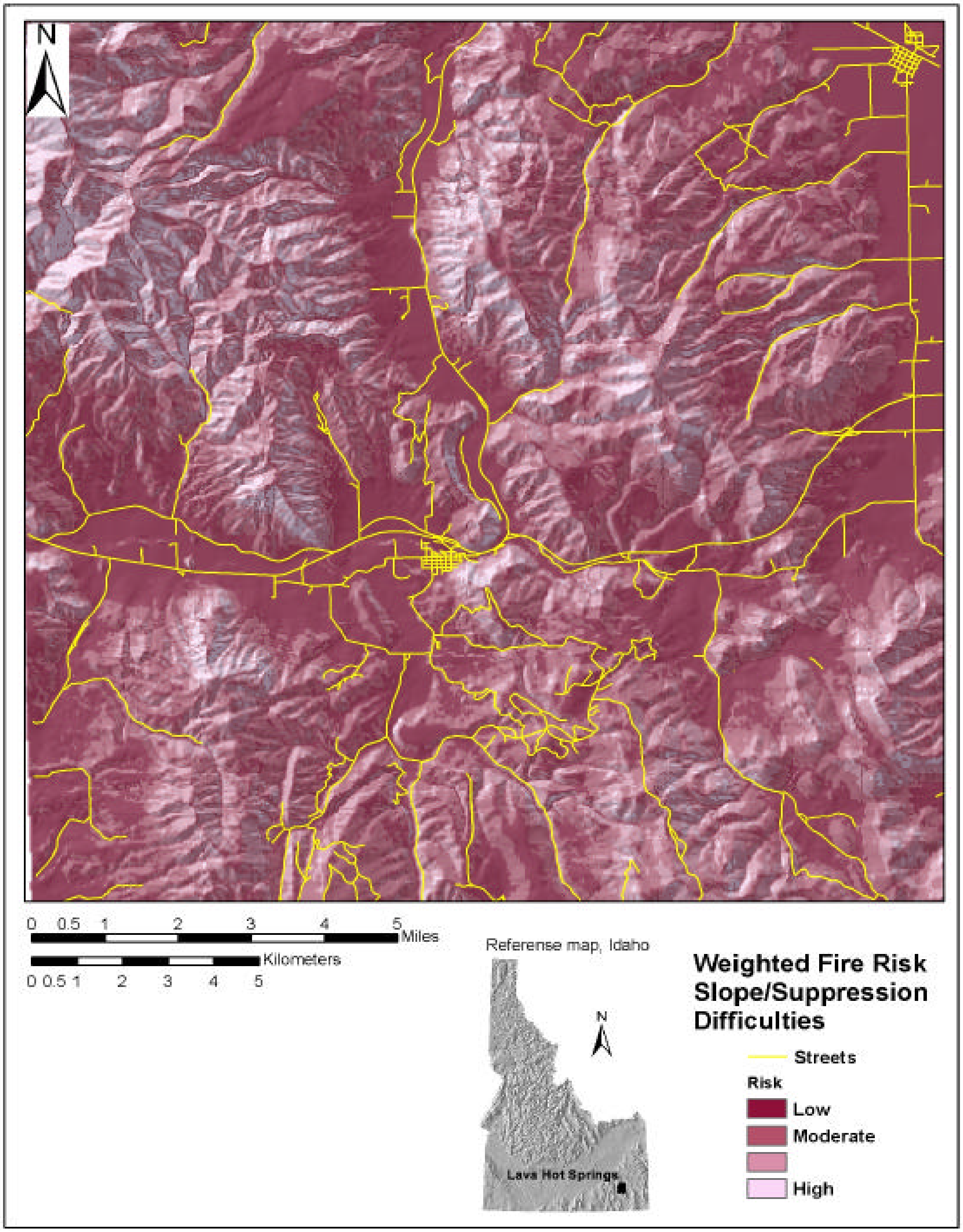


Figure 16. This map describes how the suppression difficulties increase on areas with a steeper slope than areas not as steep. Therefore, those areas have a higher fire risk.

We created a map (fig 17) that shows how the sun position and daily temperature affects fire risk in our study area.

