Fire Severity Model Accuracy Using Short-term, Rapid Assessment Versus Long-term, Anniversary Date Assessment

Keith T. Weber, GISP, Idaho State University, GIS Training and Research Center, 921 S. 8th Ave., Stop 8104, Pocatello, Idaho 83209-8104 (webekeit@isu.edu)

Steven Seefeldt, Research Agronomist, USDA-ARS, SubArctic Agricultural Research Unit, University of Alaska Fairbanks, Fairbanks, Alaska 99775

Corey Moffet, Research Rangeland Scientist, USDA-ARS, U.S. Sheep Experiment Station, Dubois, Idaho 83423

ABSTRACT
Fires are common in rangelands and after a century of suppression, the potential exists for fires to burn with high intensity and severity. In addition, the ability of fires to affect long-term changes in rangelands is considerable and for this reason, assessing fire severity after a burn is critical. Such assessments are typically carried out following Burned Area Emergency Response team or similar protocols. These data are then used by land managers to plan remediation efforts and future land uses. To complement these procedures and explore fire severity modeling of sagebrush steppe rangelands, we compared fire severity models developed using 1) short-term post-fire imagery (i.e., imagery collected within 30 days of the fire) with 2) long-term post-fire imagery (i.e., imagery collected on or about the one year anniversary date of the fire). All models were developed using Classification Tree Analysis (CTA) and Satellite Pour l'Observation de la Terre 5 (SPOT 5) imagery as well as Shuttle Radar Topography Mission (SRTM) elevation data. The results indicate that while anniversary date imagery can be used to assess fire severity (overall accuracy ~90%) it is not as accurate as using short-term imagery (overall accuracy ~97%). Furthermore, using short-term imagery allows remediation strategies to be crafted and implemented shortly after the fire. Therefore, we suggest rangeland fire severity is best modeled using CTA with short-term imagery and field based fire severity observations. The analyses and techniques described in this paper provide land managers with tools to better justify their recommendations and decisions following fires in sagebrush steppe ecosystems.

KEYWORDS: classification tree, remote sensing, wildfire, GIS

INTRODUCTION

Fires are a common occurrence throughout the Intermountain West. While historic plant communities may be adapted to fire, the frequency and intensity of today's wildfires is different compared to what occurred in the past (DeBano et al., 1998; Thoren and Mattsson 2002). The change in frequency and intensity can be attributed to 1) fire suppression efforts that have inadvertently created fuel stockpiles (Pyne et al 1996) and 2) the conversion of sagebrush-grass communities to fire-promoting cheatgrass (*Bromus tectorum* L.) dominated communities (Brooks et al 2004). The consequences of these differences are manifest in various impacts on wildlife habitat, forage production, potential soil erosion (Pierson et al., 2001; Finley, 2006; Moffet et al., 2007), and rangeland health (Pyke et al., 2002). Assessing the effect of wildfires is important to land management agencies to minimize threats to life/property and prevent unacceptable degradation of natural and cultural resources (Sharon Paris, pers. comm.; Department of Interior 2004). However, due to the broad extent and distribution of wildfires in the Intermountain West the ability of land managers to closely evaluate each and every fire can be logistically difficult if not impossible. For these reasons, the application of remote sensing models that accurately and reliably classify fire severity may be useful (Lentile et al 2006).

Several image processing methods have been used to model fire severity (Garcia and Chuvieco, 2004) with most being designed around forested ecosystems (Turner et al., 1994; White et al., 1996; Patterson and Yool, 1998; Van Wagtendonk et al., 2004; Brewer et al., 2005; Epting et al., 2005). Prior to 1999, the most widely used fire severity modeling method was an NDVI-based technique to estimate biomass loss, and hence, fire severity (Salvador et al., 2000; Diaz-Delgado et al., 2003; Flasse et al., 2004). In 1999, the normalized burn ratio (NBR) technique was developed and has been widely applied and accepted (Key and Benson 1999; Salvador et al., 2000; Key and Benson, 2006).

