Creating a Burn Severity Map Using Classification and Regression Tree (CART)

By

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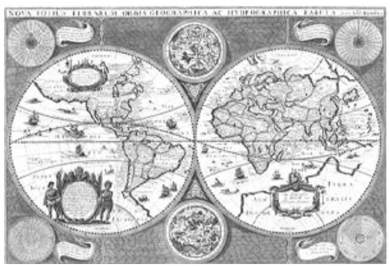

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Contents

List of Figures

List of Tables

Introduction

Generating a burn severity map is a critical element for assessing natural resources damages post wildfire. That is, the burn severity map is used as one of the data inputs for modeling potential soil erosion post-fire in computer programs such as GeoWEPP (Miller, MacDonald et al. 2011). Furthermore, the burn severity map is used to gage and quantify vegetation, ecological, and wildlife impacts at the landscape scale.

It is important to differentiate between fire severity and burn severity. Fire severity is the immediate and direct effects of fire on the environment (Robichaud, Rhee et al. 2014). Conversely, burn severity is defined as the degree to which an ecosystem has change owing to the fire (Robichaud, Rhee et al. 2014).

After a wildfire event a team of experts is usually assemble to assess damages to natural resources. These experts usually include a hydrologist, soil scientist, geologist, wildlife biologist, forester, and a fire ecologist, just to name a few. This group of experts are collectively called the Burn Area Emergency Response (BAER) team. The organization that leads this effort is mostly dictated by land ownership and or land management responsibilities where the fire occurred. For example, if the land is owned and managed by the United States Forest Service (USFS); then, the USFS is often the lead agency orchestrating the BAER team.

The BAER team assess damages immediately after a wildfire event. The BAER team usually assess post-fire soil burn severity (Robichaud, Rhee et al. 2014) following guide lines outline in Parsons, Robichaud et al. (2010). Conversely, first order wildfire burn severity damages (effects) are evaluated one-year post-fire (Chen, Zhu. et al. 2008). Furthermore, second order wildfire burn severity damages (effects) (Chen, Zhu. et al. 2008) are evaluated two or more years post-fire.

The first order effects are the direct consequences of the fire combustion. The first order effects are usually measured no more than one year post-fire. Conversely, the second order effects include vegetation succession, delayed tree mortality, and landscape changes (Chen, Zhu. et al. 2008). These second order effects may take two or more years post-fire to occur. Remote sensing is an ideal tool to capture both first and second order effects.

The methods outlined in this document can be used to model soil burn severity for the BAER team, first order burn severity effects, and second order burn severity effects. In addition this method can accommodate LandSat7-ETM+, LandSat8-OLI or WorldView-2 multispectral data (Appendix 1). Moreover, this technique is robust and repeatable and produces accuracy assessment values by burn severity class.

Previous researchers such as Key and Benson (2006); Miller and Thode (2007); and Parsons, Robichaud et al. (2010) have develop methods and techniques to assess burn severity. The methods discussed here are merely designed to build on other researches efforts and not intended to recreate the burn severity map generation process. Finally, this example is evaluating first order burn severity effects using manually generated field data.

The following is an example of an actual fire; however, the field sample data were contrived for demonstrative purposes. The goal of the following information is to illustrate a modified methodology for computing soil burn severity, first order effects, and second order effects due to wildfire.

The Happy Camp Fire Complex was a lighting cause fire and began on August 12, 2014 and was extinguish on October 31, 2014 (figure 1). The reason for conducting this demonstration on this particular fire are two-fold: 1) I am familiar with the area, and 2) the time period of the wildfire event facilitated the use of LandSat8-OLI data.

This example cannot be compared to the Monitoring Trends in Burn Severity (MTBS) soil burn severity map for the Happy Camp Fire Complex for myriad reasons. First, different LandSat data were used over a different time period. Second, different sample points were used to produce the final burn severity surface. Finally, a different methodology was used to generate the Difference in Normalized Burn Reflectance (dNBR) break points. Therefore, it makes no sense to compare the MTBS soil burn severity data to the first order effects burn severity map generated in this document for the Happy Camp Fire Complex.

Methods

To compute the first order burn severity effects for the Happy Camp Complex, two LandSat8-OLI images were acquired from the United States Geological Survey http://earthexplorer.usgs.gov/. The first image was from June 20th, 2014 (pre-fire) and the second image was from July 25th 2015 (post-fire). Using the workflow outlined in Appendix 1 for LandSat8-OLI a dNBR surface was created (figure 2). In addition, a fire boundary and soil burn severity map were downloaded from the Monitoring Trends in Burn Severity (MTBS) (http://www.mtbs.gov) website.

Next sample points were manually generate by the following method. That is, with the MTBS final soil burn severity map as a backdrop surface, sample points were manually created and attributed with a burn severity class that corresponded to the MTBS final soil burn severity surface (figure 3). A total of 398 sample points were manually generate and attributed by burn severity class (table 2).

