BURN SEVERITY ASSESSMENT IN THE OKANOGAN-WENATCHEE FOREST USING NASA SATELLITE MISSIONS

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ABSTRACT

Fire severity is an increasingly critical issue for forest managers. A long history of fire suppression has led to millions of acres of dry western forests and a buildup of fuels. Satellite imagery offers a cost-effective and feasible tool for fire severity assessment and can provide near real-time data for mitigation measures. This study focused on the Tripod Complex Fire that burned more than 175,000 acres of the Okanogan-Wenatchee Forest in Washington in 2006. Field data were collected in order to calculate the Composite Burn Index (CBI), a ground-based measurement of burn severity which can directly correlate with satellite measurements. These *in-situ* data were used to calibrate the satellite data from the Landsat TM5 and the MODIS sensor on board the NASA Terra satellite. The satellite data were used to calculate the differenced Normalized Burn Ratio (dNBR) and the Relative dNBR (RdNBR). These algorithms use the relationship between the near infrared and the shortwave infrared to quantify burn severity. After comparing these two algorithms, it was determined that there was no significant difference between dNBR and RdNBR. Using the burn severity map created with the dNBR data, an analysis was performed to examine the relationship between burn severity and variables such as slope, aspect, and vegetation type. The relationships between several measures of burn severity are discussed.

INTRODUCTION

Decades of fire suppression have resulted in extensive fuel loading which has lead to an increase in wildfire size, severity, and frequency (McKenzie *et al*., 2004).The fire regime of the western United States has been characterized historically by haphazard fires typically peaking during the dry summer season (Westerling *et al*., 2003). However, fire suppression and large crown fires are departures from those regimes that have prevailed for the past 10,000 years. Just in June 2008 alone, there were over 2,000 wildfires burning in California. These wildfires have costly effects in both millions of dollars and on biodiversity (Ryan, 2002). This trend is expected to continue under future scenarios of global warming. It has been demonstrated that under the high global warming scenario, the predicted precipitation loss in the Pacific Northwest would change the mean area burned by greater than a factor of 5. Under a low climate change scenario, the area burned is predicted to double (McKenzie et al., 2004) That is why forest managers need accurate burn severity maps in order to implement new fuel reduction strategies and prevent future catastrophic wildfires.

The Pacific Northwest has a long fire return interval of one century, often involving crown fires. The Tripod Complex Fire in the Northern Cascades of Washington State was a high intensity crown fire and is the subject of study in this project. This study has three objectives: (a) to demonstrate the efficacy of using field and satellite measures of burn severity for quantifying change caused by fire and for creating burn severity maps, (b) to evaluate the characteristics of high burn severity areas using three burn assessment variables: CBI, dNBR, and RdNBR, (c) to quantify the change in biomass and the associated carbon released from the Tripod Complex Fire and (d) assess the relationship between burn severity and the variables slope, solar radiation, and vegetation types within the fire perimeter. Estimates of burn severity are important for understanding the effects that fire has on vegetation succession and provide a useful tool for carbon modeling (Epting et al., 2005). The work presented in this paper represents a one-year post-fire extended assessment with field data sampled one and two years post-fire, and satellite images from one-year post-fire.

Field data were sampled using the Composite Burn Index (CBI) developed by Key and Benson (2006). CBI is a field method used to evaluate burn severity and has an extended application to remote sensing measures of burn severity such as the differenced Normalized Burn Ratio (dNBR) and the Relative differenced Normalized Burn Ratio (RdNBR) (Key & Benson, 2006) . The dNBR is derived using a time-differenced (i.e. pre-and post-fire) ratio of near infrared and shortwave infrared spectral bands. RdNBR is a relative index used to obtain more accurate results in heterogeneous fires. Assessments in this study will use CBI field data from 2008 (2 years post-fire) and dNBR data to predict dNBR thresholds for map classification. This study also determines if RdNBR increases the accuracy of map classification.

METHODOLOGY

Study Area

The Okanogan-Wenatchee Forest is located in Washington State covering more than 4 million acres. The forest stretches from the Canadian border down 290 km near the southern border of the state (US Forest Service). The angular crest of the Cascade Mountains creates an intense rain shadow affect resulting in rapid climatic changes and variations in precipitation and humidity. The rain shadow effect is especially noticeable in the northern region with prolonged periods of no rain during the summer months. This is due to the geology of the northern section where mountains were shaped by glaciation and continental uplifting, resulting in higher and wider mountains with steeper slopes and jagged summits that encourage steep climatic gradients (Lillybridge et al., 1995). The area of concentration is a fire perimeter within this rugged section of the forest (Fig. 1).

The year 2006 was a particularly dry, hot year in the Okanogan-Wenatchee Forest, marking a painstaking drought (www.ncdc.noaa.gov). Nine fires burned within the forest from July through September (Levinson & Lawrimore, 2006). On July 24, 2006, a lightning storm ignited three independent fires that grew and joined into one large fire. This fire was called the Tripod Complex Fire, and it burned over 175,000 acres in the northern section of the forest. The area burned supported three dominant species of trees including Lodgepole Pine (*Pinus contota*), Subalpine Fir (*Abies lasiocarpa*), and Douglas Fir (*Pseudotsuga menziesii*). Other species with considerable populations within the perimeter were Ponderosa Pine (*Pinus ponderosa*) and Engelmann Spruce (*Picea engelmanii*) (Lillybridge *et al*., 1995). The intensity of the fire was severe, leaving behind dramatic fire effects.

