Comparing Fire Severity Models from Post-Fire and Pre/Post-Fire Differenced Imagery

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ABSTRACT

Wildland fires are common in rangelands worldwide. The potential for high severity fires to affect long-term changes in rangelands is considerable, and for this reason assessing fire severity shortly after the fire is critical. Such assessments are typically carried out following Burned Area Emergency Response teams or similar protocols. These data can then be used by land managers to plan remediation and future land uses. To complement these procedures and explore fire severity modeling of sagebrush steppe rangelands, we compared models developed using 1) post-fire imagery only with 2) differenced imagery (pre-fire minus post-fire imagery). All models were developed from Classification Tree Analysis (CTA) techniques using Satellite Pour l'Observation de la Terre 5 (SPOT 5) imagery and Shuttle Radar Topography Mission (SRTM) elevation data. The results indicate that both techniques produced similar fire severity models (model agreement = 98.5%) and that little improvement in overall accuracy was gained by using differenced imagery (0.5 %). Therefore, we suggest the use of CTA models developed using only the post-fire imagery. The analyses and techniques described in this paper provide land managers with tools to better justify their recommendations and decisions following wildland fires in sagebrush steppe ecosystems.

KEYWORDS: classification tree, remote sensing, wildfire, GIS

INTRODUCTION

Wildland 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); most have been designed for 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).

While fire severity studies reported by Finley (2006) and Norton (2006) suggest the NBR techniques may not be well-suited to sagebrush-steppe ecosystems, more recent research (Weber and Seefeldt, 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).

A previous study reported by Weber et al (2008) described fire severity models created using post-fire satellite imagery only. The goals of this study were to model fire severity in semi-arid rangelands and compare the results derived using post-fire imagery only with results from differenced imagery (i.e., derived from pre- and post-fire differenced imagery). Specifically, we will test whether the CTA model derived using post-fire only imagery satisfactorily classifies high severity fire areas in the sagebrush steppe.

METHODS

Study Area

This study focuses upon the Hitching Post pasture burn at the U. S. Sheep Experiment Station (USSES) near Dubois, Idaho (Figure 1). The prescribed burn was begun September 14th and was 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).

