Fire Severity Modeling of Sagebrush-Steppe Rangelands in Southeastern Idaho

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ABSTRACT
The potential for high severity fires to affect changes in rangelands is considerable, and for this reason, assessing fire severity is critical. We explored fire severity modeling in rangelands by applying post-fire field observations to Satellite Pour l'Observation de la Terre 5 (SPOT 5) imagery using Classification Tree Analysis (CTA) techniques at two 2005 burns. The results of these analyses demonstrate that CTA is equally adept at classifying areas of low severity as well as those with high severity with reliable accuracy (66-100%). Furthermore, the CTA technique is fairly uncomplicated to apply and provides an error assessment upon which land managers can better justify their recommendations.

KEYWORDS: Classification tree analysis, GIS, remote sensing.

INTRODUCTION

Wildland fire is a common occurrence throughout the Intermountain West. While historic vegetation communities may have adapted to this form of disturbance, 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 introduction of invasive weeds like *Bromus tectorum* (Cheatgrass), a fire-promoter species (Brooks et al 2004). The consequences of these differences are large-scale changes to vegetation on a landscape scale which, in turn negatively impacts wildlife habitat, forage production, soil erosion (Finley 2006), and the health of rangeland ecosystems (Pyke et al. 2002).

The effect of wildfires is perceived to be substantial and public land managers are required to assess the severity of nearly all fires occurring on public lands and prepare remediation plans for high severity burns (Sharon Paris, pers. comm. [21-September-2007]; Department of Interior 2004), especially in cheatgrass infested areas. 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 is sometimes logistically difficult if not impossible. For these reasons, the application of remote sensing models that accurately and reliably describe 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 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 (Garcia and Casseles 1991; 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)

Few techniques have been specifically developed to model fire severity in semi-arid rangelands (Smith et al. 2005; Roy et al. 2006), and to some extent, it has been accepted that the techniques applied in forested ecosystems should be equally applicable within other ecosystems. More recent studies, however, indicate this is not the case and alternative methods are required to assess fire severity within semi-arid rangeland ecosystems (Epting et al. 2005; Norton 2006). The primary reason why models developed for forests do not translate well within rangelands is the prevalence of exposed soil, in both pre- and post-burn conditions, contributing to the spectra acquired by the sensor (Okin et al 1999). In addition, a scale effect may exist related to the proportional area occupied by individual plants relative to the size of each pixel (e.g., a sagebrush plant occupies perhaps 1% of a Satellite Pour l'Observation de la Terre 5 (SPOT 5) pixel [10x10m] whereas a Douglas-fir can cover 100% of the same pixel). Consequently, the majority of pixels used in remote sensing projects over semi-arid rangelands exhibit heterogeneity within each pixel (i.e., mixed pixels or mixels), making accurate differentiation more difficult (Okin et al 2001).

Recent fire severity studies within sagebrush-steppe ecosystems in southeastern Idaho have investigated two approaches to model fire severity using image classification techniques. The first used the HyMap hyperspectral sensor (Finley 2006) while the second used SPOT 5 and Landsat 7 multispectral sensors (Norton 2006). In both cases, overall classification accuracy between low and high severity fire areas was good (72% and 67% overall accuracy respectively [K_{hat} = 0.69 and 0.33, respectively) but unfortunately, neither quite achieved the level of reliability ($\geq$75%) cited in the literature (Congalton

1991; Goodchild et al. 1994). Because of the nature of fire data (non-normal and multivariate due to the interactive effect of soil, slope, aspect, and wind) classification results better than these are not likely when using probabilistic classification techniques. Therefore, an alternative technique for fire severity modeling was investigated.

Classification tree analysis (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). CTA algorithms select useful spectral and ancillary data which optimally reduce divergence within a response variable (Lawrence and Wright 2001) such as fire severity observations. CTA uses machine-learning to perform binary recursive splitting operations and ultimately yields a classification tree diagram that is used to produce a model of the response variable. There are various splitting algorithms common to CTA: 1) entropy, 2) gain ratio, and 3) 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; Weber et al. 2006; Zambon et al. 2006).