Another form of the NBR model is known as a differenced NBR (dNBR). It estimates fire severity by comparing a pre-burn NBR model to that of a post-burn NBR model. The result is a model where the magnitude of change has been normalized by pre-burn landscape characteristics (Key and Benson 1999; Key and Benson, 2004; Van Wagtendonk et al., 2004; Cocke et al., 2005). Yet another fire severity modeling approach that has worked well within forested ecosystems relies upon long-term imagery or anniversary date imagery to fully assess the severity of the fire. This approach is based upon the concept that tree mortality is not always evident immediately after a fire and that total tree mortality (including indirect mortality [where a tree is made susceptible to insect infestation and/or disease due to the fire]) may be best determined by examining the fire area a full growing season after the fire (Fraser and Li 2002).

Recent fire severity studies reported by Finley (2006) and Norton (2006) suggest the fire severity modeling techniques developed for forested ecosystems are not well-suited to sagebrush-steppe ecosystems, and research by (Weber et al. 2008) has demonstrated the application of classification tree analysis (CTA) for fire severity modeling of rangelands with favorable results. CTA is a non-probabilistic, non-parametric statistical technique well-suited to modeling skewed, non-normal data and phenomena (Breiman et al. 1998; Friedl and Brodley 1997; Lawrence and Wright 2001; Miller and Franklin 2001). The CTA algorithms select useful spectral and ancillary data which optimally reduce divergence in a response variable (Lawrence and Wright 2001) such as fire severity observations. CTA uses machine-learning to perform these binary recursive splitting operations and ultimately yields a classification tree diagram that is used to produce a model of the response variable. Splitting algorithms common to CTA include entropy, gain ratio, and Gini. The entropy algorithm has a tendency to over-split and thereby creates an unnecessarily complex tree (Zambon, et al., 2006). The gain ratio algorithm addresses the over-splitting problem through a normalization process while the Gini algorithm attempts to partition the most homogeneous clusters first using a measure of impurity (McKay and Campbell 1982; Zambon et al., 2006).

The goal of this study was to compare a fire severity model derived using short term post-fire imagery versus one derived from long-term (anniversary date) post-fire imagery. Specifically we tested which model best described fire severity, defined as the amount of fuel (e.g., vegetation and litter) removed within the fire perimeter.

METHODS

Study Area

This study focuses upon a prescribed fire at the Hitching Post pasture at the U. S. Sheep Experiment Station (USSES) near Dubois, Idaho (Figure 1). The prescribed burn was begun September 14th and extinguished September 15th, 2005. The fire boundary encompassed 2.44 km^2 within the Hitching Post pasture (112° 7' W 44° 19' N), a 3.24 km^2 fenced parcel on the USSES that ranges in elevation from 1765 to 1800 m. Mean annual precipitation (1971 to 2000) at the Dubois Experiment Station (112° 12' W 44° 15'N, elevation, 1661 m) is 331 mm with 60% falling during April through September. Soils are mapped as complexes of Maremma (Fine-loamy, mixed, superactive, frigid Calcic Pachic Argixerolls), Pyrenees (Loamy-skeletal, mixed, superactive, frigid Typic Calcixerolls), and Akbash (Fine-loamy, mixed, superactive, frigid Calcic Pachic Argixerolls) soils on slopes less than 20 percent, but mostly 0 to 12 percent (NRCS 1995).