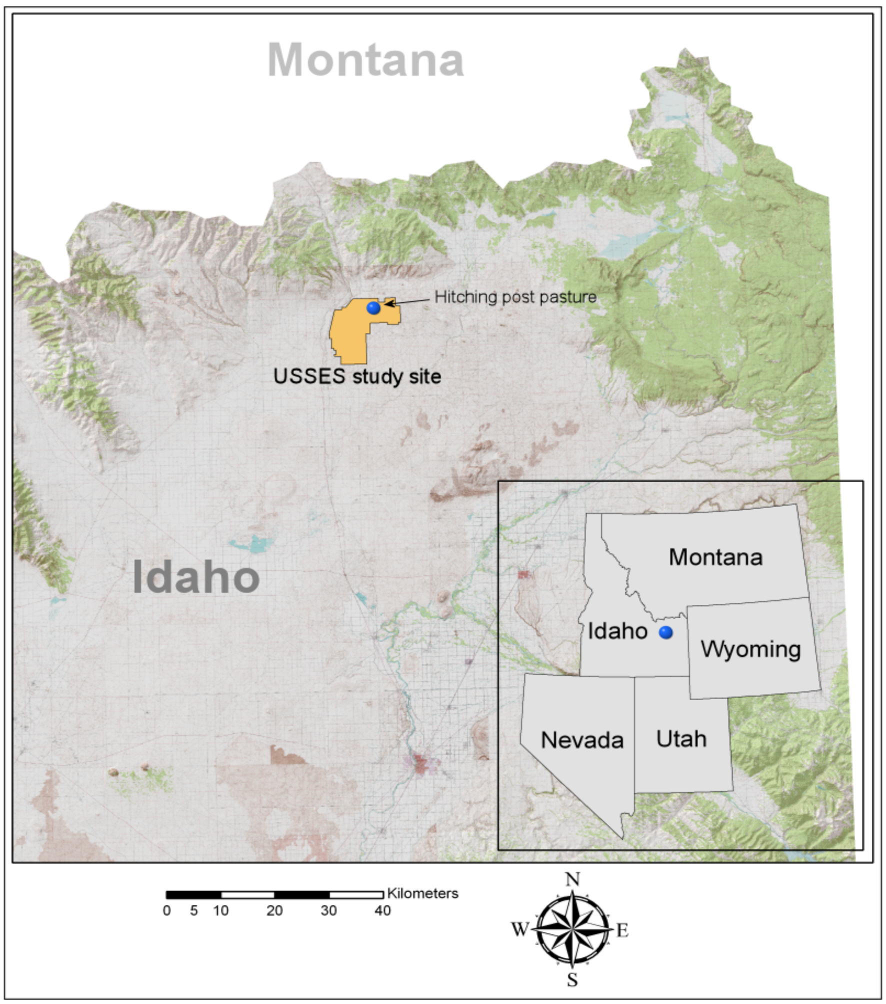

Figure 1. Location of the USDA ARS Sheep Experiment Station and site of the prescribed fire used in this study.

Vegetation on the study site is a sagebrush-grass community that is 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.

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 consumption by the fire; 2 = most of the vegetation was consumed; and 3 = burned (the area was considered a completely consumed by the fire) 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 because only 13 areas were assigned to group one which was insufficient for validation. In addition, some aspects of fire severity can be quantified but classification of general severity has proven difficult. Classification of burn or fire severity, based on the post-fire appearance 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 are not large woody component and 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 separate burned from unburned areas and for this reason all unburned sample areas were omitted from subsequent processing. We recognize that the few unburned areas within the fire perimeter (n=9) would not be classified as unburned, but most likely, would be classified as low fire severity areas based upon preliminary classification results (i.e., using unburned areas in the analysis). Preliminary analyses further indicated that spectral signatures of unburned and low fire severity sites were very similar and spectrally indistinct (Richards 1993; Lillesand and Kiefer 2000). This potential for error however, was considered acceptable because the focus of the study was to develop a model that would correctly identify high fire severity areas so land managers performing post-fire recovery planning and remediation could focus their resources on high fire severity areas.

Image Processing

Pre- and post-fire Satellite Pour l'Observation de la Terre 5 (SPOT 5) satellite imagery (10m x 10m pixels) was acquired for the USSES study site for August 27, 2005 and September 28, 2005, respectively. The imagery was georectified using 1 m National Agricultural Imagery Program orthophotography for the study area (RMSE = 3.48) using the same set of control points within ArcGIS, corrected for atmospheric effects 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 (the ratio of the short-wave infrared band divided by the visible green band [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).

In addition, topography data were 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 was 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 post-fire condition dataset contained near-infrared (NIR), NDVI, NBR, and biomass band-ratios, along with the slope layer. The pre-post fire differenced dataset contained differenced NIR (dNIR), differenced NDVI (dNDVI), differenced NBR (dNBR) (Key and Benson 1999; Key and Benson, 2004; Van Wagtendonk et al., 2004; Cocke et al., 2005), differenced biomass, and the same slope layer. In each case, image differencing was performed by subtracting the post-fire imagery from the pre-fire imagery.

To absorb georegistration error within the SPOT imagery (RMSE=3.48) 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.

RESULTS AND DISCUSSION

The CTA model developed using five post-fire satellite imagery layers (NIR, NDVI, NBR, biomass, and slope) correctly identified all 186 high fire severity validation areas (n = 186, user accuracy = 100%) (Figure 2a, Table 1). Similarly, using five differenced input layers (dNIR, dNDVI, dNBR, differenced biomass, and the same slope topography layer) user accuracy was 99.5% (Figure 2b, Table 2). While overall accuracy intially appears to be better using differenced imagery (97.1% compared with 96.6%), this slight difference is considered insignificant. Statistically testing this difference is problematic however as each model exhibits a high degree of autocorrelation (Moran’s I = 0.55 and 0.51 for post-fire and differenced imagery, respectively) and due to the large number of pixels within each model, statistical tests like mixed linear models would calculate a very small standard error (due to the high proportion of pixels in agreement) thereby causing the test to detect differences whether they were practically significant or not (Teri Peterson, pers. comm.). The authors argue that any differences reported here is not of practical significance.