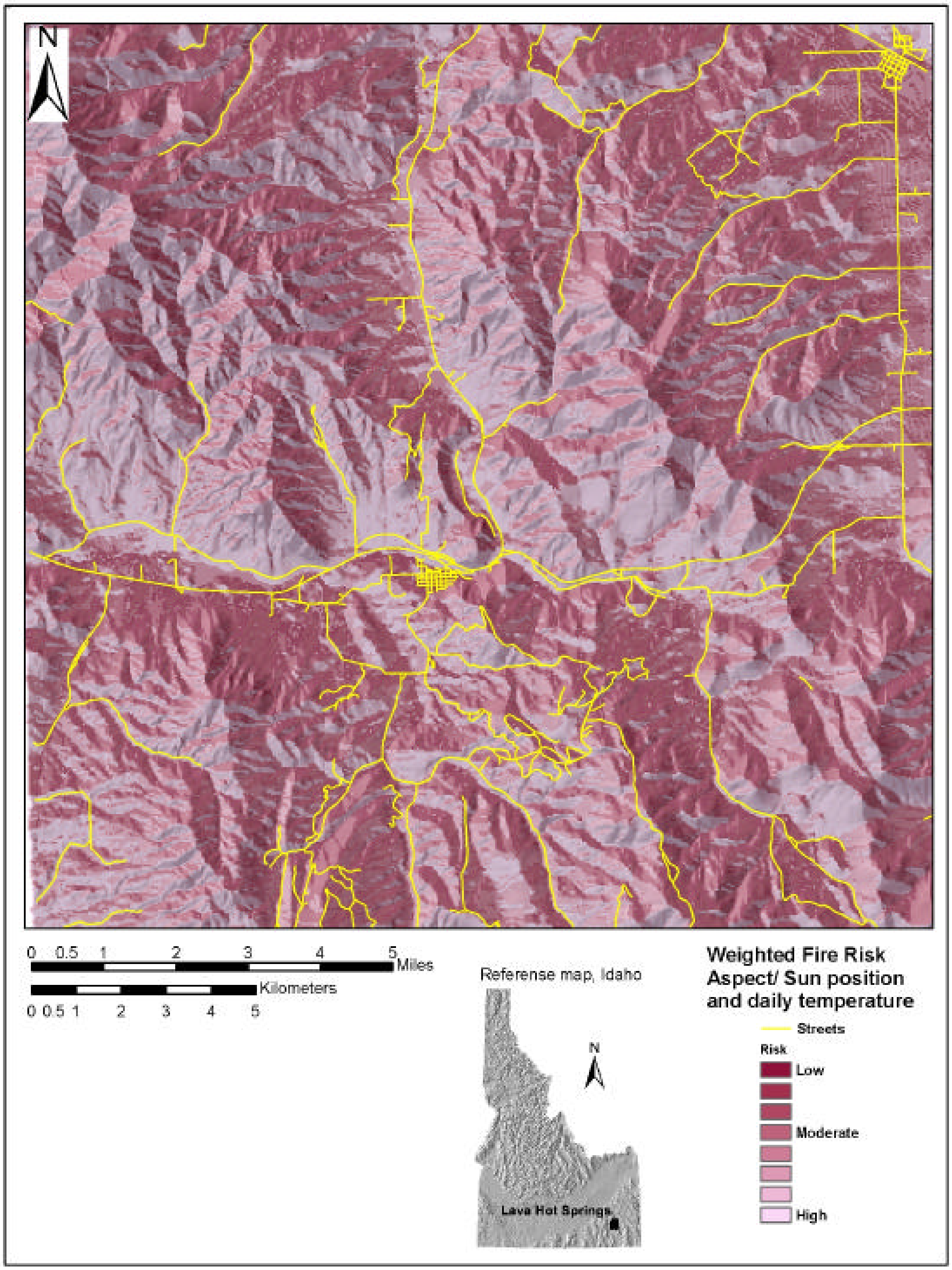


Figure 17. This map shows how sun position and daily temperature affects the fire risk.

We created a map (fig 18) that shows how response time affects the fire risk in our study area. It does not have the same risk scale as the other fire model components. This because it takes the firefighters in Lava Hot Springs 5 minutes to respond, which gives the whole area the highest risk. This map is just for showing the risk depending on response time if Lava Hot Springs had a non-volunteer fire station.