The goal of this study was not to directly compare CTA to other classification techniques and attempt to prove one or the other is better, but to explore the use of CTA to model fire severity in semi-arid rangelands. Since the acquisition of fire perimeters is already part of federal agency post-fire protocols, it was not necessary to use image processing techniques to delineate where a fire has occurred. Rather, focus was placed upon accurately identifying high fire severity areas to assist land managers in post-fire recovery plans and remediation efforts.

METHODS

Study Area

This study focuses upon two 2005 fires in southeastern Idaho: 1) the Hitching Post pasture fire at the US Sheep Experiment Station (USSES) near DuBois, Idaho (a prescribed fire) and 2) the Clover Fire(Clover), 39 km west of Twin Falls, Idaho (a lightning-ignited wildfire). The USSES (Figure 1) includes nearly 40,000 ha of land (Seefeldt and Laycock 2006) that have been assigned to the USSES or leased from the Department of Energy, USDA-Forest Service, or the Department of Interior-Bureau of Land Management. The USSES spans four Major Land Resource Areas (NRCS 2006) including the Central Rocky Mountains, Snake River Plain, Lost River Valleys and Mountains, and Eastern Idaho Plateaus. This area has been used for rangeland research since 1925 and the research that has been conducted there has contributed greatly to our understanding of western rangelands.

Mean annual precipitation varies considerably across the USSES as elevation ranges between 1615-2900 m. The dominant plant species in the sagebrush-steppe communities are Mountain Big Sagebrush (*Artemisia tridentata* Nutt. ssp. *vaseyana* (Rydb.) Beetle.), threetip sagebrush (*Artemisia tripartita* Rydb.), Antelope bitterbrush (*Purshia tridentata* (Pursh) DC.), bluebunch wheatgrass (*Pseudoroegneria spicata* (Pursh) A. Löve), thickspike wheatgrass (*Elymus lanceolatus* (Scribn. & J.G. Sm.) Gould), Sandberg bluegrass (*Poa secunda* J. Presl), arrowleaf balsamroot (*Balsamorhiza sagittata* (Pursh) Nutt.), and tapertip hawksbeard (*Crepis acuminata Nutt*. ssp. *acuminata*) (West and Young, 2000, Wright and Bailey, 2004). The Hitching Post pasture is a 324 ha fenced parcel within the Headquarters Unit of the USSES (Figure 1) at an elevation of approximately 1800 m. Mean annual precipitation ranges between 250-530 mm with most (as much as 70%) falling as snow (Seefeldt, 2005). Soils are mixed, fine-loamy, frigid Calcic Argixerolls (NRCS, 1995). Sheep and horses have grazed this pasture for the past decade, but grazing had not occurred for 2.5 yr prior to the burn. The USSES fire was a series of prescribed fires that began on September 14th and were extinguished on September 15th, 2005. The fire boundary encompassed 244 ha.

The Clover study site (Figure 1) spans two Major Land Resource areas (NRCS 2006), namely the Snake River Plain and Owyhee High Plateau. The mean annual precipitation is 175-400mm which varies somewhat with elevation which ranges between 950 and 1375 m. The site is dominated by big sagebrush (*Artemisia tridentata* Nutt.), perennial bunchgrasses such as crested wheatgrass (*Agropyron cristatum)*, needlegrass (*Achnatherum nelsonii*), and Idaho fescue (*Festuca idahoensis* Elmer). Annuals plants found at this site include cheatgrass and medusahead (*Taeniatherum caput-medusae)* (Wright 1985). Soils vary from loamy sand to silty clay, and are a mix of volcanic-derived basalts and rhyolites as well as windblown loess deposits (Wright 1985). The Clover fire was a lightning-caused wildfire which began on July 15 and was contained on July 20, 2005. The fire boundary encloses 78,042 ha, the largest wildland fire in Idaho in 2005.