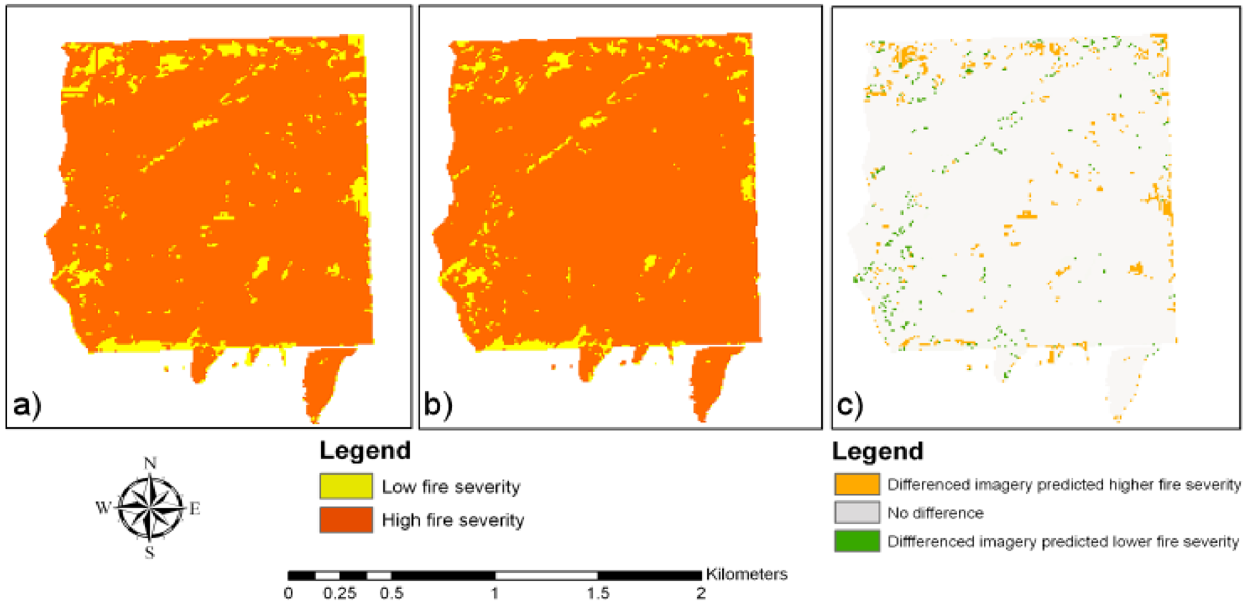

Figure 2. Resulting fire severity models produced using classification tree analysis (CTA) with post-fire imagery (a), differenced imagery (b), and differenced models (c).

Map arithmetic techniques were used to identify those areas (pixels) where the two models predicted different fire severity levels (Figure 2c). Nearly all pixels exhibited agreement in predicted fire severity (98.5%). The majority of the disagreement (73% of all disagreement pixels) was in areas where the differenced imagery model predicted a high fire severity class, but the post-fire imagery model predicted low fire severity (i.e., the differenced imagery model predicted more area burned with high fire severity).

Table 1. Classification tree analysis (CTA) results for fire severity modeling derived using 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

Based on overall accuracies and level of agreement between the two models it is clear that producing a reliable fire severity model in sagebrush steppe ecosystems can be accomplished using just post-fire imagery. Acquiring both pre- and post-fire imagery and producing differenced image layers adds tremendously to the cost and effort with no improvement in the resulting model for this burn; however, this may not be true for all rangelands. Additional studies are merited to determine whether this is true for other rangelands.

Table 2. Classification tree analysis (CTA) results for fire severity modeling derived using differenced raster layers.

	Known validation sites			
	Low fire severity	High fire severity	Total	User accuracy
Low fire severity	13	5	18	0.72
High fire severity	1	188	189	0.99
Total	14	193	207	
Producer's accuracy	0.93	0.97		0.97[a]

[a] Overall accuracy

Kappa index of agreement = 0.80

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 2a, b). Indeed when the proportions of the random sampling locations were compared with proportions of fire severity areas, the results appear equitably distributed.

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 determining fire severity in 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 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.