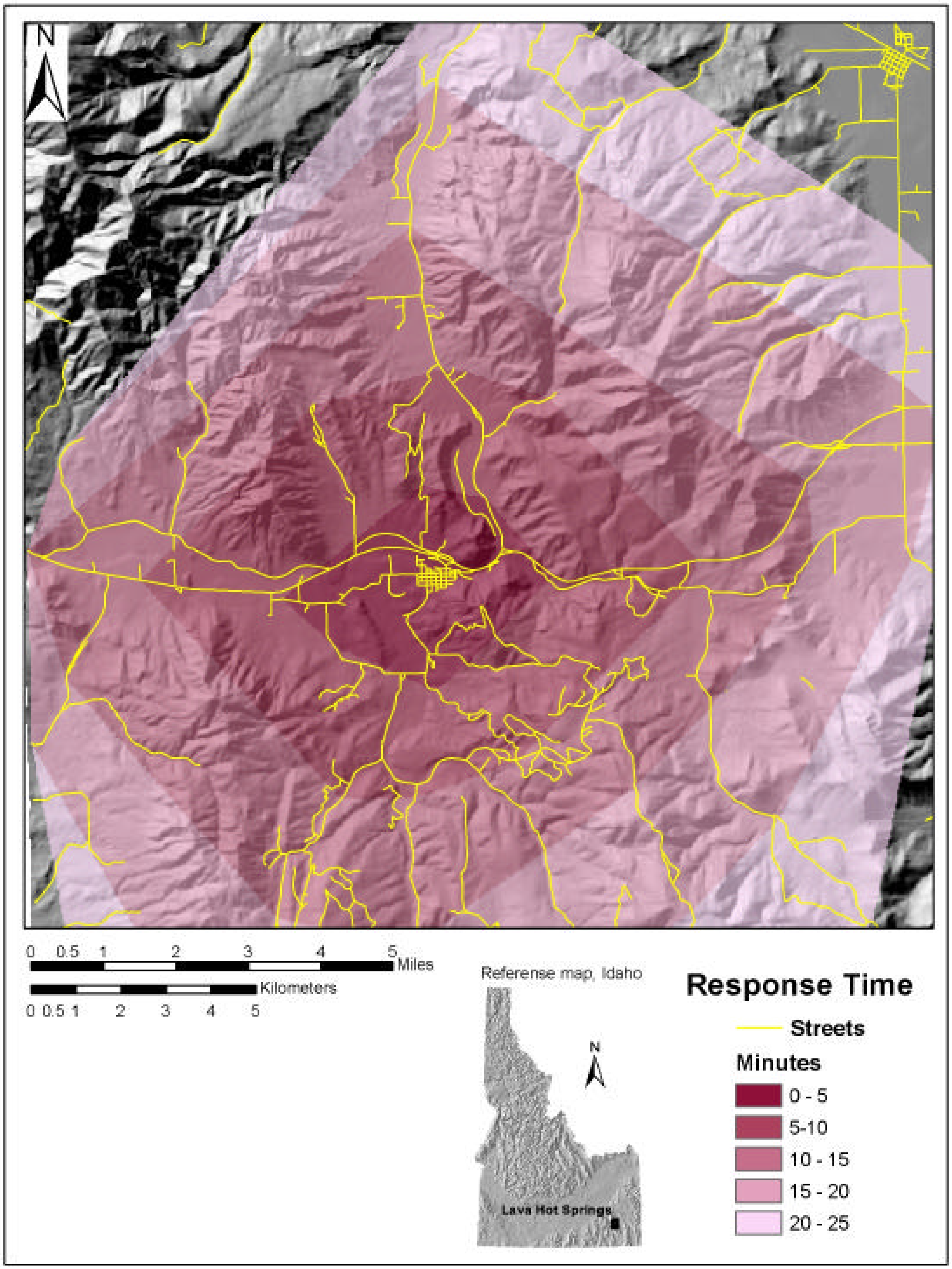


Figure 18. This map shows how the response time is distributed in our study area.

We created a map (fig 19) that shows the fire model components added together as a complete WUI risk model.