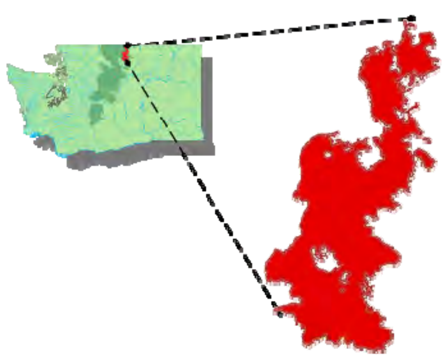

Figure 1. Tripod Complex Fire perimeter inside the Okanogan-Wenatchee forest.

Field Data

Ground measurements of burn severity were taken to assess fire effects within the Tripod Complex Fire perimeter. Ground measurements were taken two years post-fire, since vegetative survivorship and net primary productivity between one-year assessments and two-year assessments were not different when assessing long term severity (Key & Benson, 2006). CBI is measured on a consistent numeric scale that gauges the amount of change. Because the scale is consistent, and post-fire regeneration occurs slowly, CBI values from consecutive years are relatively the same. The field work measures how much change occurred relative to pre-fire conditions and relies on expert knowledge and judgment about pre-fire vegetative cover.

Sample plots were selected randomly with consideration to accessibility and topography (Key & Benson, 2006). All plots fell within a quarter mile buffer of Forest Service and timber harvesting roads and had a slope no greater than 40%. The sample selection was stratified based on the level of burn severity (unburned, low, moderate, or high). Each plot site was tested for burn homogeneity with a map created using the dNBR algorithm. A grid filter was used to ensure each surrounding pixel matched the same burn severity classification as the center pixel containing the point and to verify that differences in dNBR values between pixels were not greater than 150.

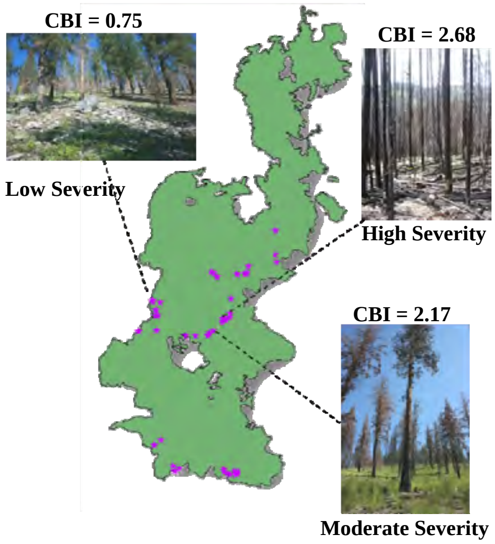

Figure 2. Sites visited within the fire perimeter with a representative of each Composite Burn Index category.

A total of 46 plots were visited with GPS units to the closest meter (Fig. 2). The center of each plot was recorded in UTM coordinates and a radius of 15 m was measured in each direction. Photographs were taken uphill and downhill from each plot center. Team members then explored the 30 x 30 m plots to visually determine the severity of the burn. Observations were made and recorded on Landscape Assessment (LA) data forms provided in Key and Benson 2006 Appendix 1. The LA data form divided the different strata of the vegetation community into five categories: *Substrates*- including soil, duff, and downed woody fuels; *Herbs, Low Shrubs and Trees*- including all grasses, shrubs and small trees less than 1 meter in height; *Tall Shrubs and Trees*- shrubbery and trees measuring between 1 to 5 meters; *Intermediate Trees*- subcanopy, pole-sized trees measuring between 10-25 cm in diameter and 8-20 m in height; and *Big Trees*- dominant and codominant trees that are larger than intermediate trees. These dominant trees generally crown in the upper canopy, but some individuals may extend above that (Key & Benson, 2006). Each category was evaluated separately, assessing individual elements within each stratum. Team members examined fuel beds of each stratum and assessed the amount of fuels that were charred, scorched, and consumed. Once a consensus was reached, the LA data form was filled out in order to calculate the CBI. Elements and strata that were missing in a plot were recorded as non-applicable and not counted in the calculations. The data were converted to CBI values ranging from 0.0 (unburned) to 3.0 (high change). Once a CBI value was acquired for each category, the five data sets were averaged to give the plot an overall value. A brief description of each plot was noted in the comments section of the LA data form, recording site specific information.

The remote sensing measure of burn severity, NBR, is an algorithm used to empirically quantify and isolate burned areas from surrounding areas. The NBR for the pre-fire image and the post-fire images were first calculated using equation 1 (Key and Benson, 2006):

$$\text{NBR} = (\text{Band 4-Band 7}) / (\text{Band 4+Band7}) \qquad (1)$$

The band values are the at-satellite reflectance values for band 4 and band 7. Band 4 (0.76-0.90 mm) is the near-infrared (NIR) band and band 7 (2.08-2.35 mm) is the short-wave infrared (SWIR), and they respond in opposite ways to burning by isolating the reflectance differences between the bands (Key & Benson, 2006). These two bandwidths work similarly to the Normalized Difference Vegetation Index (NDVI). NDVI can accurately detect burn severity; however, NDVI is inaccurate in areas with sparse pre-fire vegetation (Cocke *et al*., 2005). Most studies have concluded that using the short-wave infrared bands provides higher accuracy in burn analysis and negates atmospheric effects (Miller & Yool, 2002). Epting *et al.* (2005) also showed that NBR was the best of thirteen different remotely sensed indices in assessing burn severity. The Normalized Burn Ratio NBR was temporally differenced using the equation 2, also from Key and Benson (2006):

$$\text{NBR} = \text{NBR}_{\text{pre-fire}} - \text{NBR}_{\text{postfire}} \qquad (2)$$

Equation 2 measures burn severity which is a scaled index accounting for the ecological change caused by fire (Key & Benson, 2006).

