WILDFIRE RISK MODEL VALIDATION

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ABSTRACT

Field samples (n = 128) collected during summer 2001 were used to create a series of fuel load and wildfire risk models. Field data collected during the summer 2002 field season (n = 370) were used to determine the accuracy of these models, as well as to refine and rebuild the existing models. Using this new data, we created an updated wildfire risk model that included components on ignition risk, risk of spread, fuel moisture, fuel load, physical characteristics, and response time. We validated these models using a number of error matrix validation procedures, with the resulting accuracies ranging from 30% - 92%. The wildfire risk components provide land managers and local agencies with an additional tool for use in their decision making process.

Keywords: Fuel load, wildfire risk, model validation, Snake River Plain, SE Idaho

INTRODUCTION

Field samples (n = 128) collected during summer 2001 were used to create a series of fuel load and wildfire risk models for a NASA-funded *Wildfire Effects on Rangeland Ecosystems and Livestock Grazing* research project. During the summer 2002 field season we collected validation samples (n = 370) to determine the accuracy of these models. We then used these data to refine and rebuild the fuel load and wildfire risk models, and to create new components for an updated comprehensive wildfire risk assessment.

METHODS AND RESULTS

During the 2001 field season, technicians noted that only three of the fuel load classes described in Anderson (1982) were present in our study area: 0.74 tons/acre (grass areas), 4.0 tons/acre (sagebrush areas), and 6.0 tons/acre (juniper-woodland areas). Two new fuel load classes (1.0 tons/acre and 2.0 tons/acre) were created to more accurately represent the continuum between grass and sagebrush areas (0.74 and 4.0 tons/acre). In the Anderson fuel load classes, 1.0 tons/acre would be included in 0.74 tons/acre class, and 2.0 tons/acre would be included in 4.0 tons/acre class.

The overall accuracy of the 2001 and 2002 fuel load models were quantified in two ways. One where each fuel load class (0.74, 1.0, 2.0, 4.0, and 6.0 tons/acre) was included in the error matrix (yielding a conservative accuracy assessment), and one where classes were combined to represent the three original Anderson fuel load classes (1982).

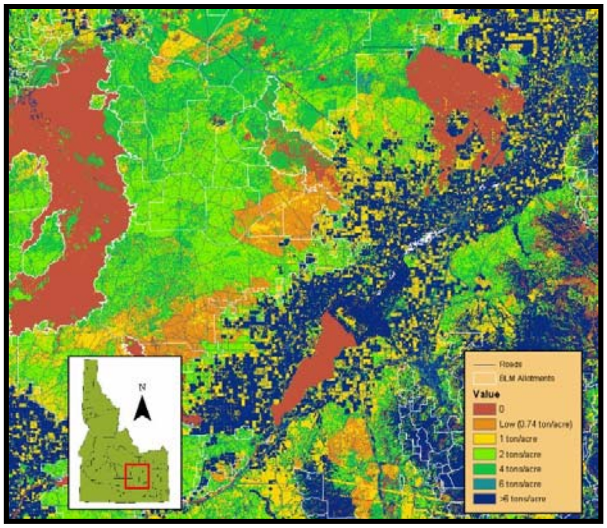

Figure 1. Initial fuel load model developed in 2001.

2001 Model Validation

Models created following the field season of 2001 included fuel load, emergency response time, lightning strike pattern, vegetation moisture, and topographic effects (slope and aspect). The fuel load model was created using maximum likelihood supervised classification, and as such was the only model where accuracy could be assessed using validation data. The overall accuracy of the 2001 fuel load model (Figure 1) was 30.27% using conservative estimates (Table 1) and 65.41% using the expanded/combined estimate method (Table 2).

Table 1 - Conservative error assessment of 2001 Fuel Load Model (5 classes)

		Field Estimation of Fuel load (tons/acre)							
	Fuel load class	0.00	0.74	1.00	2.00	4.00	6.00	Total	User's Accuracy
Modeled Fuel load (tons/acre)	0.00	0	0	0	1	1	0	2	0.00
	0.74	0	7	6	6	7	1	27	0.26
	1.00	0	25	21	26	16	0	88	0.24
	2.00	0	12	21	59	74	2	168	0.35
	4.00	0	12	23	25	25	0	85	0.29
	6.00	0	0	0	0	0	0	0	0.00
	Total	0	56	71	117	123	3	370	
	Producer's Accuracy	0.00	0.13	0.30	0.50	0.20	0.00		0.30

Note: Kappa statistic = 0.04

Table 2 - Expanded error assessment of 2001 Fuel Load Model (3 classes)