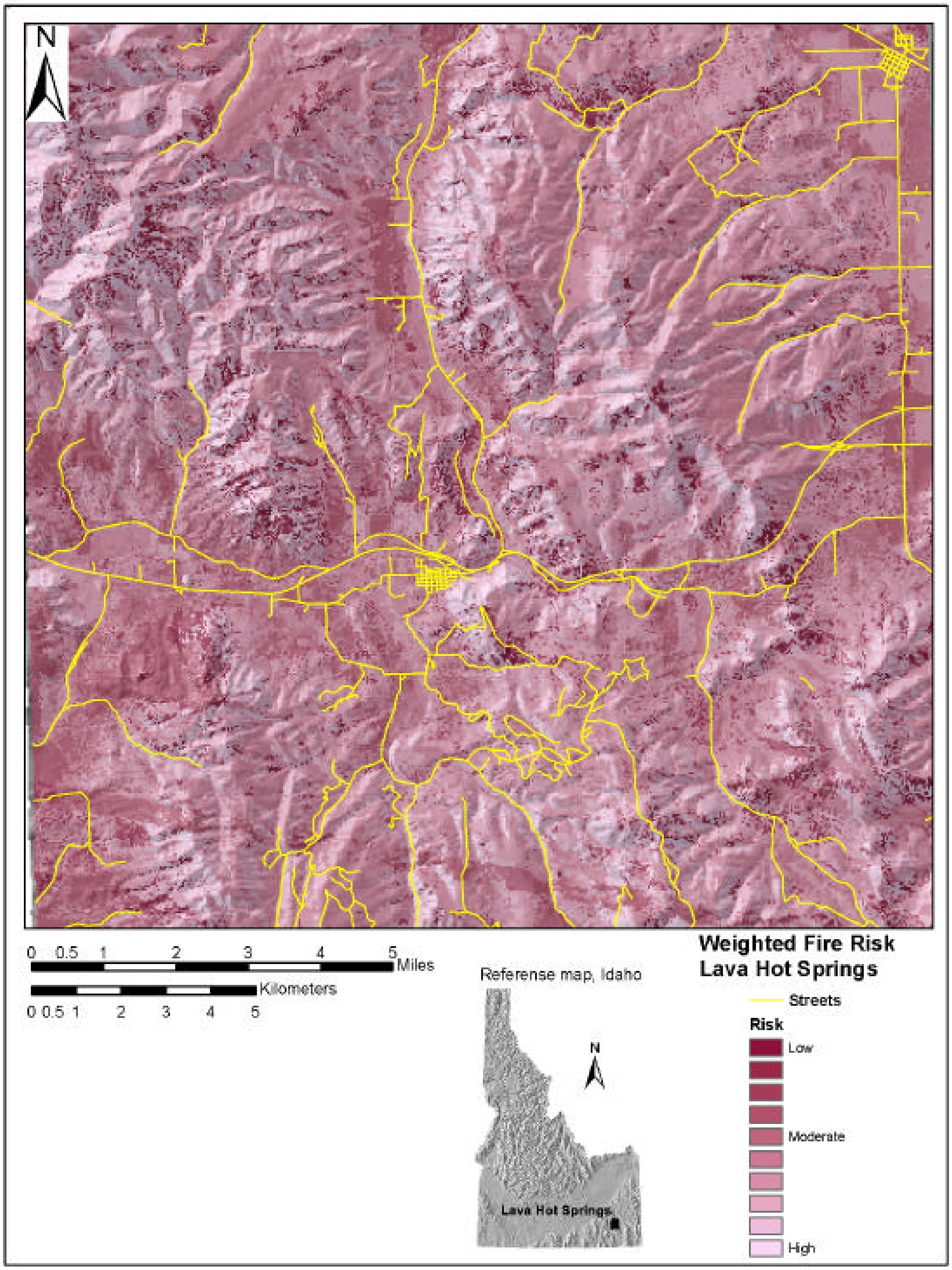


Figure 19. This map shows the result of all wildfire model components together.

We created a map (fig 20) that shows our complete fire risk model, including fires occurring after 1999, showed as unclassified risk.