Since the CBI values and dNBR results were both used to assess burn severity of the region, they were compared and found to be closely related. The results of CBI and dNBR were similar because values were reliant on pre-fire conditions to gauge a magnitude of change. Both methods produced non-absolute values that can be compared to the pre-fire environment regardless of how much time has passed since the fire (Key & Benson, 2006). Results show distinctive change in the region regardless of fire intensity. CBI is used for gauging the amount of change detected by satellites (Key & Benson, 2006).

The use of dNBR is particularly sensitive to pre-fire vegetation (Miller & Thode, 2007; Miller & Yool, 2002). For example, a densely vegetated area experiencing a stand replacing fire will be classified by dNBR as a high severity burn. RdNBR (developed by Miller and Thode) would also classify the area as a high burn. However, if a sparsely populated plot completely burns, it will have a low dNBR value because the lack of vegetation before the disturbance. Relative to the sparsely vegetated plot, the burn is of high severity because everything burned, but compared to very densely populated areas, the fire was only a weak burn. However, using the relative index would classify the plot as a high severity burn. To limit the effects of pre-fire NBR, the RdNBR creates a relative index by dividing the change with the pre-fire value. The RdNBR would correctly classify the sparsely vegetated area as high severity; because there was little vegetation to start with, a fire killing all the biomass would be classified high relative to that specific plot. The equation presented by Miller and Thode is:

$$\mathrm{RdNBR} = \left(\frac{\mathrm{PreFireNBR - PostFireNBR}}{\sqrt{\left| \frac{\mathrm{PreFireNBR}}{1000} \right|}} \right). \qquad (3)$$

Miller and Thode showed that RdNBR resulted in higher classification accuracy for the high severity category. Also, a relative index allows researchers to use a more consistent definition of burn severity across spatial and temporal scales (Miller & Thode, 2007). Numerous studies have been done to test the effectiveness of the relative index compared to dNBR (Miller & Thode, 2007; Safford *et al.*, 2008) However, researchers have found both advantages and disadvantages when using the RdNBR. In their study, Miller and Thode found that although classification accuracy improved in the high burn severity category, the accuracy actually decreased in the low and unburned areas. The overall accuracy was not improved, as they believed that the plots that became misclassified through the use of RdNBR offset any improvements made. In recent years, RdNBR has become the new standard in burn severity classification (Safford *et al.*, 2008). RdNBR removes the correlation between dNBR and pre-fire biomass by dividing the dNBR with the pre-fire NBR value. All stand-replacing fires are categorized as high severity by RdNBR; the amount of vegetation before the disturbance is not a factor.

Satellite Image Processing

One of the challenges of measuring burn severity is the spatial size that fires encompass. Standardization procedures such as those offered by Key and Benson (2006) allow fire managers to compare fires over large spatial and temporal scales using ground measures and satellite images. An extended assessment strategy offers a more accurate pattern of burn heterogeneity and takes into consideration delayed mortality (Key & Benson, 2006). Using this assessment strategy, a burn severity detection image was created to assess the severity of the Tripod fire.

The two Landsat 5 30-meter resolution scenes from August 7, 2005 and July 28, 2007 were acquired from MTBS/MRLC using the Landsat Science Archive and the MTBS/MRLC Reflectance Collection from the USGS website (http://glovis.usgs.gov/). Landsat images from 2008 were not used because MTBS images are in a specific projection; because fire severity varies from pixel to pixel, a re-projected Landsat image would include more error than can be accounted for. All the Landsat Reflectance images were geometrically and radiometrically corrected according the MRLC 2001 image processing procedures (http://www.mrlc.gov/pdf/image_processing.pdf). ERDAS Imagine was the primary software used for calculating dNBR.

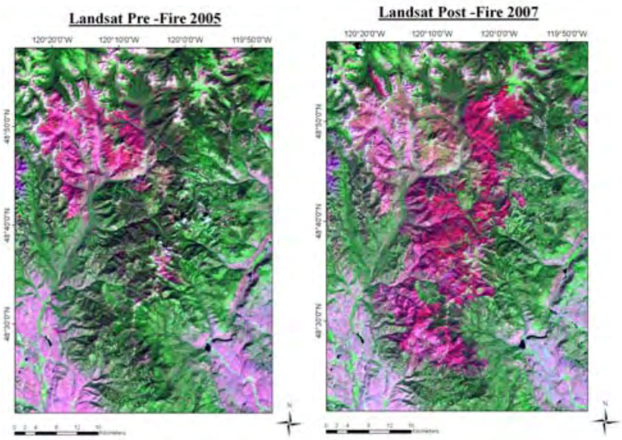

Table 1a

MTBS dNBR Severity Thresholds			
Unburned	**0**	**-2000**	**to 100**
Low Severity	**1**	**100**	**to 304**
Moderate Severity	**2**	**305**	**to 550**
High Severity	**3**	**551**	**to 1350**

Table 1

dNBR and RdNBR linear regression modeled thresholds

Severity Category	Field Measured CBI Severity Value	Predicted dNBR 2007	Predicted RdNBR 2007
Unchanged	0-0.1	< 33.6	< 64.9
Low	0.1 -1.24	33.6 - 285.3	64.9 - 465.9
Moderate	1.25 -2.24	285.3 - 506	465.9 - 823.24
High	2.25 -3.0	>=506	>=823.24

Figure 3. Landsat Pre-fire scene from August 7, 2005 (left) and Post-Fire scene from July 28, 2007 (right). Shown with bands 3, 4, and 7.