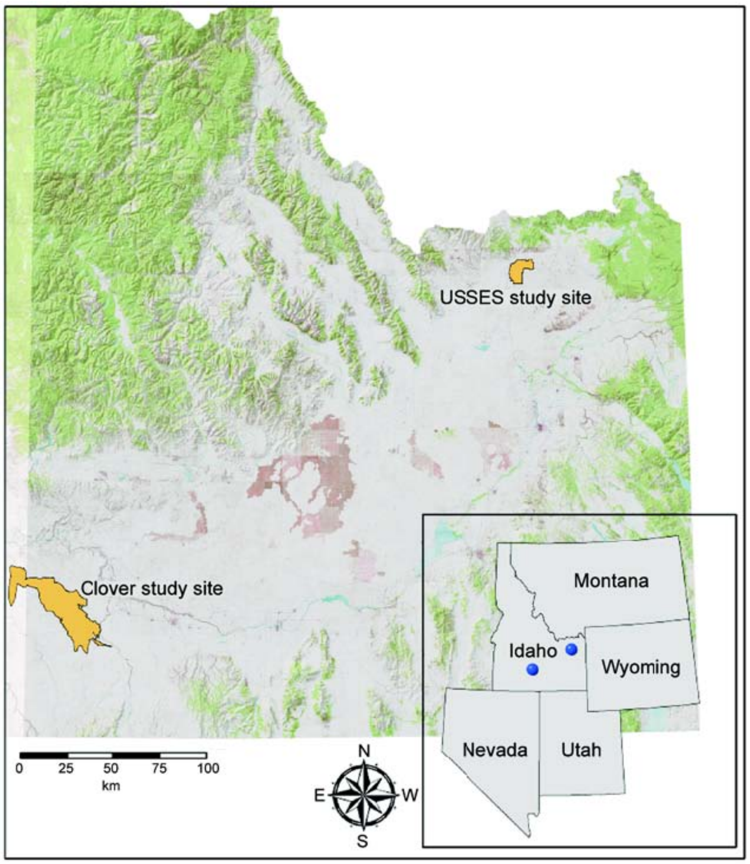

Figure 1. Location of sites compared in this study

Field Data

A standard protocol for field fire severity assessment has been developed for forested ecosystems (Key and Benson 2004). Assessing fire severity within sagebrush-steppe ecosystems cannot follow the exact procedure and for this reason fire severity was assessed using a modified ocular method based on combining the methods described by Key and Benson (1999; 2004), the USDA Forest Service BAER teams (Bobbe et al. 2001) and the US National Park Service (Switky 2003). Fire severity assessments were made beginning one week after the fire was contained and ending within two months after the fire. A total of 512 (n=277 at the USSES study site and n=235 at the Clover study site) points were randomly located within the study sites and navigated to using a Trimble GeoXT GPS receiver (+/-0.9 m @ 95% CI; Serr et al. 2007). Fire severity was then classified as either 1) unburned, 2) low severity (understory removed while shrubs retained green leaves), or 3) high severity (understory removed and shrubs charred or removed by the fire) for CTA modeling. 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 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.

All unburned sample points were omitted from subsequent processing. This was done 1) to simplify the classification process (Jensen 1996), 2) because fire perimeters were already available using more cost-effective methods such as field collection using GPS, and 3) because fire perimeter delineation was outside the scope of this study. The potential error was that unburned areas within the fire perimeter would not be identified and the authors acknowledge that some of the predicted low severity sites may indeed be unburned sites. This error was allowed because 1) the focus of this study was to correctly identify high fire severity areas to assist land managers in post-fire recovery plans and remediation efforts and 2) very few unburned sites were found within the fire perimeters.