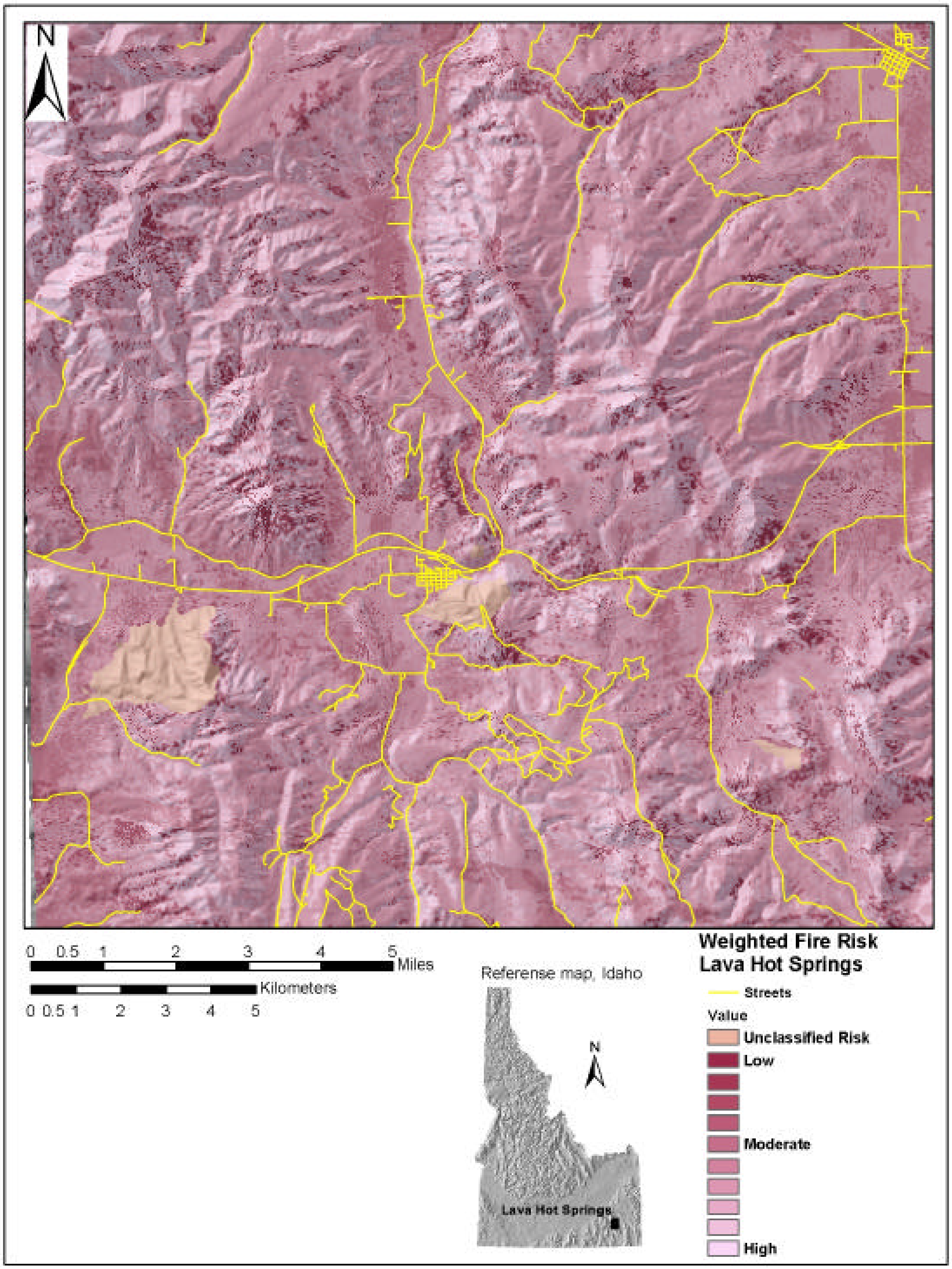


Figure 20. This map shows the final model including fires occurring after 1999 as unclassified risk.

Discussion: Early in this project we determined thresholds for no-, dry-, and moist vegetation using NDVI. We chose the value 0.01 as a threshold between no vegetation and general vegetation based on where and how well the NDVI values matched a DOQQ. We also visited Lava Hot Springs to observe the vegetation and insure it matched well. We chose the second threshold (separating dry vegetation from moisture vegetation) using similar methods. The NDVI value of 0.17 was the threshold limit between dry vegetation and moist vegetation. We based this on the vegetation observed in and around Lava Hot Springs. There is quite a lot of moist vegetation in that area and we believe, by reviewing the DOQQ's, the threshold between dry vegetation and moist vegetation is best approximated at 0.17.

After estimating the different fire model components, we decided (with Keith T. Weber) how important each component was to the fire model, depending on how high its risk is for communities.

Fuel load/Rate of Spread 25% (of total fire risk model)
The Fuel load/Rate of Spread component got the highest risk. This is because fast spreading fires are the most dangerous fires. It also gives the firefighters a shorter time to suppress the fire before it gets to the urban areas.

Fuel load/Vegetation Moisture 23%
The Fuel load/Vegetation Moisture component received the second highest risk because dry vegetation with moderate fuel load are good conditions for a fire.

Fuel load/Intensity 20%
The Fuel load/Intensity component also has a significant risk to communities. Thus if firefighters do not suppress the fire, it will keep spreading.

Slope/Suppression Difficulties 17%
The Slope/Suppression Difficulties component is a substantial fire hazard because if firefighters cannot reach the fire, it will keep burning although other components describe the area as low risk.

Slope/Rate of Spread 10%
The Slope/Rate of Spread component is also a high risk for communities, but not as important as Fuel load/Rate of Spread, that is why we rated it quite low.

Aspect/Sun position and Daily temperature 5%
The Aspect/Sun position and Daily temperature component is rated relatively low because if a fire starts on a hot day, at the end of the summer (when most of the wildfires occur), the direction the slope is facing is less important.

When we had added together the fire model components, we realized that it did not include fires that occurred after 1999. We added these fires to the final model and categorized the areas as "unclassified". This is because we could no longer rely upon the fire risk model. Nor could we set a fire risk for those areas, thus we gave them the value "unclassified".

Since much of this project is based on estimations and expert knowledge of individuals, the purpose for it is not to be a final product. The goal for our model is to be a tool to assist firemanagers 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. More research can be done on the different component and further development can be made on the unclassified areas in the final WUI fire risk model.

Assessments of errors and bias: All estimations in this report are made based upon our knowledge of the criteria. We have also discussed our analyses and results with Keith T. Weber. Except for the fuel load/vegetation moisture model, we used the same weightings that were used during the City of Pocatello project, (Mattsson and Thoren, 2002).

When we weighted the fuel load/vegetation moisture model by worst case scenario, we discovered that some classes could be calculated in two ways (e.g. class 6 could be Fuel load 3 (2 tons/acre)*2 (dry vegetation) and 6 (>6 tons/acre)*1 (no vegetation)). We discovered that many pixels in the grid had the latter combination (Appendix D). It is unlikely that you could have a combination of high fuel load (6) and no vegetation (1) in the grid. NDVI only recognizes vegetation with chlorophyll. This means there could be areas with a high amount of fuel, but vegetation (fuel) that is very dry. The NDVI will therefore not recognize it as vegetation.

The fuel load model had difficulties detecting juniper in some areas, but it has been validated during the summer (2002). Unfortunately, our WUI fire risk model used an older fuel model. Another problem with our fire risk model is that fires occurring after 1999 were not included. This resulted in "unclassified" areas in our final model, because we could not classify the fire risk in those areas.

Reference cited:

Mattsson, D. and Thoren, F., 2002. Wildland/Urban Interface and Communities at Risk
Amdahl, Gary, (2001). *Disaster Response: GIS for Public Safety* United States of America: ESRI PRESS.