At-satellite reflectance images with scene IDs 5045026000521910_REFL for August 7, 2005 and 5045026000720910_REFL for July 28, 2007 (Fig. 3) shown with bands 7, 4, and 3 were imported into Imagine and were chosen as the best possible dates for representing phenology and moisture content (Key & Benson, 2006). A dNBR model from Casey Teske* was used along with some modifications from Jess Clark† of the Forest Service to create a dNBR image. As discussed earlier, the NBR for the pre-fire image and the post-fire images were first calculated using the Equation 1. The NBR images were then temporally differenced using the dNBR algorithm (Equation 2).

The extended assessment strategy used in this study demonstrates the delayed mortality that is not necessarily evident in initial assessments, and extended assessments more clearly delineate heterogeneous burn areas (Key & Benson, 2006). After creating a dNBR image for the Tripod Complex fire, severity thresholds from MTBS were used to stratify the continuous dNBR raster into severity categories of unburned, low severity, moderate severity, and high severity (Table 1a). The dNBR raster contains values from -2000 to +2000, and the classified images were then used for field site selection in order to stratify the sample plots by severity category. In order to more accurately create a classified burn severity map, CBI was plotted against dNBR (Fig. 6a) and the regression equation was used to predict Tripod specific severity thresholds based on the Key and Benson CBI severity thresholds (Table 1b). Based on the given CBI thresholds, severity thresholds for dNBR and RdNBR (Table 1b) were created and were used for the final classification map (Fig. 4a). The final map classification shows that the majority of the Tripod Complex fire was consumed by a high intensity burn. A frequency chart created for Landsat dNBR pixels (Fig. 4b) shows 302 square kilometers were located in high severity burn areas, whereas 63 square kilometers were left unburned. A total of 641 square kilometers were burned within the entire fire perimeter.

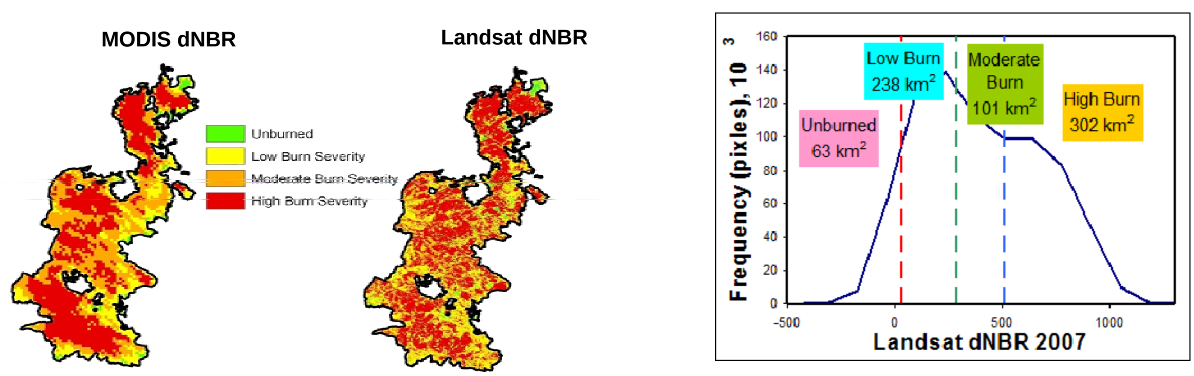

Figure 4. 4a) Burn Severity maps created using continuous dNBR rasters. 4b) Frequency chart of dNBR.

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† Jess Clark is a Remote Sensing Specialist with the Forest Service

The MODIS sensor collects spectral information in similar portions of the electromagnetic spectrum as Landsat. MODIS has the potential to record long-term fire impacts and has a high temporal resolution covering the same spot every day. Spatially, MODIS has a resolution between 250 meters and 1km. The MODIS surface reflectance product provides an estimate of the surface reflectance in the absence of atmospheric effects (Fig. 5a) shown with a band combination using the same portions of the electromagnetic spectrum as Landsat with bands 7, 2, and 1 (http://edcdaac.usgs.gov/modis/mod09gav5.asp). The pre-fire MODIS image from August 7, 2005, and the post-fire image from July 28, 2007, both of which correspond with the Landsat imagery dates, were obtained from the MODIS Land Processes Distributed Data Archive (LP DAAC) through the Earth Observing System Data Gateway (EOS Data Gateway http://edcimswww.cr.usgs.gov/pub/imswelcome/). The dNBR algorithm was applied to the MODIS Surface Reflectance daily 2G 500m V005 image (MOD09GA). For MODIS, the following algorithm was used for calculating NBR and then equation 2 was used to determine the dNBR (Loboda *et al*., 2007):

$$\text{NBR} = (\text{Band 2} - \text{Band7}) / (\text{Band 2} + \text{Band7}) \qquad (4)$$

Band 2 for MODIS is part of the NIR wavelength, and Band 7 is in the SWIR wavelength range. Using the same CBI thresholds given in Table 2, a burn severity map was created (Fig. 4a).