		Field Estimation of Fuel load (tons/acre)					
	Fuel load class	0.00	0.74 - 1.00	2.00 - 4.00	6.00	Total	User's Accuracy
Modeled Fuel load (tons/acre)	0.00	0	0	2	0	2	0.00
	0.74 - 1.00	0	59	55	1	115	0.51
	2.00 - 4.00	0	68	183	2	253	0.72
	6.00	0	0	0	0	0	0.00
	Total	0	127	240	3	370	
	Producer's Accuracy	0.00	0.46	0.76	0.00		0.65

Note: Kappa statistic = 0.23

Model Re-Building/refinement

Ignition Risk Model (component model no. 1)

There are two primary sources of wildfire ignition in the Intermountain west. Anthropogenic ignition sources account for approximately 55-90% of wildfires (Larimer County, Colo 2003). These fires are frequently started unintentionally by careless use/disposal of cigarettes, fireworks, and campfires. Ignition sites are characteristically close in proximity to municipalities, homes and campsites. Consequently they are also in close proximity to roads. This fact allowed us to model anthropogenic ignition sources using roads as a surrogate indicator for ignition risk.

Lightning strikes account for approximately 10-45% of wildfires. During the fire season (typically July-September) dry-thunderstorms are commonplace. Such storms are characterized as having little or no rainfall (< 0.25") and a large number of cloud-to-ground lightning strikes (e.g., a storm event on July 26, 2000 recorded 2,599 cloud-to-ground lightning strikes). The ignition risk model first modeled each source independently, and then combined them to create a single ignition source model.

Anthropogenic Ignition Sources

The 2002 anthropogenic ignition risk model was created using a maximum-likelihood classification (Wang 1990, Lillesand and Kiefer 2000) of vegetation types consistent with increased risk of anthropogenic ignition, a distance-from-roads proximity model (to account for probability of ignition), and a vegetation moisture model to adjust for relative moisture content and the real risk of ignition.

Vegetation types consistent with increased risk of anthropogenic ignition model:

We created a maximum likelihood supervised classification using our 2002 field data as training sites for vegetation types consistent with increased risk of human-caused ignition events. For this model, we focused on presence of fine fuels (grass, litter/duff) as a primary component of ignition risk, and shrub presence as a secondary component of risk. The five classes consisted of:

Low-risk (shrub, grass, and litter/duff cover < 15%) (weight = 1)
Moderate-risk (shrub cover > 15% and *either* grass cover or litter/duff cover > 15%) (weight = 2)
High-risk (shrub cover < 15% and *both* grass cover and litter/duff cover > 15%) (weight = 3)
Severe-risk (all categories > 15%) (weight = 4)

Distance-from-roads model:

We buffered a vector transportation coverage (including roads, railroads, etc.) by 30, 60, and 90 meters and weighted each buffer region (3, 2, and 1 respectively, with 0 being the value for all areas >90 meters from a transportation vector) to account for increased risk related to proximity to roads. This coverage was converted to a grid for use in creating the final anthropogenic ignition risk model.

Vegetation moisture model:

We used a tasseled cap transformation (Kauth and Thomas 1976) to create a relative vegetation moisture grid and reclassed the grid to values between -1 and 1 in order to account for the impact the relative vegetation moisture would have on the risk of ignition.

Final 2002 Anthropogenic Ignition Risk Model:

The three models were added together in image calculator using their respective weightings (1-4 for vegetation, 0-3 for proximity to roads, and -1 to 1 for vegetation moisture) to create an image with values between 0 and 8. This image was reclassed to fit between 0 and 5 to create the final anthropogenic risk model.

Lightning Ignition-Risk Model

The 2002 lightning ignition risk model was created using a maximum-likelihood classification (Wang 1990, Lillesand and Kiefer 2000) of vegetation types consistent with increased risk of ignition, a lightning strike potential model (cf. chapter 6), and a vegetation moisture model to adjust for relative moisture content and the real risk of ignition.

Vegetation types consistent with increased risk of anthropogenic ignition model:

We created a maximum-likelihood supervised classification (Wang 1990, Lillesand and Kiefer 2000) using our 2002 field data as training sites for vegetation types consistent with increased risk of lightning caused ignition events. For this model, we focused on the presence of woody vegetation (e.g., shrubs and trees) as the primary risk and the presence of fine fuels as the secondary risk. Our risk categories were:

Low-risk (shrub, grass, and litter/duff cover < 15%) (risk rating = 1)
Moderate-risk (shrub cover < 15% and *both* grass cover and litter/duff cover > 15%) (risk rating = 2)
High-risk (shrub cover > 15% and *either* grass cover or litter/duff cover > 15%) (risk rating = 3)
Severe-risk (all categories > 15%) (risk rating = 4)

Lightning Potential Model:

The lightning potential model was created using data acquired from global atmospherics. The model building process and results are discussed in detail in chapter 6. Risk of lightning strike was classified as 1 (>10km from mountains), 2 (6-10km from mountains), and 3 (<6km from mountains).