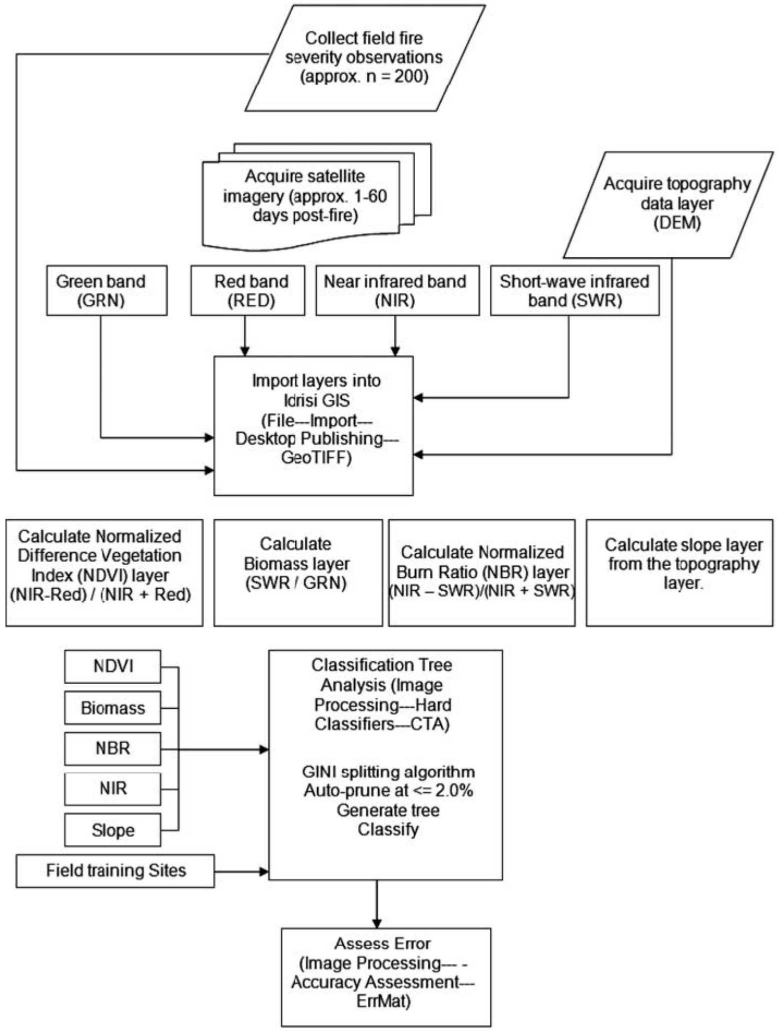

Figure 3. Cartographic model of the process followed to produce a fire-severity model using classification tree analysis at both the Clover and USSES study sites.

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LITERATURE CITED

Bobbe, T., M. V. Finco, B. Quayle, B., and K. Lannon. 2001. Field measurements for the training and validation of burn severity maps from spaceborne, remotely sensed imagery. Remote Sensing Applications Center, Salt Lake City, Utah: USDA Forest Service, Final Project Report, Joint Fire Science Program-2001-2. Project # 01B-2-1-01, pp. 15 URL: http://www.fs.fed.us/eng/rsac/baer/final_report_01B-2-1-01.pdf Visted April 2007.

Breiman, L., Friedman, J. H., Olshen, R. A., and Stone C. J., 1998, Classification and Regression Trees. Chapman and Hall, CRC press, Boca Raton, Florida. 358 pp.

Brewer, C.K., J. C. Winne, R. L..Redmond, D. W. Opitz, and M. V. Mangrich. 2005. Classifying and mapping wildfire severity: A comparison of methods. Photogrammetric Engineering and Remote Sensing, 71:11, 1311-20.

Brooks M. L., C. M D'Antonio, D. M. Richardson, J. B. Grace, J. E Keeley, J. M. DiTomaso, R. J. Hobbs, M. Pellant, and D. Pyke. 2004. Effects of Alien Plants on Fire Regimes. Bioscience. 54(7):677-688.

Cocke, A.E., P. Z. Fule, and J. E. Crouse. 2005. Comparison of burn severity assessments using differenced normalized burn ratio and ground data. International Journal of Wildland Fire, 14: 189-98.

DeBano, L.F., Neary, D.G., and Pfolliott, P.F., 1998, Fire's Effects on Ecosystems: New York, John Wiley and Sons, 333 pp.

Department of the Interior (DOI). 2004. Departmental Manual, Part 620 Chapter 3, Burned Area Emergency Stabilization and Rehabilitation (620DM3), 16 pp.

Diaz-Delgado, R., F. Lloret, and X. Pons. 2003. Influence of fire severity on plant regeneration by means of remote sensing imagery. International Journal of Remote Sensing, 24:8, 1751-1763.

Epting, J., D. Verbyla, and B. Sorbel. 2005. Evaluation of remotely sensed indices for assessing burn severity in interior Alaska using Landsat TM and ETM+. Remote Sensing of Environment, 96, 328-339.

Elumnoh A. and R. P. Shrestha. 2000. Application of DEM Data to Landsat Image Classification: Evaluation in a Tropical Wet-Dry Landscape in Thailand. Photogrammetric Engineering and Remote Sensing. 66(3):297-304.