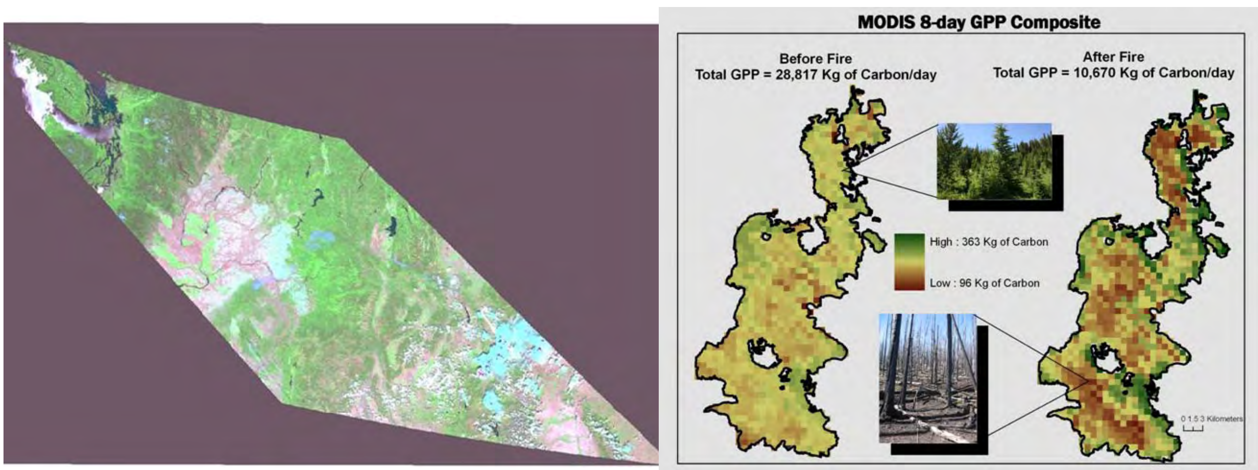


Figure 5. 5a) MODIS pre-fire scene from August 7, 2005 shown with bands 1,2 and 7. 5b) MODIS 8-day Gross Primary Production composite product.

RESULTS AND DISCUSSION

Gross Primary Productivity

MODIS/Terra Gross Primary Productivity 8-day L3 Global 1km V005 (MOD17A2) is a cumulative composite for 8 days and measures Gross Primary Production (GPP) and Net Primary Production (NPP) in kg of carbon/m^2 as a sum over the eight days (MODIS user's guide) and was also obtained through the LP DAAC. GPP estimates the rate at which light energy is converted to plant biomass; GPP is the sum of these processes over a specific area (Heinsh *et al*., 2003). This product was used to assess the amount of sequestration and respiration that the Okanogan-Wenatchee Forest experienced before and after the fire for a specific time period during the summer months. The MODIS GPP product estimates that the entire forest before the fire sequestered 31.7 tons of carbon per day during the summer, whereas after the fire, the entire forest now only sequesters 11.7 tons of carbon per day during the summer, representing a 63% loss in gross primary productivity (Fig. 5b).

Carbon Emissions

In order to estimate the carbon emissions for the Tripod Complex Fire the following equation was applied:

$$\text{Emission} = A * B * CE * e_i \qquad (5)$$

In this equation, A is the area burned, B is the mass of biomass per area, CE is the combustion efficiency and the e_i is the emission factor for species (Wiedinmyer *et al.*, 2006). The burn severity map created earlier was used to focus only on the high severity areas of the fire since those are the only areas inside the fire perimeter where the trees burned completely. Using a vegetation layer created by the Utah State University from Thematic Mapper (TM) Landsat 5 for 2004, the area of vegetation (A) of each high burn severity was extracted. Then the vegetation types inside the high burn severity were matched with the GLC2000 land cover classes presented in Wiedinmyer *et al.* (2006) to obtain the corresponding total fuel loading (B), combustion efficiency (Alleaume *et al.*, 2005) and emission factors (e_i) for CO_2 and CO. This analysis showed that 4.75 million metric tons of CO_2 and 0.268 million metric tons of CO were emitted from the Tripod Complex fire in 2006. The total carbon emissions of the fire (Table 2) represent approximately 5.8% of the total carbon emissions of the state of Washington for the previous year (provided by the EPA).

Table 2. Comparison between CO_2 emissions from the Tripod Complex Fire and the annual CO_2 emissions from anthropogenic sources for the state of Washington in 2005.

CO_2 emissions for Washington State 2005 (Million Metric tons)					
Tripod Complex Fire (2006)	**Commercial**	**Industrial**	**Residential**	**Transportation**	**Electrical Power**
4.75	**3.31**	**19.50**	**5.03**	**43.84**	**13.94**

The estimated value of CO_2 emissions proposed in this paper for the Tripod Complex Fire was lower when compared with other values published (Wiedinmyer & Neff, 2007) since this paper took into account the different severity classes and focused only on the high burned areas. A recent article published the monthly CO_2 emissions from fires for the state of Washington (Wiedinmyer & Neff, 2007) and the sum of the emissions for the three months that the Tripod complex fire lasted showed a total of 31 million metric tons of CO_2. There are several reasons for such a high CO_2 emission value. First of all, that value includes the whole state of Washington for the months of July, August, and September 2006 which showed high fire activity with at least two other wildfires burning at the same time. It is also important to acknowledge that this value assumes that the whole area burned in the same manner while this study's results take into account the difference in burn severity inside the Tripod Complex fire perimeter.