Image Processing

SPOT 5 satellite imagery was acquired for both the USSES (September 28, 2005) and Clover (September 1st, 2005) study sites. The acquisition dates for these data reflect post-fire scenes corresponding to only 12 days post-fire (USSES) and 43-days post-fire (Clover). The imagery was georectified (RMSE = 3.48 for the USSES study site and RMSE = 0.298 for the Clover study site) using nearest neighbor resampling and then atmospherically corrected using the Cos(t) algorithm in Idrisi Kilimanjaro (Chavez 1996). The imagery was then projected into Idaho Transverse Mercator (NAD 83).

Using reflectance data, 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. In addition, topography data was assembled for use as ancillary data within the CTA process (Elumnoh and Shrestha 2000). The elevation data for both study sites was 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 the elevation models 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 ten input images available for the classification process: green, red, near-infrared (NIR), and shortwave-infrared (SWIR) reflectance bands (1-4), NDVI, NBR, and biomass band-ratios, and elevation, slope, and aspect topography layers.

To absorb georegistration error within the SPOT imagery for the USSES study site (RMSE=3.48) and ensure sample points fell within representative pixels (Weber 2006) the USSES sample points were buffered by 5m (note: this process was not required for the Clover study site as georegistration error of the SPOT imagery was quite low [RMSE=0.298]). The resulting layers were rasterized using ArcGIS 9.1 and subset into training and validation sites. A total of 474 training sites (i.e., pixels) (n=385 at the USSES study site and n=89 at the Clover study site) and 288 validation sites (n=207 at the USSES study site and n=81 at the Clover study site) were created. These data were then used within Idrisi Kilimanjaro for CTA.

RESULTS AND DISCUSSION

The USSES and Clover study sites differed in most every factor (elevation, precipitation, and soils) including fire type, seasonality, and size. These differences increase the challenges of developing a fire severity model, especially when trying to determine explanatory variables that would be consistent.

While ten input images were available for the classification, CTA consistently selected biomass, NBR, and NDVI band-ratio, NIR, and slope layers (note: layers are listed alphabetically and the order listed is not indicative of the layer's importance). 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).

Using these five layers, high fire severity areas were correctly identified in most cases, having a user accuracy of 100% and 79% at the USSES and Clover study sites, respectively (Tables 1 and 2). These results improve upon previous fire severity classifications for the same study sites (Finley 2006; Norton 2006) in nearly all cases such as calculated overall accuracy (72% compared with 86% using CTA at the Clover study site; 67% compared with 97% using CTA at the USSES study site) and the Kappa statistic (0.69 compared with 0.65 at the Clover study site; 0.33 compared with 0.78 at the USSES study site [Congalton 1991]).

Table 1. CTA results for the USSES study site.

		Known validation sites			
		Low fire severity	High fire severity	Total	User accuracy
Model results	Low fire severity	14	7	21	0.66
	High fire severity	0	186	186	1.00
	Total	14	193	207	
	Producer's accuracy	1.00	0.96		Overall = 0.97

Kappa index of agreement = 0.78

Assessment of error and bias

While the resulting overall accuracies were better than those reported using more traditional, probabilistic classification techniques such as maximum-likelihood (Norton 2006) and spectral angle mapper (Finley 2006), using CTA for fire severity modeling in sagebrush-steppe rangelands was fairly simple and straightforward, requiring only post-fire imagery and ground observations. Achieving satisfactory results appears to be a function of sample size as in both cases the class (low fire severity or high fire severity) with a larger number of samples resulting in better classification accuracy. The minimum number of observations to maintain accuracy will need to be determined and provided to land managers.

Table 2. CTA results for the Clover study site.

		Known validation sites			
		Low fire severity	High fire severity	Total	User accuracy
Model results	Low fire severity	50	7	57	0.88
	High fire severity	5	19	24	0.79
	Total	55	26	81	
	Producer's accuracy	0.90	0.73		Overall = 0.85

Kappa index of agreement = 0.65

At the USSES study site, the prescribed fire burned relatively dense vegetation at close to optimal burn conditions (low humidity, high temperature, slight breeze) resulting in 92% of the field observations rating a high fire severity compared to 8% at a low severity. In contrast, field observations for the Clover study site were opposite, with 33% high fire severity compared to 67% low fire severity (Figure 2). 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). Model proportions of high and low severity areas were the same as estimated by observation (Figure 2). The similarity of these results (Table 3) indicates the model is robust in comparing a large range of overall fire severities.