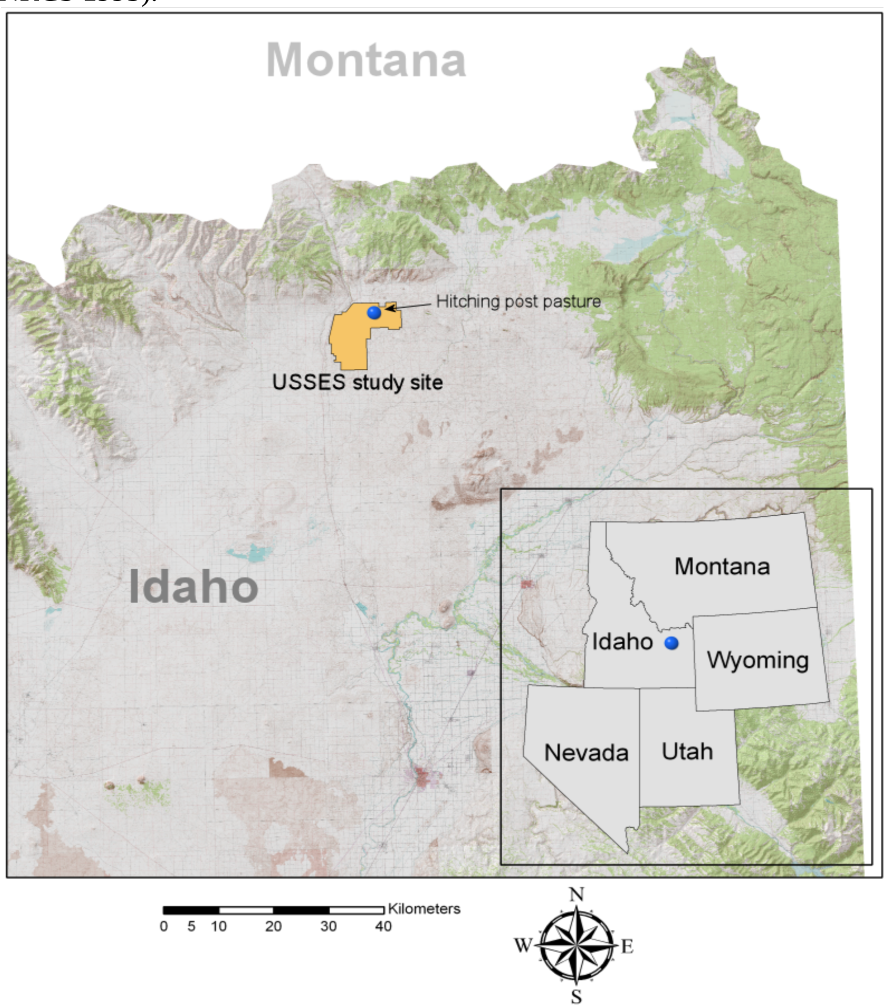

Figure 1. Location of the USDA ARS Sheep Experiment Station and site of the prescribed fire used in this study.

Vegetation on the study site is a sagebrush-grass community dominated by mountain big sagebrush (*Artemisa tridentata* ssp. *vaseyana* [Rydb.] Beetle) and threetip sagebrush (*A. tripartita* Rydb.). Subdominant shrub species include antelope bitterbrush (*Purshia tridentata* [Pursh] DC.), yellow rabbitbrush (*Chrysothamnus viscidiflorus* (Hook.) Nutt.), and spineless horsebrush (*Tetradymia canescens* DC.). There are a few small patches of the exotic forbs leafy spurge (*Euphorbia esula* L.) and spotted knapweed (*Centaurea stoebe* L. ssp. *micranthos* [Gugler] Hayek) and trace amounts (<1% of overall plant cover) of the exotic annual cheatgrass. Lupine (*Lupinus argenteus* Pursh) is the most plentiful forb on the study site and the graminoids present are thickspike wheatgrass (*Elymus lanceolatus* [Scribn. & J.G. Sm.] Gould ssp. *lanceolatus*), bluebunch wheatgrass (*Pseudoroegneria spicata* [Pursh] A. Löve ssp. *spicata*), and plains reedgrass (*Calamagrostis montanensis* Scribn. ex Vasey).

The management of this pasture for the past decade has been light, short duration, grazing with sheep and horses in spring and/or fall. There was no grazing in this pasture during the 2.5 years prior to the prescribed burn of September 14th and 15th, 2005.