Vegetation moisture model:

We used a tasseled-cap transformation (Kauth and Thomas 1976) to create a relative vegetation moisture model and reclassified the model into values ranging between -1 and 1. This was done to account for the effect vegetation moisture would have on ignition risk.

Final 2002 Lightning Ignition Risk Model:

The three models described above were summed together with ArcMap raster calculator (values were 1-4 for vegetation type, 1-3 for lightning strike potential, and -1 to 1 for vegetation moisture). This yielded a model where values ranged from 1 to 8, with 8 being the highest ignition risk level. This model was reclassified so that the values ranged between 0 and 5 to create the final ignition risk model.

Final Ignition-Risk Model (model component no.1)

The Anthropogenic Ignition Risk model and Lightning Ignition Risk model were summed together to create the Final Ignition Risk model (Figure 2) where risk values range between 0 and 10. This formed component 1 of the comprehensive wildfire risk model and was given an overall weighting of 22.5%.

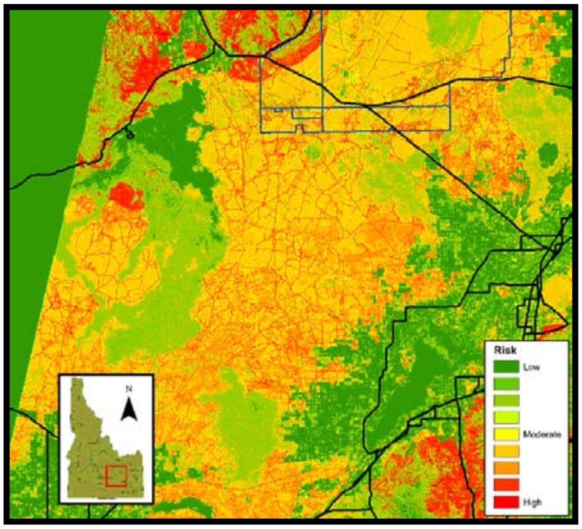

Figure 2. Component 1- Ignition risk model

Fuel Continuity Model (model component no. 2)

The 2002 fuel continuity model (Figure 3) was created using a maximum likelihood classification of vegetation types consistent with risk of escalated rate of spread following an ignition event. This model attempts to delineate area where *both* fine fuels (grass and cheatgrass) and shrubs (sagebrush, rabbitbrush, etc.) are present. Risk categories were assigned as follows:

No risk (sage <5%, grass/cheatgrass <15%) weight = 0
Low risk (sage <5% and grass/cheatgrass 16-50%) weight = 1
Moderate risk (sage 6-25% and grass/cheatgrass 16-50%) weight = 2
High risk (sage 26-50% and grass/cheatgrass <15%) weight = 3
Severe risk (sage 26-50% and grass/cheatgrass 16-50%) weight = 4

The output of the classification was reclassified into values ranging from 0 - 10 for consistency. The fuel continuity model is component 2 of the comprehensive wildfire risk model (weight 22.5%).

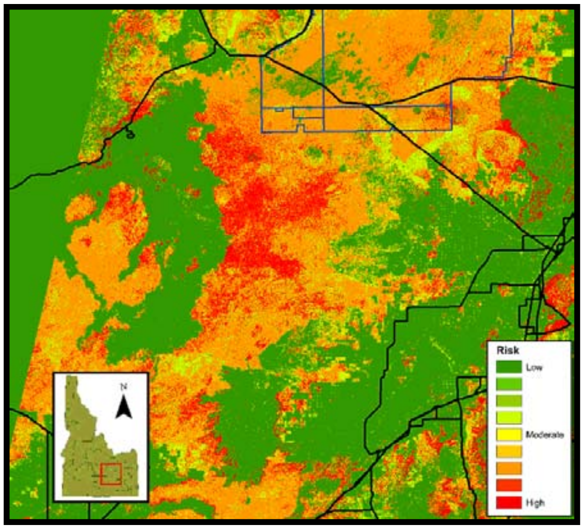

Figure 3. Component 2- Fuel continuity model.

Fuel Moisture Model (model component no. 3)

The 2002 fuel moisture model (Figure 4) was created using the vegetation moisture component of a tasseled cap transformation (Kauth and Thomas 1976) of Landsat ETM7+ imagery combined with the 2002 fuel load model (component 4). We combined the fuel load model (component 4, values 0-10) and the vegetation moisture model (values -1 to 1) by multiplying the two images using ArcMap raster calculator, and reclassifying output to values ranging from 0 - 10. The lowest values are areas that have both low fuel load levels and relatively moist vegetation. Moderate values represent either dry/moderate fuel load levels or wet/heavy fuel load levels. High values represent high fuel load levels that are also dry. This model was weighted 22.5% in the final comprehensive wildfire risk model).