Flasse, S., S. Trigg, P. Ceccato, A. Perryman, A. Hudak, M. Thompson, B. Brockett, M. Dramé, T. Ntabeni, P. Frost, T. Landmann, and J. le Roux. 2004. Remote sensing of vegetation fires and its contribution to a fire management information system. In J.G. Goldammer and C. de Ronde (Eds.), *Wildfire Management Handbook for Sub-Sahara Africa* (pp.158-211). The Hague, Netherlands: SPB Publishing.

Finley, C. D. 2006. Field evaluation and hyperspectral imagery analysis of fire-induced water repellent soils and burn severity in southern Idaho rangelands. Idaho State University. URL: http://giscenter.isu.edu/Research/techpg/nasa_tlcc/to_pdf/cfthesis.pdf visited April 2007. 237pp.

Friedl, M. A. and Brodley, C. E., (1997), Decision tree classification of land cover from remotely sensed data. Remote sensing of environment. 61(3):399-409.

Garcia, M. and E. Chuvieco. 2004. Assessment of the potential of SAC-C/MMRS imagery for mapping burned areas in Spain. Remote Sensing of Environment, 92, 414-423.

Gu, Y., Brown, J. F., Verdin, J. P., and Wardlow B. 2007, A five-year analysis of MODIS NDVI and NDWI for grassland drought assessment over the central Great Plains of the United States. Geophysical Research Letters, 34(L06407). 6 pp.

Hungerford, R.D. 1996, Soils. Fire in Ecosystem Management Notes: Unit II-I. USDA Forest Service, National Advanced Resource Technology Center, Marana, Arizona

Hunt, E. R. and Yilmaz, T. 2007, Remote sensing of vegetation water content using shortwave infrared reflectance. Summaries of International Society for Optical Engineering. URL: http://ars.usda.gov/research/publications/publications.htm?seq_no_115=209592 visited January 2008.

Hunter, B. 2004, Overview of Methodology for Remote Sensing/GIS Analysis of Lakes Lewisville and Grapevine Shoreline Management Project. University of North Texas, URL:

Inouye, R. 2002. Sampling Effort and Vegetative Cover Estimates in Sagebrush Steppe. *Western North American Naturalist* 62(3): 360-364.

Jensen, J. R. 1996, Introductory Digital Image Processing. Prentice Hall, New Jersey. p. 238

Key, C.H. and N. C. Benson. 1999. The Normalized Burn Ratio (NBR): A Landsat TM Radiometric Index of Burn Severity. URL: http://www.nrmsc.usgs.gov/research/ndbr.htm; visited April 2007.

Key, C.H. and N. C. Benson. 2004. Remote Sensing Measure of Severity: The Normalized Burn Ratio. FIREMON Landscape Assessment (LA) V4 Sampling and Analysis Methods. pp. LA1-16.

Key, C.H. and N. C. Benson. 2006. Landscape Assessment (LA) Sampling and Analysis Methods. USDA Forest Service Gen. Tech. Rep. RMRS-GTR-164-CD. pp. 55.

Lawrence, R. L. and A. Wright. 2001. Rule-based Classification Systems Using Classification and Regression Tree (CART) Analysis. Photogrammetric Engineering and Remote Sensing. 67(10):1137-1142.

Lentile, L. B., Z. A Holden, A. M. S. Smith, M. J. Falkowski, A. T. Hudak, P. Morgan, S. A. Lewis, P. E. Gessler, and N. C. Benson. 2006. Remote Sensing Techniques to Assess Active Fire Characteristics and Post-Fire Effects. Intl. Journal of Wildland Fire. 15(3):319-345.

Lillesand T. M. and R. W. Kiefer. 2000. Remote Sensing and Image Interpretation. 4th Ed. John Wiley and Sons, New York, NY. 724pp.

McKay, R.J. and Campbell, N.A. 1982. Variable selection techniques in discriminant analysis II: Allocation, British Journal of Mathematical and Statistical Psychology, 35, 30-41.

Miller, J. and J. Franklin, 2001. Modeling the distribution of four vegetation alliances using generalized linear models and classification trees with spatial dependence. Ecological Modeling, 157: 227–247.

Mirik, M., J. E. Norland, R. L. Crabtree, and M. E. Biondini. 2005. Hyperspectral One-Meter-Resolution Remote Sensing in Yellowstone National Park, Wyoming: II Biomass. Rangeland Ecology and Management. 58(5):459-465.