Table 3. Comparison between the proportion of field observations and fire severity areas as modeled.

	Proportion of total fire area (and field observations)	
Study site	Low severity fire	High severity fire
USSES	0.08 (0.08)	0.92 (0.92)
Clover	0.67 (0.68)	0.33 (0.32)

There were other potential differences between the fires at the two study sites which could have caused a potential bias such as:

1) The post-fire SPOT imagery acquired for the USSES study site was collected only 12 days after the fire, while the imagery for the Clover study site was not collected until 43 days after the fire. This difference could not be avoided due to the widespread smoke and haze caused during the early parts of the 2005 fire season (July and August). As a result the earliest clear imagery available (coincident with a SPOT imaging date) was September 1^{st}. However, lack of precipitation reduced changes to post-fire vegetation at the Clover site.
2) The fire at the USSES study site was a prescribed fire whereas the fire at the Clover study site was a lightning ignited "natural" fire.
3) The scale of the two fires was different with the USSES fire covering 244 ha whereas the Clover fire covered over 78,000 ha.
4) The seasonality of the two fires was also different with the USSES fire occurring in September while the Clover fire occurred in July. While both occurred in the same year, we correctly expected that a late season fire (under continued dry/drought conditions) would yield a fire of higher severity as the fuels had become increasingly desiccated.

Given all the differences listed above, the fire severity models, which were prepared in nearly identical ways using post-fire field observations collected in a very similar fashion (although by two separate field teams) were quite robust. As a result, CTA was able to produce fire severity models with good user accuracy (mean = 83% [note: this is the mean of all user accuracy values]), indicating the resiliency of this modeling technique (see Figure 3 for a step-by-step approach of this technique).

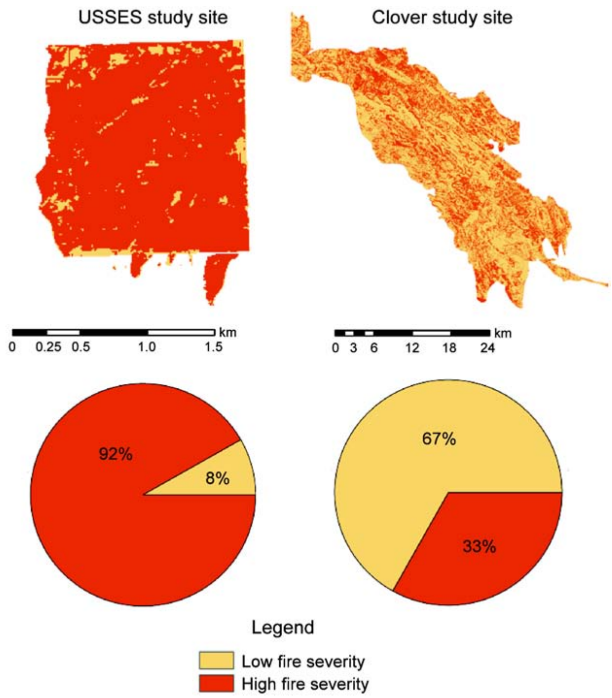

Figure 2. The resulting fire-severity models were different, with the USSES fire having a much larger proportion of high-fire-severity areas (92%) relative to the Clover fire with only 33% considered high fire severity