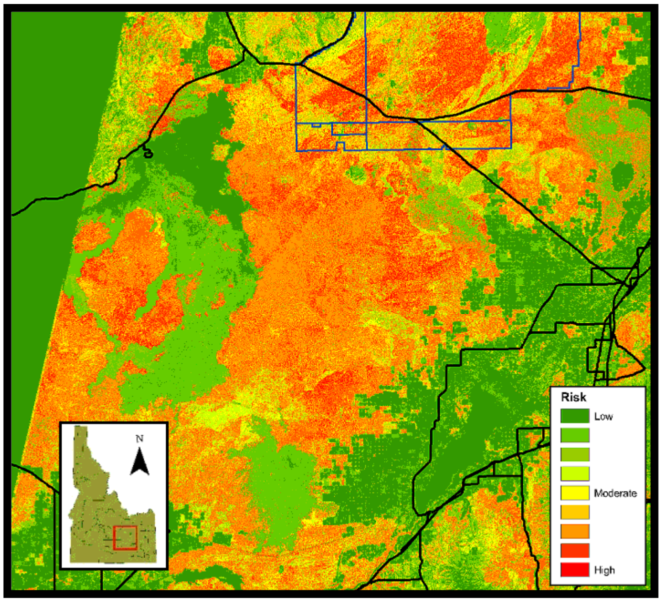

Figure 4. Component 3- Fuel moisture model.

Fuel Load Model (component model no. 4)

The 2002 fuel load model (Figure 5) was created using maximum likelihood classification. We used 2002 field data (*n* = 370) to create training sites for each of the five fuel load classes (0.74, 1.0, 2.0, 4.0, and 6.0 tons/acre). We applied a 30 m buffer to these points and converted the resulting polygons into a grid for use as a training site image in Idrisi. To account for the effect of bare soil on spectral signatures, each fuel load class (with the exception of 6.0 tons/acre) was divided into two sub-classes based on an arbitrary threshold of bare soil present at each sample point, resulting in nine fuel load classes. Following the creation of the maximum likelihood supervised classification model, each sub-class was then reclassified into its original fuel load category for validation and further model development (e.g., fuel moisture and comprehensive wildfire risk models). The fuel load classes were reclassified to values between 0 - 10 (0 - no fuel, 2 - 0.74 tons/acre, 4 - 1.0 tons/acre, 6 - 2.0 tons/acre, 8 - 4.0 tons/acre, and 10 - 6.0 tons/acre). This model formed component 4 of the comprehensive wildfire risk model (weight 22.5%).

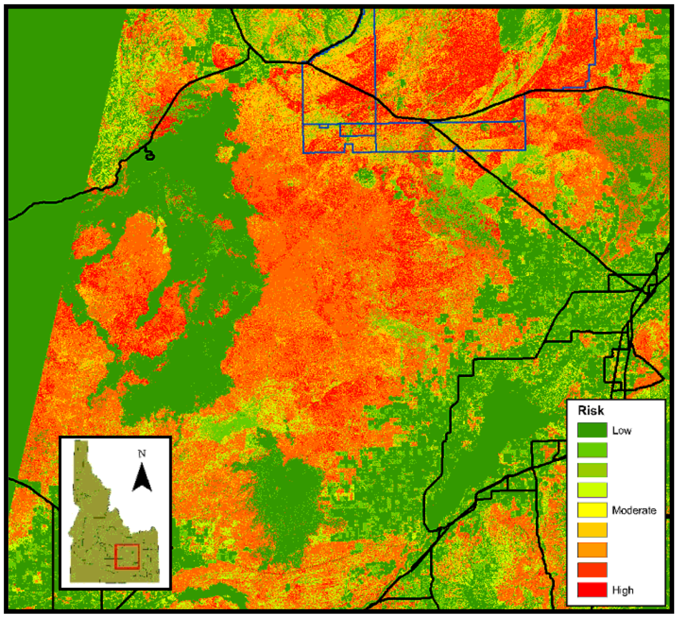

Figure 5. Component 4- Fuel load model developed in 2002.

Suppression Difficulty/Terrain associate risk model (component model no. 5)
Slope and aspect models were created using a digital elevation model for the entire AOC (80 mpp) to represent areas of increased risk due to increased fire spread rate on steep slopes, increased severity (e.g., southwestern facing slopes), and increased suppression difficulty (steep slopes where firefighting machinery would have difficulty accessing the fire). The Snake River plain is relatively flat, so slope and aspect has less impact on fire risk in this area compared to other, more mountainous areas within the AOC. The slope and aspect models were reclassified to values between 0 - 5 and summed together to form component 5 (values range from 0 to 10) of the comprehensive wildfire risk model (weight 10%) (Figure 6).