Analysis

The dNBR and CBI regression showed consistency in categorizing burn severity, as seen in different studies (Cocke et al., 2005; Miller & Thode, 2007). A regression of these two variables (Fig. 6a) showed a moderately high coefficient of determination of 0.6994. A regression between dNBR and the overstory CBI (Fig. 6b) showed a slight increase of the R^2 to 0.7373. This increase could be attributed to the fact that satellite imagery captured mainly the overstory of the forest; changes in the overstory would be most apparent. Since CBI and dNBR were both used to assess burn severity and were closely related by gauging the magnitude of change based on pre-fire conditions, dNBR was used as the basis for the rest of the statistical analysis.

In an earlier study, S. Prichard sampled 253 permanent plots in 2007 and converted the field data into CBI values. In order to confirm that the conversion to CBI matched the field data collected in the summer of 2008, a scatter plot was made of those data and the team's data of six of the permanent plots with a one-to-one line. The RMSE of 0.14 was very low, showing that the data were consistent. However, some possible sources of error included the low number of plots for comparison and the clustering of CBI values around 2. Without more plots of lower and higher severity, the accuracy of the temporally spaced plots was not certain. The data from the 2007 permanent plots were used to confirm the accuracy of the regression line. Values for dNBR were predicted using the CBI values, and actual dNBR values were taken from satellite imagery. A scatter plot was made (Fig. 6d), along with a one-to-one line. The RMSE value of 171.9 was 4.3% of the dNBR range, showing good agreement. However, the regression line appeared to over predict for the lower values and under predict for the high values. The predicted dNBR values reached a limit because at the maximum CBI value of 3.0 the predicted dNBR value was 674.

To ascertain if RdNBR showed a stronger relationship with CBI than dNBR as done in Miller and Thode (2007), the RdNBR values were then used to create a regression line (Fig. 6c). Compared to dNBR, the R^2 value increased to 0.7915. The use of a relative index accounted for the increase in coefficient of determination, as was discussed earlier. Using the regression lines, severity thresholds were created for dNBR and RdNBR map

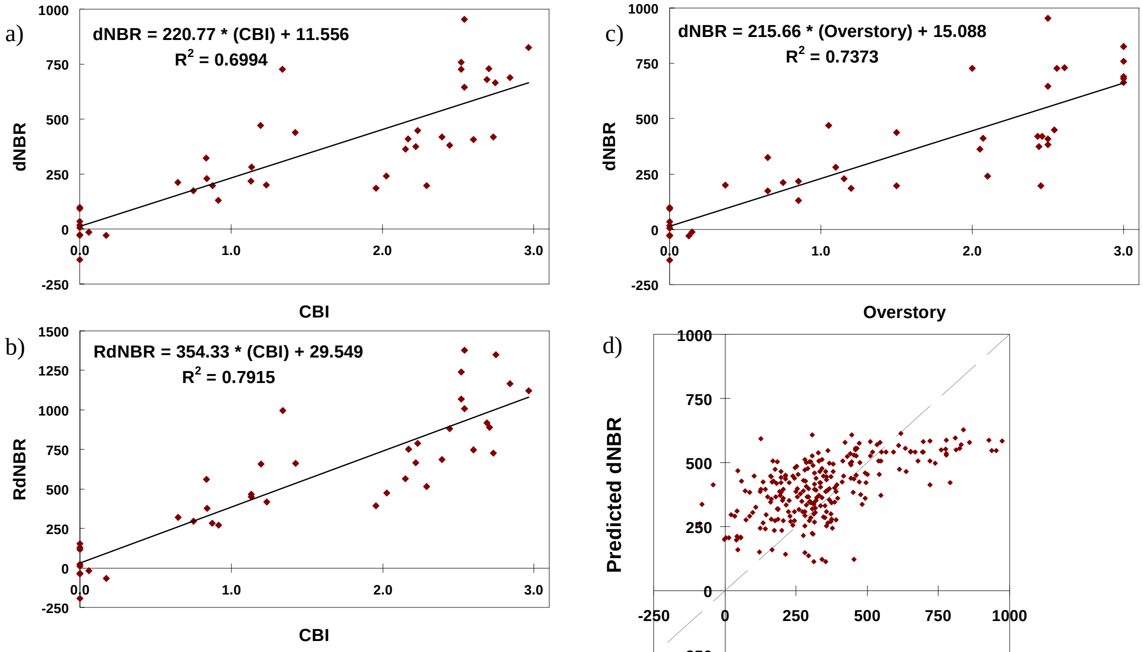


Figure 6 a, b, c, d. Regressions between field CBI measures and satellite measures of burn severity.

classification (Table 1b). The thresholds for CBI were taken from Miller and Thode (2007). Confusion matrices were created for dNBR and RdNBR, showing most of the accuracies were similar (Table 3). The user's accuracy for the low category increased, while both the user's and producer's accuracy in the moderate category increased when using the relative index. The producer's accuracy for the high class also increased. The overall classification accuracy increased by 4.7% with RdNBR. However, the evidence was not significant enough to state that RdNBR produces better accuracy in burn severity classification. Based on the Kappa values that were calculated, the dNBR classification was 55.4% better than that expected if a severity class was randomly assigned to each image pixel, while the RdNBR was 61.8% better. In addition to the Landsat imagery, MODIS was also used to calculate dNBR values. In order to check the validity of the coarser MODIS data, the Landsat imagery was first re-sampled to 500 m resolution. Then, a scatter plot was made with a one-to-one line, showing an RMSE value of 156.77, which is 3.9% of the dNBR range (Fig. 7). This confirms that dNBR data taken from MODIS corresponds well with Landsat data.