Sampling Design

If this were a true field experiment preliminary sample points would be generated and initially partitioned by the potential burn severity classes. Key and Benson (2006) give initial break points for the raw dNBR values. These initial break points are extremely useful for stratifying the field samples prior to actual field data collection. Next, field data would be collected with a Global Positioning System (GPS). Using instructions contained in table 1, field crews would collect the sample locations coupled with the associated burn severity class.

In the field data collection phase of the study, it is a good idea to collect samples as close as possible to the time period of the post-fire image. This concept keeps the field data and the post-fire imagery temporally coincident. In the first year and to a lesser extent the second year post-fire many landscape changes are taking place. That is, soils are eroding and vegetation is re-growing and/or delayed tree mortality due to secondary effects may be evident. Therefore, it is important to capture these events in both the imagery and field data collection so that classification errors are minimized.

When collecting field data all desired burn severity classes must contain sample points. A general rule is to have a minimum of twenty samples per burn severity class. Therefore if four final burn severity classes (e.g. unburned, low, moderate, and high) are required; then, eighty sample points are a minimum number. This number is likely to vary due to the size of the fire and the fire burning complexity. It is paramount to have good samples that are truly representative of each burn severity class. A large number of samples that poorly or ambiguously represent the burn severity classes can be a hindrance.

When choosing an area to sample it is acceptable to bias the field sample locations. That is, the goal of this effort is to create a model depicting burn severity over the landscape and not hypothesis testing. Wildfires generally burn in a patchy mosaic composed of many burn severity classes. Therefore to capture the variability over the landscape, field samples need to be representative in both type and area of the various burn severity classes described in the model.

Further compounding the burn severity landscape variability element is the fact that LandSat8-OLI has a 30 meter by 30 meter pixel size. Therefore, LandSat8-OLI has a minimum sample unit of 900 square meters. Every pixel in the fire footprint needs to be put into a discrete burn severity class. This is often a difficult task because wildfires do not burn uniformly in 30 meter by 30 meter units. Therefore, a single pixel may contain multiple burn severity categories. Hence, choosing a sample location that is representative of a single burn severity class and is 30 meter by 30 meter in size can be challenging even for experienced field crews.

As a general concept in choosing an area to sample it would be optimum to locate regions that are 60 meters by 60 meters in size (four LandSat pixels) and uniform with respect to a single burn severity class. On large wildfire (> 50,000 acres) that contain hundreds of acres of continuous late seral stage vegetation or climax forest types, often exhibit large regions of uniform burn severity classes. The burn severity classes of most concern are the moderate and high. These classes are where most of the resource damage occurs and are the most challenging to classify accurately.

When using WorldView-2 (multi-spectral) imagery more flexibility with respect to field sample locations exists. That is, WorldView-2 (multi-spectral) imagery contains pixels that are two-meters by two-meters in size. Therefore, the likelihood of finding areas that are four meters square or 16 meters square (four WorldView-2 pixels) within the fire footprint and are uniform to a single burn severity class is high. However, small pixel sizes require the use of a GPS unit that collects accurate locational data at one to three meters. The hand held Trimble Juno GPS units coupled with post-processing are ideal for this task (Navigation 2016).

Data Processing

Using ArcGIS (ESRI 2015) the raw dNBR values (digital numbers) that were spatially coincident with the generated sample points were extracted and put into a text file. The output text file in this process contains two data columns. The first column contains the burn severity class value from the generated points. The second column contains the corresponding digital number from the raw dNBR surface.

Next using the statistical program R (R Development Core Team 2008) coupled with the Tree Library (Ripley 2014) a Classification and Regression Tree (CART) analysis was conducted. CART generates discrete break points for the raw dNBR surface using the output text file generated by the field data via ArcGIS. A custom R script must be written to execute the CART step. The results of the CART analysis are contained in figure 3. To read the CART output, figure 3, all one has to do is follow the logic of the Tree. The Tree is read by this rule, if the value at the top of the tree is true; then, follow the tree (branch) to the left. If the value at the top of the tree is false; then, follow the tree (branch) to the right. Contained in table 3 are the break points from the CART (figure 3) output in table format.

Results

Now that the break points for the dNBR are known the surface can be classified into discrete severity classes. ArcGIS (ESRI 2015) has many ways of classifying raster data; however, they are cumbersome to use and results can be unreliable. Therefore a custom python script, using arcpy, was written by ERIA Consultants, LLC that quickly and consistently classified the raw dNBR values into the desired classes. The final burn severity map using the generated field data and driven by the break points contained in table 3 are illustrated in figure 4. Contained in table 4 are the acres by discrete burn severity classes generated by the CART.

Accuracy Assessment

The proper way to conduct accuracy assessment on remotely sensed data partitioned in into discrete classes is the confusion matrix (Congaltion, Green et al. 1993, Tuffly 1995). The confusion matrix for the Happy Camp Fire Complex using the generated points coupled with the classified dNBR surface are in table 5.