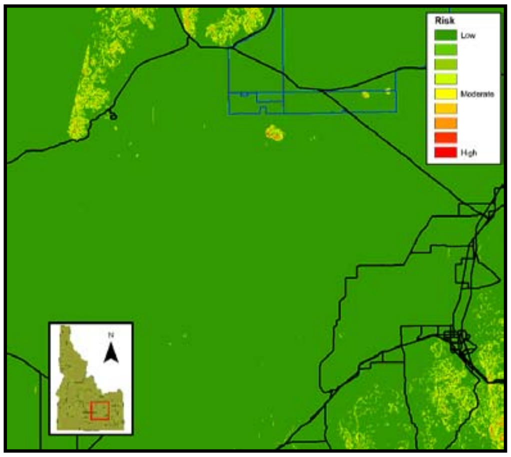

Figure 6. Component 5- Terrain associated risks.

Comprehensive Wildfire Risk Model

The five component models described above were weighted (component 1: Fuel load = 22.5%, component 2: Ignition risk = 22.5%, component 3: Fuel continuity 22.5%, component 4: Fuel moisture 22.5%, and component 5: Terrain associated risk (slope/aspect influences) 10%) and combined using ArcMap image calculator to create the 2002 comprehensive wildfire risk model (Figure 7). This model shows areas of increased risk for significant wildfire events given the potential for ignition and spread of the fire.

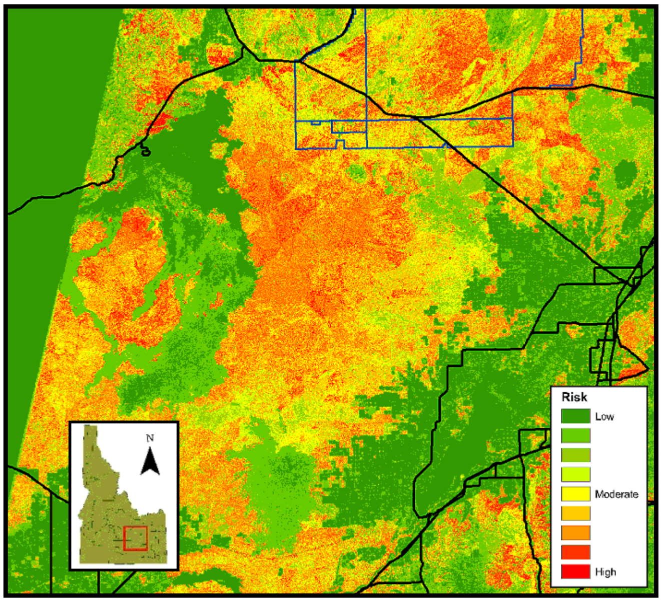

Figure 7. Comprehensive wildfire risk model

Comprehensive Wildfire Risk Model (with response time)

To account for suppression efforts by various agencies to control wildfires following ignition and detection, a response time model was developed to delineate areas that may be at increased risk due to their isolation, as well as areas that may experience decreased risk due to quick response. We created a response time model using ESRI's Network Analyst software. This model was combined with the existing comprehensive wildfire risk model (figure 7) to create a comprehensive wildfire risk model (w/response time) (Figure 8). The weightings used for each component of this risk model were 90% comprehensive wildfire risk model, and 10% response time model.

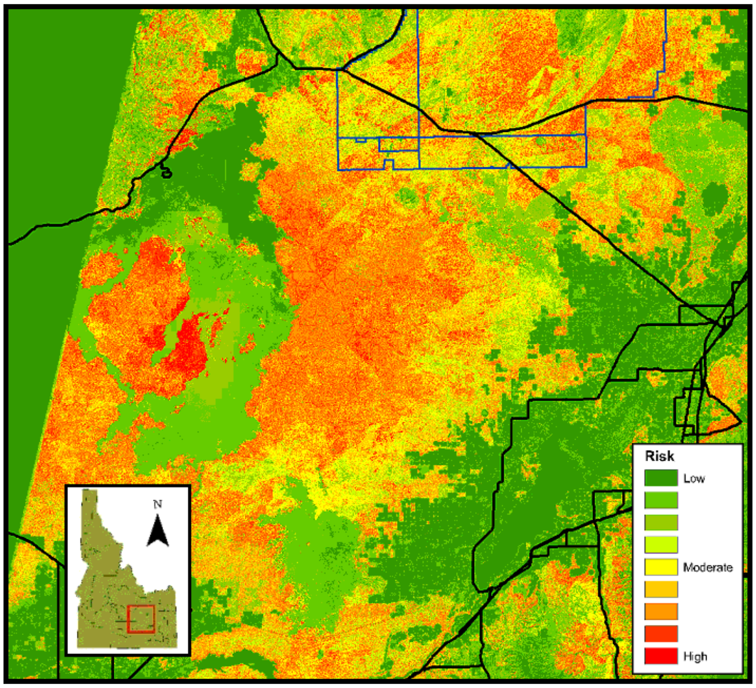

Figure 8. Comprehensive wildfire risk model including response time.