Analysis was then done with slope, solar radiation, aspect, and vegetation to determine if there was a relationship between these variables and dNBR values, specifically in the high severity areas of the Tripod Complex

Confusion matrix of CBI (columns) vs dNBR classified data

Kappa = 0.5542

Class Name	Unchanged	Low	Moderate	High	Total	User's Accuracy
Unchanged	6	1			7	0.857
Low	3	8	2	1	14	0.571
Moderate		2	5	4	11	0.455
High			1	9	10	0.900
Total	9	11	8	14	42	
Producer's Accuracy	0.667	0.727	0.625	0.643		0.667

Confusion matrix of CBI (columns) vs RdNBR classified data

Kappa = 0.6179

Class Name	Unchanged	Low	Moderate	High	Total	User's Accuracy
Unchanged	6	1			7	0.857
Low	3	8	1		12	0.667
Moderate		2	6	4	12	0.500
High			1	10	11	0.909
Total	9	11	8	14	42	
Producer's Accuracy	0.667	0.727	0.750	0.714		0.714

Table 3. Confusion matrices from dNBR and RdNBR

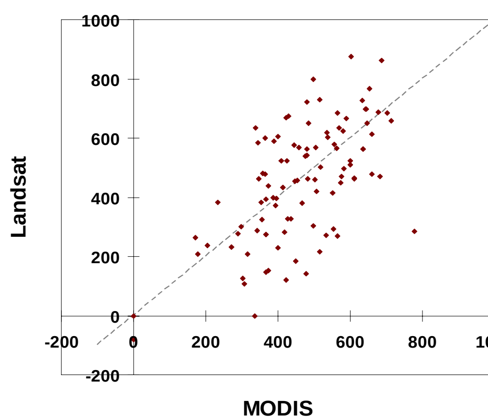


Figure 7. Scatterplot from the resample Landsat image and MODIS.

Fire. Initial regressions between these variables and dNBR show that in the Tripod Fire there is not a significant relationship (Table 4). However in previous studies, slope and aspect were found to be intermediate influences on burn severity (Wimberly & Reilly, 2007). One possible reason that these variables might not be significant was because of the high intensity of the fire. Vegetation was the next variable of interest. Both dNBR and RdNBR show highest averages in the Subalpine Forest type. However after creating conditional plots holding Subalpine Forest constant, there was still not a significant relationship between dNBR and the variables slope, aspect, and solar radiation.

Table 4. Coefficients of determination for dNBR and the variables: solar radiation, aspect and slope.

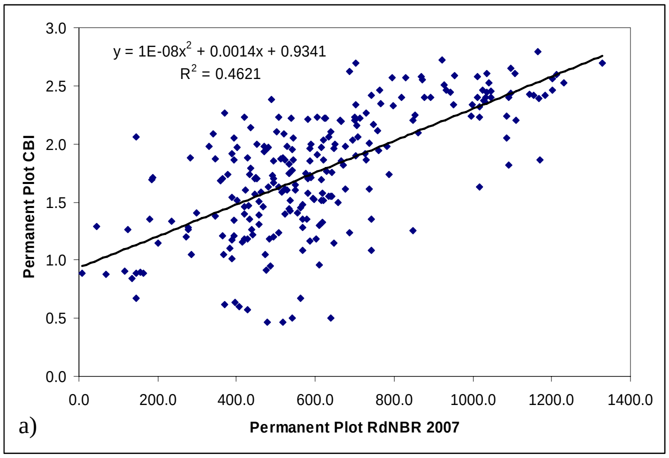
R^2 Values of Regression			***R^2 Values of Regression Holding subalpine Forest Constant***		
Variable	**dNBR**	**RdNBR**	**Variable**	**dNBR**	**RdNBR**
Solar Radiation	0.0288	0.0577	Solar Radiation	0.0003	0.0065
Aspect	0.0332	0.0020	Aspect	0.0288	0.0501
Slope	0.0004	0.0267	Slope	0.0003	0.0026

Permanent Plots

Different methods for assessing the relationship between slope, aspect, and vegetation have been proposed. Wimberly *et al*. (2007) used satellite-derived dNBR as a predictor of CBI, and then used CBI to assess the variation of burn severity based on vegetation, slope, aspect, and elevation. Miller and Thode (2006), however, used CBI as predictors of dNBR for map classification and to determine whether RdNBR produces a better relationship than dNBR. After following the methods of Miller and Thode (2006) for map classification in the present study, the methods of Wimberly *et al*. (2007) were used for analysis of vegetation, slope, aspect, and solar radiation

Following the methods of Wimberly *et al*. (2007), CBI predictions were used for the analysis of the variables solar radiation, slope, and aspect; however, this analysis uses RdNBR instead of dNBR because of the potential increase in accuracy. Field data from a total of 46 plots from 2008 and 253 from 2007 were used, the latter of which were permanent plots. Based on the low RMSE of 0.14 between the 2008 plots and the 2007 permanent plots (Fig. 8), the permanent plots were used in the statistical analysis for predicting CBI for the rest of the Tripod Fire. Instead of using dNBR to predict CBI, RdNBR was used because of the potential slight increase in accuracy. The RdNBR and CBI values from the permanent sites were plotted, and the relationship between the two was non-linear. Based on a 2nd order polynomial function similar to the one used in a recent article (Van Wagtendonk *et al*., 2004), equation 6 was used to predict CBI as a function of satellite derived RdNBR:

$$CBI = 1E^{-08}x^2 + 0.0014x + 0.9341 \qquad (6)$$

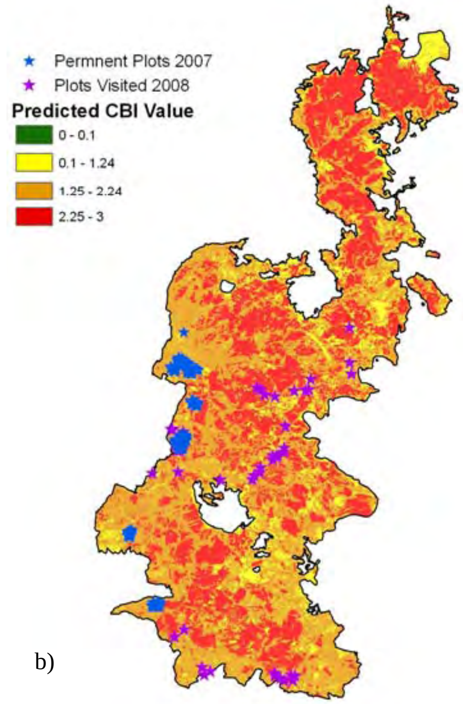


a)

Predicted CBI Regression

c)

Variable	**R^2**
Solar Radiation	0.0185
Aspect	0.0023
Slope	0.0267



b)

Fig.8: a) Permanent plot RdNBR and CBI regression. b) Predicted CBI map. c) Coefficient of determination for CBI and the variables solar radiation, aspect and slope.

The model shows an R^2 of 0.4621 (Fig. 8a), and the model was then applied to the RdNBR image to generate a predicted CBI map (Fig. 8b) for the entire area within the Tripod complex perimeter. After using the permanent plot CBI data, and predicting CBI as a function of RdNBR, a regression analysis (Fig. 8c) between the predicted CBI and the variables slope, aspect, and solar radiation shows no relationship, similar to the findings from the regression with dNBR (Table 4). An analysis of vegetation type and the resulting average CBI for each vegetation type shows that subalpine forest types have a higher average CBI than the other forest types, the same result seen when dNBR was used. Previous studies show that there is a positive relationship between CBI, slope, elevation, aspect, and vegetation type, demonstrating that topography and vegetation both have strong effects on the spatial pattern of fire severity (Wimberly & Reilly, 2007). However, this study shows that within the Tripod fire perimeter, a relationship was not found using both dNBR and CBI measures of burn severity. High severity and homogeneous fires such as the Tripod complex fire could be accounting for the non-spatial relationship found in this study (Ryan, 2002). Using CBI to assess these variables reaffirms the conclusions that were made after assessing dNBR with slope, aspect, solar radiation, and vegetation.

DISCUSSION

Fire Behavior

Once a wildfire has been ignited, the fire's inception, growth, and behavior are influenced by the complex of fuel, topography, and air mass components present in the environment. These non-static factors are interrelated, influencing a fire's intensity and severity. The topographic factors of slope and aspect influence both the fuel loading and weather of the region (Contryman, 2004).

Slope has the greatest influence of all on fire intensity, encouraging fire to grow and spread. Fire moves faster on an incline than on level ground; the steeper the gradient, the faster the fire spreads over a forested terrain (www.bcwilfire.ca, 2007). The aspect of the mountain face is also very important in wildfire behavior. Due to exposure to the sun and weather patterns, fire behavior varies on different faces of the mountain. The amount of solar radiation that warms surface fuels is partially dependant on aspect (Ryan, 2002).

Typically a trend of high burn severity can be seen on steep slopes and aspects that support drier and warmer surface fuels. However, these trends were not apparent in the Tripod Complex Fire of 2006. High burn severity was found regardless of slope gradient and direction of aspect; burn severity of the Tripod Fire was characterized by other factors. Interruptions of natural disturbances result in a loss of biodiversity while heterogeneity in vegetation structure and microenvironment lead to heterogeneity in fire behavior and effects (Ryan, 2002). The Okanogan-Wenatchee Forest has experienced the effects of prolonged forest fire suppression for more than 100 years, resulting in the emergence of three dominant tree species. Along with a homogeneous vegetation community, the environment, which burned, had a consistently steep rugged terrain resulting in a larger and more uniform fire.

Our study showed that the Tripod Complex Fire emitted in four month more carbon than the total of carbon emissions produced by the commercial sector of the whole state of Washington in a year. This puts in perspective the amount of greenhouse gases release into the atmosphere by high severity wildfires. Every summer wildfires sweep through the forests of western part of the United States, but in recent years the severity and extent of these fires has increase to the point where these fire emissions are having an effect in climate (Wiedinmyer & Neff, 2007).

CONCLUSION

The Composite Burn Index values from 46 plots evaluated within the Tripod Complex Fire showed a strong correlation with both dNBR and RdNBR. Although the study did not show a great difference in the accuracy between dNBR and RdNBR, RdNBR should be used in future studies to assess its potential for improving accuracy. The fire effects of the Tripod fire did not show a direct relationship between dNBR and the variables slope, aspect, solar radiation, and vegetation type. These results are due to the homogeneous, steep-sloped landscape as well as the low level of biodiversity in the vegetation community. The assessment of fire severity using field and satellite measurements in this study can provide enhanced burn severity maps, enabling forest managers to improve fuel reduction treatments. Fuel reduction treatments, if done correctly, can reduce the frequency and magnitude of severe wild land fires.

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