Field Sampling

Beginning one week after the prescribed burn, 277 randomly selected sample areas (60 x 60 m) were visited to assess fire severity. The sample areas were located on the ground by navigating to the preselected area with a GPS receiver using real-time positioning. These positions were later post-process differentially corrected to achieve a horizontal positional accuracy of <1m (Serr et al. 2006). While subjective, a fire severity rating (0 = Unburned, no vegetation change; 1 = little vegetation/fuel burned; 2 = most of the vegetation was burned; and 3 = burned (all vegetation was considered completely burned) was assigned to each area visited following methods modified from the combined work of US Forest Service field methods (Bobbe et al., 2001), the US Park Service field methods (Switky 2003), and Key and Benson's (Key and Benson 1999; 2004) composite burn index (CBI). Groups one (n=13) and two (n=57) were later combined as the13 areas assigned to group one were insufficient for validation. Furthermore, some aspects of fire severity can be quantified but classification of general severity has proven difficult. Classification of burn or fire severity, based on post-fire appearances of litter and soil (Ryan and Noste 1983), are useful for placing severity into broadly defined, discrete classes, ranging from low to high. A general burn severity classification developed by Hungerford (1996) in forest situations relates burn severity to soil resource response and has three classes; low, moderate, and high. In rangeland ecosystems the medium and high severity classes described by Hungerford merge as there is not a large woody component and a deep duff layer, whose response to burning differentiates the classes. Therefore, we chose a simple classification of low or high severity and as a result, three classes remained, 0 (unburned), 1 (low fire severity), and 2 (high fire severity).

It was not an objective of this study to differentiate burned from unburned areas with remote sensing/image processing techniques and for this reason all unburned sample areas (n=9) were omitted from subsequent processing.

Image Processing

Post-fire Satellite Pour l'Observation de la Terre 5 (SPOT 5) imagery (10m x 10m pixels) was acquired for the USSES study site on September 28, 2005 (short term post-fire imagery) and September 27, 2006 (long term post-fire imagery). The imagery was georectified using 1 m National Agricultural Imagery Program orthophotography for the study area (RMSE = 3.48 and 4.71) using ArcGIS 9.1, corrected for atmospheric effects using Idrisi and projected into Idaho Transverse Mercator (NAD 83) using a first order affine transformation and nearest neighbor resampling.

Normalized difference vegetation index (NDVI), normalized burn ratio (NBR), and biomass estimates (Mirik et al., 2005) were calculated within Idrisi Kilimanjaro using SPOT reflectance data. The biomass layer is a simple ratio-type vegetation index where reflectance values from the short-wave infrared region (band) are divided by reflectance values from the green band. While Mirik et al. (2005) demonstrated a strong empirical relationship (R^2 = 0.87) between this index and total rangeland biomass, the relationship of the biomass index and actual rangeland biomass was not performed as part of this study. The biomass index differs from the normalized difference infrared index (NDII [Hunt and Yilmaz 2007]) in that the biomass index is a simple ratio-type index as opposed to a normalized difference-type index and the biomass index does not make use of the infrared band as does NDII. Another related normalized difference-type index is the normalized difference water index (NDWI) which uses the ratio of the difference between the near infrared and thermal infrared bands divided by the sum of these same bands (Gu et al. 2007). Neither the NDII nor NDWI were used in this study (NDWI cannot be used with SPOT imagery as this sensor does not include a thermal infrared band). Topography layers were also assembled for use as ancillary data within the CTA process (Elumnoh and Shrestha 2000). Elevation data were acquired from the shuttle radar topography mission (SRTM) and resampled to 10m to match the spatial resolution of the SPOT 5 imagery. Slope and aspect models were derived from these elevation data using Idrisi Kilimanjaro.