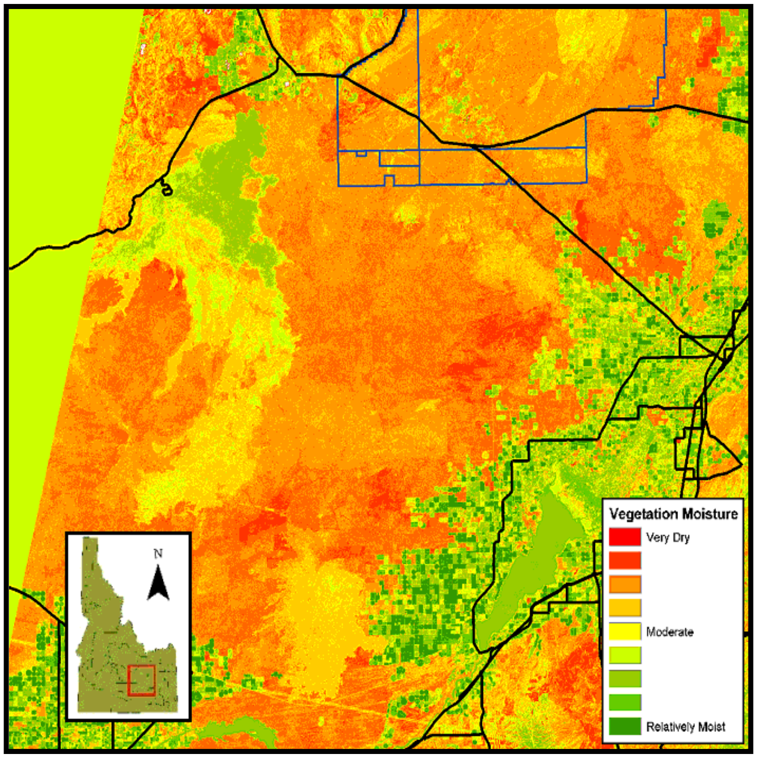

Figure 9. Vegetation moisture model (relative moisture estimates derived from Tasseled-cap transformation.

DISCUSSION

Assessment of Error and Bias

Each component of the comprehensive wildfire risk model was validated independently using three methodologies. The first was a standard error matrix (i.e., contingency table) where each predicted (modeled) class was compared against the measured (field) class at all sample point locations. The second method was a modified error matrix where similar classes were combined and accuracy determined using these super-classes. The third validation procedure used fuzzy set theory (Congalton and Green 1999) whereby a threshold of acceptable error was first established. This validation procedure allowed us to better address the difficulties associated with using multispectral imagery to delineate vegetation types having similar spectral signatures. In our case, the fuzzy set threshold was +/-1 class (i.e., this validation procedure determined whether the predicted (modeled) class was within one class of the field-observed class). We did not employ all three methods for each component. The results of these tests are reported in the text as *standard/expanded, clumped, and fuzzy-set-theory* accuracies, respectively. Note: Error matrices were calculated using the entire sample point data set (*n* = 370) to develop and validate the model unless stated otherwise. We explored the use of a validation subset (*n* = 185) and development subset (*n* = 185) and found no difference in resulting accuracy (chapter 10). This may be a result of our large sample size and the relatively small effect that each individual sample point had on the multi-dimensional data cloud for each spectral signature. Alternatively, it may be attributable to the relative homogeneity of our training sites. Since the results of the validation did not differ, we opted for the simpler process of including all points in both model development and accuracy assessment.

Ignition Risk Model

This model was developed as described above. Note however, that some sub-components of the ignition risk model do not involve image processing/classification but rather GIS spatial analysis based upon empirical proximity to roads or mountains, etc. This makes validation quite challenging since risk of ignition does not have a field-based dataset to compare with modeled values. Further, measuring ignition risk in the field is extremely difficult --if not impossible. As a result, the accuracy assessment of this model was in essence an assessment of the vegetation type sub-component of the ignition risk model. Further, vegetation type was collected at 267 points. Thus, validation was performed with 267 samples instead of 370.

The standard/expanded accuracy assessment used four classes of ignition risk (overall accuracy was 52% (Table 3)). In the second (clumped) assessment, the two middle classes (moderate and high risk and ignition) were combined, resulting in an increase in overall accuracy (73% (Table 4)). Using the fuzzy-set-theory method, the ignition risk model yielded an overall accuracy of 85% (cf. highlighted cells, Table 3).

Table 3 - Standard/expanded accuracy assessment of vegetation types used in the ignition risk model (Kappa = 0.253).