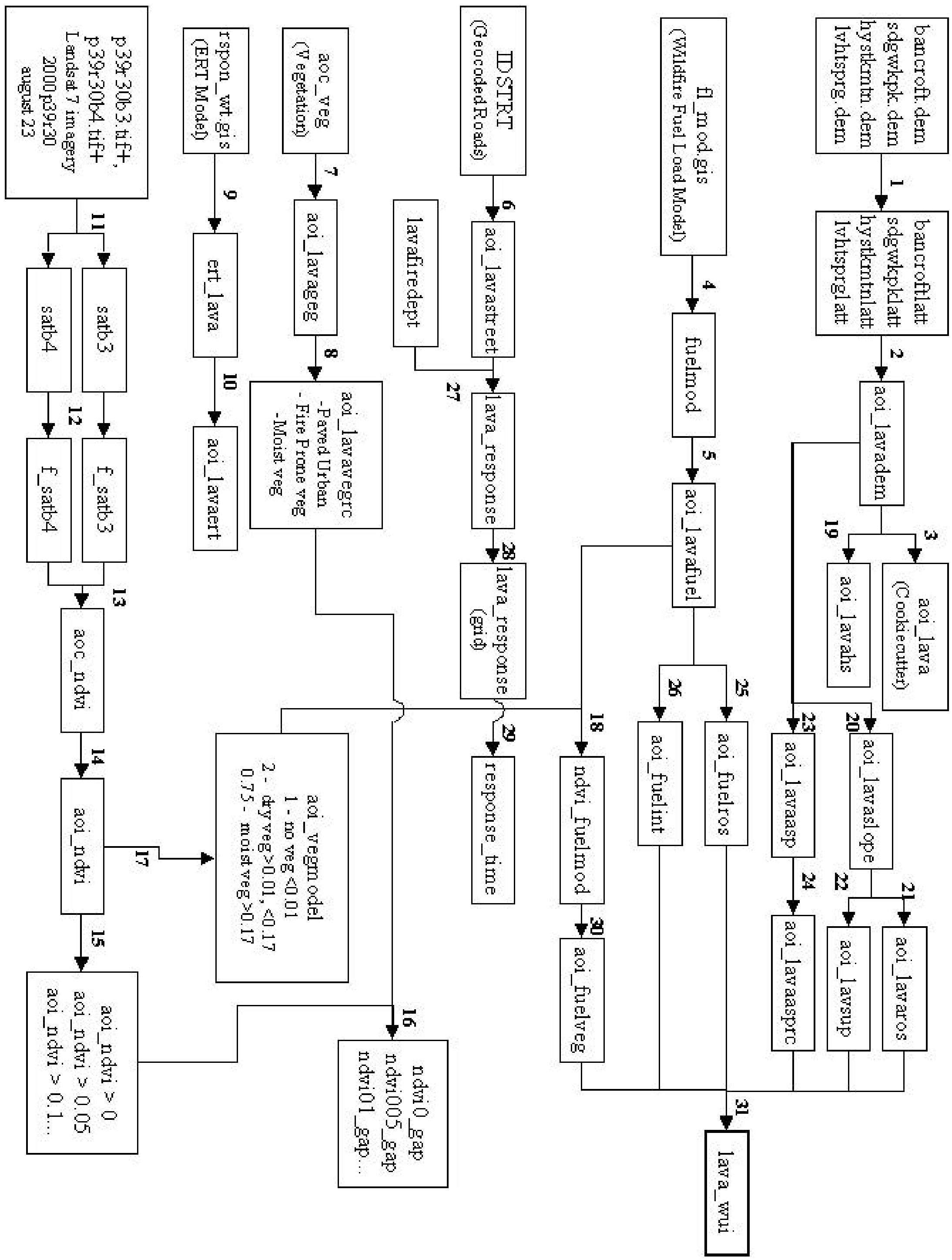
Acknowledgements:

On July 29, 2002 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.

These people were attending:
Felicia Burkhardt, GIS Coordinator, USRD BLM
Fred Judd, Fire Mitigation and Education Officer, USDR BLM
Don Gosswiller, Fire Mitigation and Education Officer, USDR BLM
Keith T. Weber, GIS Director, Idaho State University (ISU), GIS Training and Research Center (GISTReC)
Cecilia Jansson, GIS Intern, ISU, GISTReC
Oskar Pettersson, GIS Intern, ISU, GISTReC