Polygon shapefiles describing the fire perimeters were rasterized and used as a mask for all raster data. Field observations were similarly masked and only those points falling inside the fire perimeter were used in the CTA. This masking process was done to help facilitate classification by prudently applying ancillary knowledge to better inform the classifier. This process is a well accepted technique referred to as “cluster busting” (Jensen 1996; Hunter 2004). CTA was performed using the Gini splitting algorithm (Zambon et al., 2006) with five input images. The datasets contained near-infrared (NIR), NDVI, NBR, and biomass band-ratios, along with the slope layer. These layers were selected based upon performance results from previous work reported in Weber et al. 2008.

To absorb georegistration error within the SPOT imagery (RMSE=3.48 and 4.71) and ensure correct and representative pixels were included in the analysis, all sample areas were buffered by 5m (Weber 2006). The resulting layers were rasterized using ArcGIS 9.1 and subset into training and validation sites. As a result, a total of 385 training site pixels and 207 validation site pixels were created. The CTA was performed with Idrisi Kilimanjaro using these data.
The resulting fire severity models were compared using a full cross-classification/cross tabulation procedure in Idrisi. Cramer’s V and the Kappa Index of Agreement were used to determine the level at which the models agreed with one another (Rosenfield and Fitzpatrick-Lins 1986; Cartensen 1987).

RESULTS AND DISCUSSION

The CTA model developed using short-term post-fire imagery (NIR, NDVI, NBR, biomass, and slope), correctly identified all 186 high fire severity validation areas (n = 186, user accuracy = 100%). Similarly, the CTA model developed using long-term post-fire imagery correctly identified 179 of the 186 high fire severity validation areas (user accuracy = 93%). However, user accuracy of the low fire severity area decreased from 66% using short-term imagery to 39% using long-term imagery (Tables 1 and 2, respectively). In addition, the Kappa index of agreement similarly declined from 0.78 to 0.44 respectively.

The confusion with the low fire severity class was most likely due to the regrowth of vegetation following the fire. Field observations made during the summer of 2006 (n = 233) recorded over 100 sample points with 16-25% cover of grasses. In addition, nearly 100 sample points were recorded having 6-15% shrub cover, the majority of which was rabbitbrush (*Chrysothamnus spp*.) that established following the fire. Yet another factor affecting ground cover at the USSES was the presence of a large amount of forbs, primarily lupine. Ninety six of 233 sample points had forb cover estimates (i.e., lupine) between 16-25%.

Table 1. Classification tree analysis (CTA) results for fire severity modeling derived using short term post-fire raster layers.

	Known validation sites			
	Low fire severity	High fire severity	Total	User accuracy
Low fire severity	14	7	21	0.66
High fire severity	0	186	186	1.00
Total	14	193	207	
Producer's accuracy	0.93	0.97		0.97[a]

[a] Overall accuracy

Kappa index of agreement = 0.78

Table 2. Classification tree analysis (CTA) results for fire severity modeling derived using long term (anniversary date) post-fire raster layers.

	Known validation sites			
	Low fire severity	High fire severity	Total	User accuracy
Low fire severity	9	14	23	0.39
High fire severity	5	179	184	0.97
Total	14	193	207	
Producer's accuracy	0.64	0.93		0.91[a]

[a] Overall accuracy

Kappa index of agreement = 0.44

Cross-classification and cross-tabulation of these models showed 87.6% overall agreement due to the similarity in how these two models predicted high fire severity areas. This comparison further reinforced a disagreement regarding low fire severity areas. As mentioned above, a number of areas exhibited a relatively rapid re-growth of lupine which accounts for the change classification of high severity fire in the short-term model to a low severity fire in the long-term model. In contrast, a less well understood change in classification was also brought to attention through the cross-tabulation procedure; nearly 16 ha (6%) of the study area changed from low fire severity (in the short-term model) to high fire severity in the long-term model (Figure 2 and Table 3). Since field-based data corroborates the predictions of the short-term model better than the long-term model, one is left to speculate about what may have occurred in these areas during the year following the fire. Analysis of 2006 field data and photo points offer a few possible explanations: While the mean bare ground cover class recorded in all areas considered low fire severity in the short-term model was 16-25% (n=16), the mean shrub cover class in areas in agreement for low fire severity was 6-15% while those areas in disagreement for low fire severity had a mean shrub cover of 1-5%. This may indicate that some of the areas within the perimeter of the fire recovered more slowly (which could be as much attributable to environmental factors as to the severity of the fire) it must be remembered that this speculation is based upon only 16 field observations. Further post-fire sampling should be conducted to monitor the recovery of these areas and determine if any real differences truly exist.