		Risk of Ignition					
		Low	moderate	high	severe	Total	User's Accuracy
Modeled risk of ignition	Low	6	6	4	3	19	0.32
	moderate	4	90	24	6	124	0.73
	High	2	32	30	9	73	0.41
	severe	0	25	12	14	51	0.27
	Total	12	153	70	32	267	
	Producer's Accuracy	0.50	0.59	0.43	0.44		0.52

Table 4 - Clumped accuracy assessment of vegetation types used in the ignition risk model. Note: the mod-high category consists of moderate and high categories (cf. table 3) (Kappa = 0.256).

		Risk of Ignition				
		Low	mod-high	severe	Total	User's Accuracy
Modeled risk of ignition	low	6	10	3	19	0.32
	mod-high	6	176	15	197	0.89
	severe	0	37	14	51	0.27
	Total	12	223	32	267	
	Producer's Accuracy	0.50	0.79	0.44		0.73

Fuel Continuity Model

The overall accuracy of the fuel continuity model was determined using standard/expanded methodology (overall accuracy = 67.84% (Table 5)) and fuzzy-set-theory methodology (overall accuracy = 92.97% (cf. highlighted cells, Table 5)).

Table 5: Accuracy assessment of the fuel continuity model (Kappa = 0.21).

		Field estimated fuel continuity						
	class	none	low	moderate	high	severe	Total	User's Accuracy
Modeled fuel continuity	none	3	4	2	0	0	9	0.33
	low	0	17	8	1	0	26	0.65
	moderate	7	57	227	24	11	326	0.70
	high	0	0	0	0	0	0	0.00
	severe	0	1	4	0	4	9	0.44
	Total	10	79	241	25	15	370	
	Producer's Accuracy	0.30	0.22	0.94	0.00	0.27		0.68

Fuel Moisture Model

The fuel moisture model was a combination of the fuel load model (component 4, Figure 5) and the vegetation moisture model (Figure 9). To validate the accuracy of the vegetation moisture model we first reclassified the Idaho GAP vegetation dataset into three categories (i.e., wet, moderately moist, and dry, table 6). We also reclassified our vegetation moisture model (with index values ranging from -1.0 to 1.0) into three similar categories (-1.0 - -0.2, -0.2 - 0.2, 0.2 - 1.0). Accuracy was estimated as the percent agreement between these two layers as determined using standard cross-tabulation techniques (Rosenfield and Fitzpatric-Lins 1986, Carstensen 1987). Overall agreement was only 17% (Table 7), however there was very high agreement between the vegetation moisture model's wet and dry classes and the equivalent GAP-derived wet and dry classes (98% and 92% respectively). Some of the disagreement observed is attributable to the coarse nature of the GAP vegetation dataset (2.5 ha MMU) and to vegetation changes (e.g. fires, urban development and agricultural conversion) that have occurred since the last release of GAP data (2002).

Table 6- Reclassification applied to Idaho GAP dataset (2002) to determine agreement with vegetation moisture models.

Moisture category	GAP Vegetation Type
Wet	wet meadows, riparian, wetland, open water
Moderately-wet	deciduous forest, coniferous forest
Dry	high desert vegetation types (grass, shrubs, juniper), lava, barren

Table 7- Cross-tabulation agreement between GAP-derived vegetation moisture categories and our vegetation moisture model.

		GAP-derived moisture category				
	class	Wet	moderately-wet	Dry	Total	User's agreement
Vegetation Moisture model	wet	625,212	31	10,753	635,996	0.98
	mod-wet	4,755,339	526,003	11,798,562	17,079,904	0.03
	dry	192,254	6,554	2,402,117	2,600,925	0.92
	Total	5,572,805	532,588	14,211,432	20,316,825	
	Producer's agreement	0.11	0.99	0.17		0.17

Fuel Load Model

The overall accuracy of the fuel load model was determined using the three methodologies introduced earlier (standard/expanded, clumped, and fuzzy set). For the standard/expanded accuracy assessment, each fuel load class (0.74, 1.0, 2.0, 4.0, and 6.0 tons/acre) was used in the calculation yielding an overall accuracy of 47%. (Table 8). The clumped accuracy assessment, combined the fuel load classes as originally developed by Anderson (1982) (overall accuracy = 73%, table 9). Our revised model represents an improvement in classification accuracy of 13% (cf. Table 2). Estimated accuracy using fuzzy-set-theory methodology (Congalton and Green 1999) was 83% (cf. highlighted cells, Table 8).