Moffet, C.A., F.B. Pierson, P.R. Robichaud, K.E. Spaeth, and S.P. Hardegree. 2007. Modeling soil erosion on steep sagebrush rangeland before and after prescribed fire. Catena, 71:218-228.

Natural Resources Conservation Service (NRCS). 1995. Soil investigation of Agriculture Research Service, United States Sheep Experiment Station headquarters range, US Department of Agriculture. Rexburg, ID: NRCS. 133pp.

Norton, J. 2006. The Use of Remote Sensing Indices to Determine Wildland Burn Severity in Semiarid Sagebrush Steppe Rangelands Using Landsat ETM+ and SPOT 5. Idaho State University. URL: http://giscenter.isu.edu/Research/techpg/nasa_tlcc/to_pdf/jnthesis.pdf visited April 2007. 111pp.

Patterson, M.W. and S. R. Yool. 1998. Mapping fire-induced vegetation mortality using Landsat Thematic Mapper data: A comparison of linear transformation techniques. Remote Sensing of Environment, 65, 132-42.

Pierson, F.B., P.R. Robichaud, and K.E. Spaeth. 2001, Spatial and temporal effects of wildfire on the hydrology of a steep rangeland watershed. Hydrological Processes, 15:2905-2916.

Pyke D. A., J. E. Herrick, P. Shaver, and M. Pellant. 2002. Rangeland health attributes and indicators for qualitative assessment. Journal of Range Management 55:584-597.

Pyne, S. J., P. L. Andrews, and R. D. Laven. 1996. Introduction to Wildland Fire. John Wiley and Sons, New York. 769 pp.

Richards, J.A., 1993. Remote Sensing Digital Image Analysis, Springer-Verlag, New York, NY. 363 pp.

Ryan, K. C.; Noste, N. V. 1983, Evaluating prescribed fires. Pages 230-238 in Lotan, J. E.; Kilgore, B. M.; Fischer, W. C.; Mutch, R. W. (tech. cords.), *Proceedings, symposium and workshop on wilderness fire*. General Technical Report INT-182. Ogden, UT: U.S. Department of Agriculture, Forest Service, Intermountain Research Station.

Salvador, R., J. Valeriano, X. Pons, and R. Diaz-Delgado. 2000. A semi-automatic methodology to detect fire scars in shrubs and evergreen forests with Landsat MSS time series. International Journal of Remote Sensing, 21, 655-71.

Serr, K., Windholz, T. K., and Weber K. T. 2006. Comparing GPS Receivers: A Field Study. URISA Journal. 18(2):19-24.

Switky, K.R. 2003. Fire monitoring handbook: Boise, ID, 274 pp., NPS Fire management program center, National Interagency Fire Center, 274pp.

Thoren, F.and D. Mattsson. 2002. Historic Wildfire Research in Southeastern Idaho. URL: http://giscenter.isu.edu/research/techpg/blm_fire/historic/wildfire_report.pdf visited April 2007. 16pp.

Turner, M.G., W. W. Hargrove, R. H. Gardner, and W. H. Romme. 1994. Effects of fire on landscape heterogeneity in Yellowstone National Park, Wyoming. Journal of Vegetation Science, 5, 731-42.

Van Wagtendonk, J.W., R. R. Root,., and C. H. Key. 2004. Comparison of AVIRIS and Landsat ETM+ detection capabilities for burn severity. Remote Sensing of Environment, 92: 397–408.

Weber, K. T. 2006. Challenges of Integrating Geospatial Technologies Into Rangeland Research and Management. Rangeland Ecology and Management. 59(1):38-43.

Weber, K. T., S. S. Seefeldt, J. Norton, and C. Finley. 2008. Fire Severity Modeling of Sagebrush-steppe Rangelands in Southeastern Idaho. GIScience and Remote Sensing (*in press*).

White, J.D., K. C. Ryan, C. H. Key, and S. W. Running. 1996. Remote sensing of forest fire severity and vegetation recovery. International Journal of Wildland Fire, 6, 125-36.

Wright, H. E. and A. W. Bailey. 2004. Fire Ecology: United States and Southern Canada. Wiley Interscience. 528pp.

Zambon, M., R. Lawrence, A. Bunn, and S. Powell. 2006. Effect of alternative splitting rules on image processing using classification tree analysis. Photogrammetric Engineering and Remote Sensing, 72(1): 25–30.