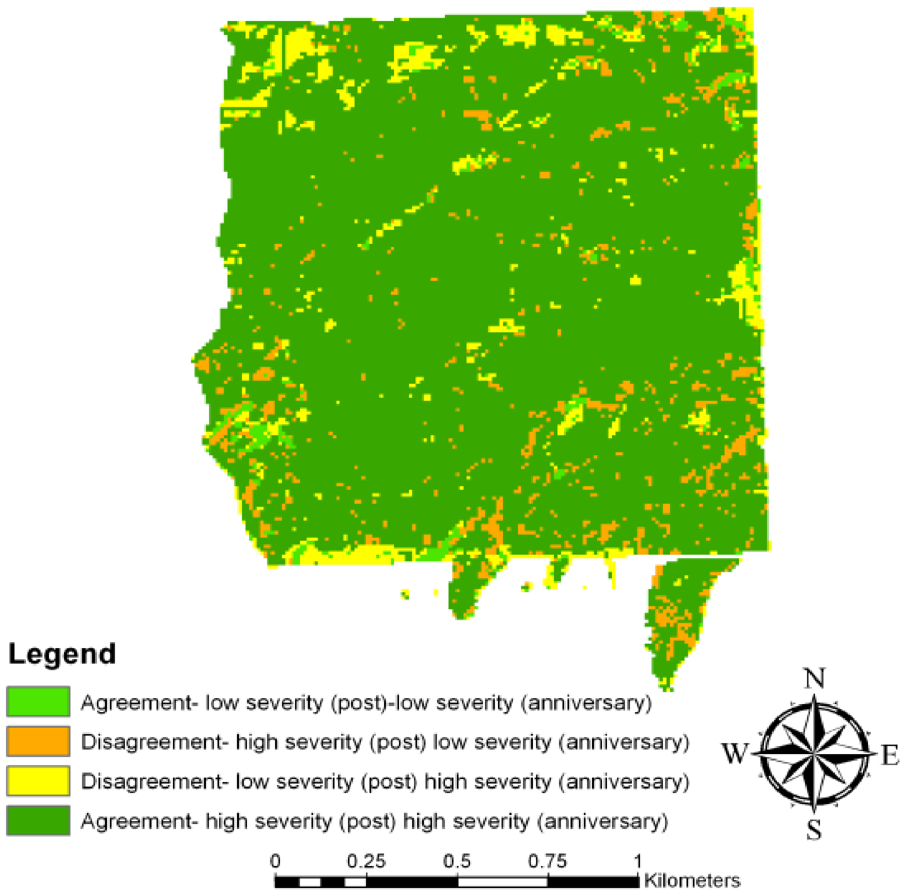

Figure 2. Cross-tabulation between short-term (post-fire imagery) and long-term (anniversary date imagery) fire severity models.

Table 3. Cell-by-cell cross-tabulation comparison of fire severity models produced using short-term (post fire) imagery (columns) and long-term (anniversary date) imagery (rows). Percent of pixels in each category are given in parenthesis.