Table 8- Standard/expanded accuracy assessment of fuel load modeling (Kappa = 0.27)

		Field Estimation of Fuel load (tons/acre)							
	Fuel load class	0.00	0.74	1.00	2.00	4.00	6.00	Total	User's Accuracy
Modeled Fuel load (tons/acre)	0.00	0	0	0	0	0	0	0	0.00
	0.74	0	24	13	8	3	0	48	0.50
	1.00	0	7	22	17	9	0	55	0.40
	2.00	0	13	18	44	27	0	102	0.43
	4.00	0	12	18	46	80	0	156	0.51
	6.00	0	0	0	1	1	3	5	0.60
	Total	0	56	71	116	120	3	366	
	Producer's Accuracy	0.00	0.43	0.31	0.38	0.67	1.00		0.47

Table 9 - Fuel load model accuracy assessment using USFS categories (Kappa = 0.39)

		Field Estimation of Fuel load (tons/acre)					
	Fuel load class	0.00	0.74 - 1.00	2.00 - 4.00	6.00	Total	User's Accuracy
Modeled Fuel load (tons/acre)	0.00	0	0	0	0	0	0.00
	0.74 - 1.00	0	66	37	0	103	0.64
	2.00 - 4.00	0	61	197	0	258	0.76
	6.00	0	0	2	3	5	0.60
	Total	0	127	236	3	366	
	Producer's Accuracy	0.00	0.52	0.83	1.00		0.73

Suppression Difficulty/Physical Risks Model

The suppression difficulty/physical risks model was created using a digital elevation model (DEM) of our study area (80mpp). Vertical positional error for this model was assumed to be the same as the error reported for standard USGS DEM's (+/- 15 meters for 90% of all well-defined points (USGS 1990)).

Wildfire Risk Model and Wildfire Risk Model (with response time)

The final wildfire risk models are weighted composites of the previously described components. It is not possible to determine the accuracy of the final wildfire risk models apart from independently assessing the accuracy of its components.

Each component of the comprehensive wildfire risk model can be used independently to explore specific types of risk (e.g., suppression difficulty, risk of ignition, risk of spread following ignition, etc.). The ignition model (component 1) is useful for identifying vegetation types consistent with increased risk. The ignition model can also be used to account for temporal variations in ignition risk (seasonality as related to phenology and vegetation moisture content, use patterns (recreational, professional, and holidays (e.g. increased recreational use on holiday weekends and firework use on and around July 4)). While the ignition risk model provides a description of areas composed of vegetation types consistent with increased risk of wildfire ignition, other factors can alter the risk (especially those that vary temporally) and must be understood and evaluated to determine the real risk at a specific time or place.

The fuel continuity model (component 2) focuses on vegetation structure characteristics to identify regions having elevated risk of wildfire spread following ignition. This model is also sensitive to the effects of temporal fluctuations resulting from phenology and weather, but less sensitive to patterns of human use. The fuel continuity model is useful to identify regions of highly continuous fuel. These areas may be candidates for fuel load reduction prescriptions (using fire, planned grazing, mechanical treatments or a combination of treatments depending on the primary fuel type.

The fuel moisture model (component 3) identifies relative risk of wildfire spread based on a combination of the amount of relative moisture (vegetation moisture) and fuel load. This model allows land managers to identify regions that not only have a large amount of fuel, but dry fuel as well. This model is susceptible to fluctuations in weather and phenology. Phenological status of plants alters the relative moisture content of vegetation as the growing season progresses. Precipitation also alters vegetation moisture but it does so over localized areas. While this model provides an overview of fuel moisture content, land managers will need to adjust the model based on seasonality and recent weather events that may have affected the model.

The fuel load model (component 4) predicts tonnage of fuel present at any given location within the study area. This model allows managers to identify regions of high fuel load that may be a consideration for fuel load reduction prescription.

The slope/aspect/suppression difficulty model (component 5) provides an overview of the topography within the study area. Severe topographic characteristics hinder fire suppression efforts and increase the rate of fire spread.

The power of these models lies in their combined use as it pertains to the particular needs of land managers. This is especially relevant when considering areas that may be candidates for fuel load reduction prescriptions. Recent studies at ISU's GIS TReC have shown that both fire and grazing can effectively reduce fuel load, with grazing more selectively removing herbaceous material, and fire removing varying levels of fuel, depending on the intensity of the fire (Weber et. al in-review, 2003). In addition, land managers can now identify regions to be protected (e.g., cultural resource and significant natural resources (habitat of threatened or endangered species)) in case wildfires threaten those regions.

CONCLUSIONS

These models provide land managers with a number of tools and applications, including predictive models of wildfire risk, identification of regions that may be candidates for fuel load reduction, identification of regions with high wildfire risk containing important cultural and natural resources, and identification of regions that where homes and structures are at risk. Local, regional, and federal agencies will benefit by using these models to 1) coordinate land management efforts to reduce fire suppression expenditures by implementing alternative means by which wildfire risk may be reduced, and 2) prevent catastrophic wildfire events that result in loss of human life, destruction of property, and damage to cultural and natural resources.

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