Appendix A – Cartographic Model

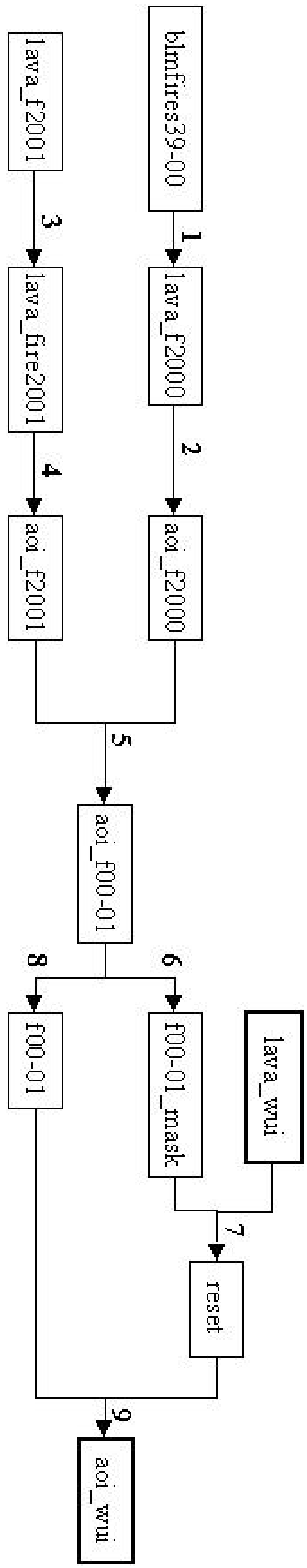
Cartographic Model



Description

1 We converted the DEM quadrangles to DEM-lattice in ArcInfo Workstation
2 We merged the DEM lattices together with ArcInfos mosaic
3 By using the footprint of the merged grid, we created a “cookie cutter” with gridclip
4 We converted the image to grid with ArcInfos imagegrid
5 By using the cookiecutter, we clipped the fuelmodel
6 By using the cookiecutter, we clipped the streets
7 By using the cookiecutter, we clipped the vegetation
8 We reclassed the vegetation by using Spatial Analyst’s reclassify
9 We converted the image to grid with ArcInfos imagegrid
10 By using the cookiecutter, we clipped the Emergency Response Time Model
11 We converted the satellite band images to grids with ArcInfos imagegrid
12 To make the grids able to handle decimals, we used the ArcInfos float
13 In grid we made aoc_ndvi = (f_satb4 - f_satb3) / (f_satb4 + f_satb3)
14 By using the cookiecutter, we clipped the ndvi to our area of concern
15 In raster calculator we made classes for everything > 0, 0.05, 0.1, 0.15, 0.2, 0.25 and 0.3, then we compared these with aoi_lavaveg
16 We multiplied aoi_lavavegrc and the ndvi classes to see if the ndvi classes says it is vegetation where aoi_lavavegrc says it is paved urban
17 We made three new classes of the ndvi, no veg, dry veg and moist veg
18 We multiplied aoi_vegmod with aoi_lavafuel
19 We made a hillshade to make it easier when we compare different grids
20 We made a slope from aoi_lavadem in Spatial Analyst → surface analysis → slope
21 We reclassed the slope grid to the “suppression difficulties” values
22 We reclassed the slope again but to the “rate of spread” values
23 From aoi_lavadem we made an aspect in Spatial Analyst → surface analysis → aspect
24 We reclassed the aspect to the “aspect/sun position and daily temperature” values
25 We reclassed the aoi_fuelmodel to the “rate of spread” values
26 We reclassed the aoi_fuelmodel again but to the “fire intensity” values
27 From aoi_lavastreet and lava fire dept (position of fire station), we made lava_response in Network Analyst - service area
28 We converted lava_response to a grid
29 We weighted the hole lava_response with 10 and got response_time
30 We weighted the ndvi_fuelmodel which resulted in aoi_fuelveg
31 We merged aoi_lavaros, aoi_lavasup, aoi_lavaasprc, aoi_fuelros, aoi_fuelintco, and aoi_fuelveg by adding them together

Cartographic model



Description

1 We selected all fires from 2000 and then we converted them to a grid
2 We clipped lava_f2000 with the cookiecutter in gridclip
3 We selected the fire within our area of interest
4 We converted feature to grid
5 We merged aoi_f200 and aoi_f2001 together by adding them (No Data=0 in both)
6 We reclassed aoi_f00-01 (class 1=0, class 2=0, No Data=1)
7 With arithmetic, we multiplied lava_wui and f00-01_mask
8 We reclassed aoi_f00-01 (class 1=1, class 2=1, No Data=0)
9 With arithmetic, we multiplied F00-01 and reset, and we have our final product.

Appendix B – Weightings

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

Class	Weights
0	0.25
0.75	1.5
1	0.5
1.5	2
2	3
2.25	2.5
3	4
3.75	5
4	6.5
4.5	6
5	2
6	7
8	8.5
10	10
12	10

Table 6. Weighting data for Fuel load/ Vegetation Moisture. Compare with figure 2 in report.

Classes (tons/acre)	Weight
< 0.74	0
0.74	8
1	8.5
2	9.5
4	10
6	8.5
> 6	6

Table 7. Weighting data for Fuel load/Rate of Spread. Compare with figure 3 in report.

Classes (tons/acre)	Weight
< 0.74	0
0.74	0.74
1	1
2	2
4	4
6	6
> 6	10

Table 8. Weighting data for Fuel load/Intensity. Compare with figure 4 in report.

Angle/degree interval	Weight
0 -- 10	0.41
10 -- 20	1.37
20 -- 30	2.56
30 -- 40	4.89
40 -- 50	10

Table 9. Weighting data for Slope/Rate of Spread. Compare with figure 5 in report.