		Short-term (post-fire) imagery		
		Low fire severity	High fire severity	Total
Long-term (anniversary date) imagery	Low fire severity	432 (2%)	1452 (6%)	1884 (8%)
	High fire severity	1580 (6%)	20941 (86%)	22521 (92%)
	Total	2012 (8%)	22393 (92%)	24405 (100%)

Based on the comparison of accuracies and overall agreement between the two models it seems clear that performing a fire severity assessment one year after a fire in sagebrush steppe rangelands yields little benefit for the land manager. In both cases, most high fire severity areas remain clearly distinguishable (further corroborating the accuracy of the short-term fire severity model) even one year post-fire, but the benefit of having an accurate fire severity model to plan remediation efforts shortly after a fire offers numerous distinct advantages for land managers such as starting remediation before winter and developing plans and collecting resources in the winter for early spring restoration activities.

Assessment of error and bias

Models developed using CTA were able to classify high fire severity areas with good user accuracy (~100%) (cf. Figure 3 for a step-by-step approach and cartographic model of this technique). However, achieving satisfactory results appears to be a function of adequate sample size for each class considered (low fire severity or high fire severity). Initially, it may appear that a disproportionately large number of validation sites were used in high fire severity areas (n=193, 92%; Tables 1 and 2). However, as fire severity is primarily a function of the fire's behavior --which is closely tied to factors such as the amount and type of fuels and the weather during the fire (Pyne et al. 1996) -- the proportion of high fire severity sites (used for both modeling and validation) agreed well with field observations where 92% of the study area was recorded as high severity (Figure 4). Indeed when the proportions of the random sampling locations were compared with proportions of fire severity areas, the results appear equitably distributed.

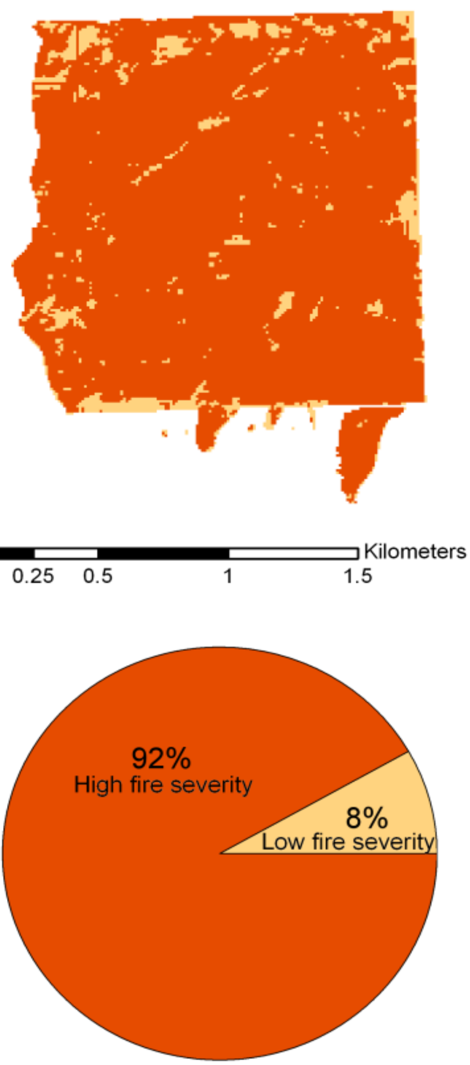

Figure 3. Relative proportions of fire severity.

Management Implications

Land managers who are tasked with assessing fire severity in rangelands and developing remediation plans within a short time of fire control cannot rely on field inspection to provide adequate coverage, especially on large fires. The use of easily obtained SPOT 5 satellite imagery, soon after the fire, combined with a moderate amount of field sampling will result in an accurate delineation of high severity burn areas where remediation efforts will need to be focused. The cost of obtaining the imagery will be recouped by the savings from reduced field time and the speed with which remediation plans of improved quality and accuracy can be developed.