CONCLUSIONS

Time of fire, fire severity, climate before and after fire, and vegetation before fire all influence vegetation recovery after fire in sagebrush steppe rangelands (DeBano et al. 1998). Only one of these influences, fire severity, cannot be determined using relatively easy to obtain records. The large sizes of many fires in sagebrush steppe rangelands increase the difficulty of mapping burned and unburned areas, let alone delineating low and high burn severity areas. Yet many land management agencies are charged with developing remediation plans for high severity burn areas. The model described in this manuscript uses easy to obtain satellite imagery (SPOT 5) that can be rapidly analyzed to identify those high severity burn areas. This model, as opposed to NBR, does require some field observations, but the required data (location [GPS point] and observed fire severity rating [unburned, low, or high]), can be collected fairly quickly and accurately. The advantage of collecting field data is that managers will have an error assessment that validates the model. The model is equally effective in picking out the few high severity spots in a large low severity fire as in picking out the few low severity spots in a large high severity fire in the sagebrush steppe.

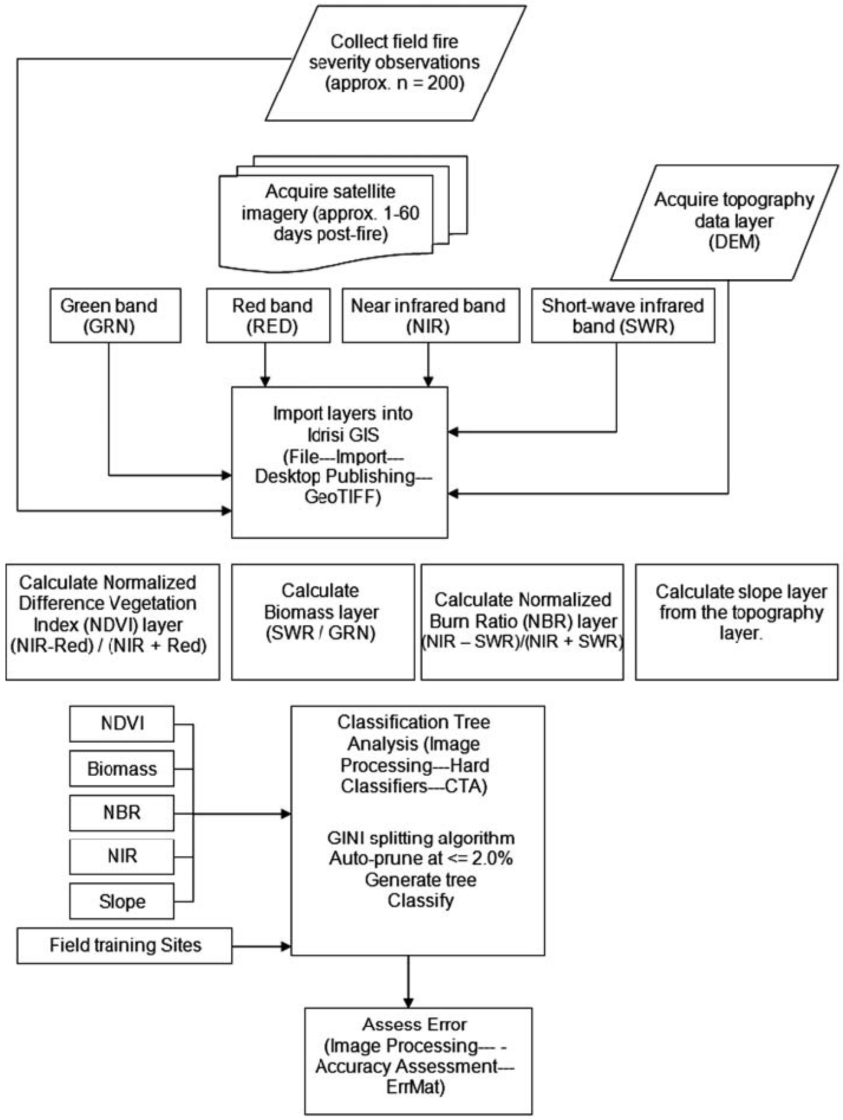

Figure 3. Cartographic model of the process followed to produce a fire-severity model using classification tree analysis at both the Clover and USSES study sites.

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