Angle/degree interval	Weight
0 -- 10	1
10 -- 20	2
20 -- 30	8.5
30 -- 40	10
40 -- 50	10

Table 10. Weighting data of Slope/ Suppression Difficulties. Compare with figure 6 in report.

Degree interval	Aspect	Weight
0 -- 22.5	N	1
22.5 -- 67.5	NE	1.5
67.5 -- 112.5	E	3
112.5 -- 157.5	SE	8
157.5 -- 202.5	SE	10
202.5 -- 247.5	SW	10
247.5 -- 292.5	W	7
292.5 -- 337.5	NW	2
337.5 – 360	N	1
-1	Flat	5

Table 11. Weighting data of Aspect/Sun position and Daily temperature. Compare with figure 7 in report.

Time (seconds)	Weight
30	2.92
60	3.19
90	3.67
120	4.03
150	4.44
180	5.00
210	5.97
240	6.94
270	8.19
300	10.00

Table 12. weighting data of Response time. Compare with figure 8 in report.

Appendix C – Data dictionary

Data dictionary

Catalog structure				File name	Format	Description
\\Alpine\urbint\Lava\						
	Data					
		Grid				
			DEM			
				aoi_lavadem	Raster Dataset	Digital Elevation Model, Area Of Interest
				aoi_lavaasprc	Raster Dataset	Aspect reclassified, Area Of Interest
				aoi_lavahs	Raster Dataset	Hillshade, Area Of Interest
				aoi_lavaslope	Raster Dataset	Slope, Area Of Interest
				aoi_lavaros	Raster Dataset	Slope, Rate Of Spread, Area Of Interest
				aoi_lavasup	Raster Dataset	Slope, Suppression Difficulties, Area Of Interest
			Response_time			
				lava_response	Raster Dataset	Response time 5 - 30 min in Area Of Interest
				response_time	Raster Dataset	Response time in Area Of Interest, weighted
			Fuelload			
				aoi_lavafuel	Raster Dataset	Fuel load, Area Of Interest
				aoi_fuelros	Raster Dataset	Fuel load, Rate of Spread, weighted, Area Of Interest
				aoi_fuelint	Raster Dataset	Fuel load, Fire Intensity model, weighted, Area Of Interest
			VEG			
				aoi_lavavegrc	Raster Dataset	Classified vegetation (GAP), Area Of Interest
				aoi_ndvi	Raster Dataset	NDVI, Area Of Interest
				aoi_fuelveg	Raster Dataset	Fuel Load with vegetation moisture model, weighted, Area Of Interest
			Wildfires_lava			
				aoi_lavawui	Raster Dataset	WUI (without fires 00-01), Area Of Interest
				aoi_f00-01	Raster Dataset	Fires in 2000 and 2001, Area Of Interest
				aoi_wui	Raster Dataset	Wildland Urban Interface model, Area Of Interest (Final product)
		Vector				
			Fire_deps			
				lavafiredept	Shapefile - Point	Lava Hot Springs' Fire Department
			Elevated_risk			
				sites w-elevated risk	Shapefile - Point	Sites with elevated risk in Area Of Interest
			Streets			
				aoi_lavastreet	Shapefile - Line	Streets in Area Of Interest
			Cookie_cutter			
				aoi_lava	Coverage	Cookie cutter, Area Of Interest
				aoi_lava	Shapefile - Poly	Cookie cutter, Area Of Interest
	Report					
				Data_Dictionary	Excel file	Data dictionary
				Report	Word file	Report
				Cartographic_model	PowerPoint file	Cartographic model
				Presentation_Lava	PowerPoint file	Presentation fot the Lava Hot Springs' WUI-project
				Wildfire risk map	TIF-image	Map of Wildfire Risk Model (ArcPress (TIF), 300dpi, 41*36 inches)

Appendix D – Errors in the worst criteria scenario

This figure shows the different ways to calculate the fuel load/vegetation moisture classes. The fuel load/vegetation moisture model is the result of vegmodel (NDVI-based grid) and lavafuel (fuel load model) multiplied together. It also shows how many pixels each way of calculation have in the grid.

Class 2		
	value	count
vegmodel		
	0	587754
2*1	100	28939
1*2	200	340
lavafuel		
	0	587754
1*2	1	340
2*1	2	28939

Class 3		
	value	count
vegmodel		
	0	600704
4*0.75	75	7485
3*1	100	8844
lavafuel		
	0	600704
3*1	3	8844
4*0.75	4	7485

Class 4		
	value	count
vegmodel		
	0	571795
4*1	100	21519
2*2	200	23719
lavafuel		
	0	571795
2*2	2	23719
4*1	4	21519

Class 6		
	value	count
vegmodel		
	0	589919
6*1	100	25150
3*2	200	1964
lavafuel		
	0	589919
3*2	3	1964
6*1	6	25150