CONCLUSIONS

Post-fire vegetation management in western rangelands should be based on pre-fire vegetation, post-fire weather conditions, soils, available resources (such as seeds, equipment, and personnel), and fire severity. Given the size and distribution of western fires, land managers face an almost impossible task in trying to determine fire severity within a time frame useful for the preparation of remediation plans. The development of GIS layers that combine vegetation information, climate, soils, and fire severity could ease the task of creating predictive models for more effective remediation plan development. The results of this research addresses mapping of fire severity, which can be used as one layer within a GIS-based remediation and decision support model. Using easily obtained post-fire SPOT 5 imagery, high severity burn areas can be accurately, rapidly, and inexpensively delineated; resulting in a GIS layer useful for remediation plan development.

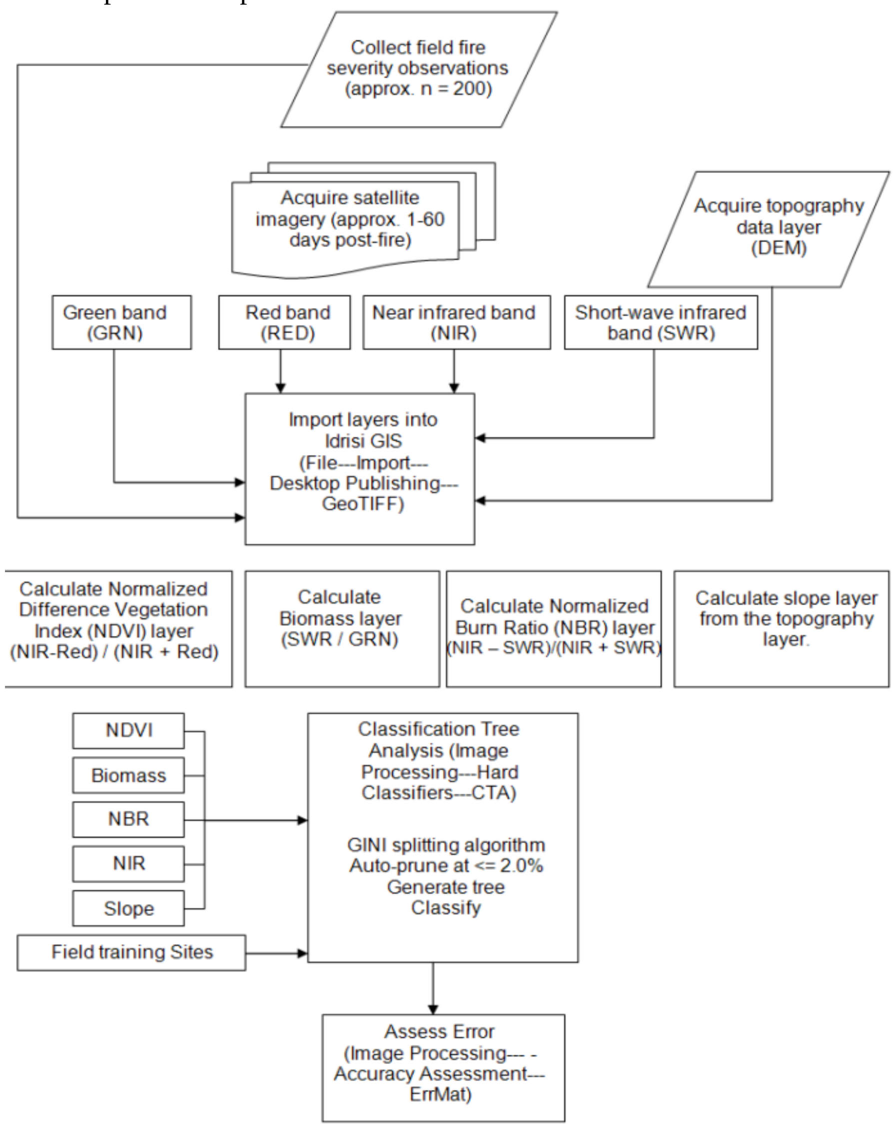

Figure 4. Cartographic model of the process followed to produce a fire severity model using classification tree analysis at the USSES study site.

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