Discussion

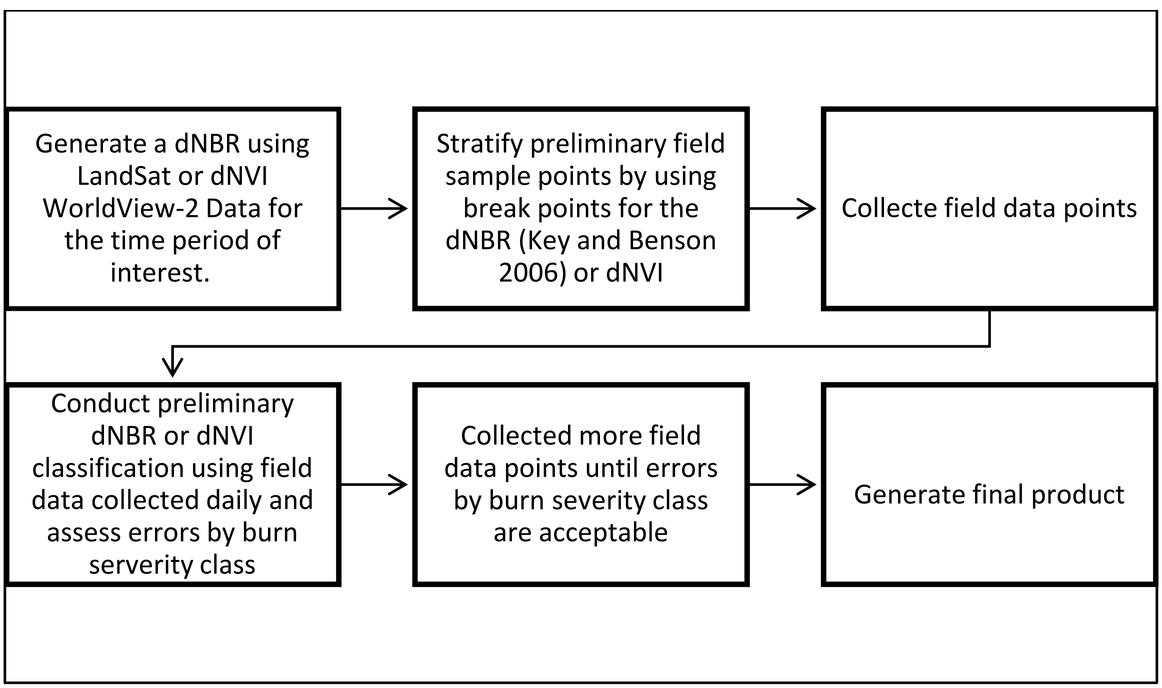
This is a contrived experiment; however, the results contained in the confusion matrix are remarkably similar to other work I have executed on other fires. That is, the moderate and high burn severity classes have the highest error rates. In previously work I have made an attempt to ameliorate these errors, by splitting the moderate and high categories into four classes (e.g. moderate-low, moderate, high-low, and high) (table 1). In some instances this has proven to be useful. Moreover, these classes (e.g. moderate-low, moderate, high-low, and high) can also be combined and or partitioned among other adjacent classes. For example, inspecting the confusion matrix (table 5) it is clear the 14 sample points should have been in the moderate class; however, they were classes as low. In addition 11 points were classified as moderate when they should have been high. It is possible that these errors occurring at the fringe of the moderate and high burn severity classes could be resolved or reduced if the field data are partitioned into the classes contained in table 1.

In many cases moderate and high burn severity are isolated to the mid to late seral or climax vegetation types coupled with a high percentage of canopy cover. This environment provides fuels that often generate a great deal of heat. If the correct conditions occur, areas with high canopy cover may result in a crown fire. Crown fires do not necessitate high soil burn severity; but, will display significant first and second order effects.

Moderate and high severity may occur when a great deal of large forest surface fuels have accumulated. For example, if ideal fire weather conditions occur (e.g. dry, hot, and windy) combined with moderate to steep terrain coupled with a large accumulation of dry ground fuels; then, moderate to high fire severity may occur in these areas despite the fact that early to mid-successional plant species occupy the site. This assemblage of ground fuel accumulation are likely to be present in areas where existing vegetation mortality due to pests, pathogens, or an atmospheric event (e.g. wind throw) has occurred.

Once the raw dNBR (LandSat) or Difference Vegetation Index (dNVI) (WorldView-2) surface is created and potential field sample locations are identified. The most time consuming task is field data collection. This is owed to the fact that many wildfires often occur in areas that are difficult to access due to a lack of roads, steep terrain, and long travel distances. Therefore to maximize field sampling efforts a great deal of time and attention should be allocated to the moderate and high burn severity class. It is these classes where most of the resources damage occurs. Furthermore, to save time some of the unburned classes may be sampled outside of the fire footprint (Chen, Zhu. et al. 2008). However, when sampling outside of the fire footprint strict sample rules must be followed. That is, the image footprint used to generate the raw dNBR or dNVI must be larger than the actual fire footprint so that these off-site samples are included in the dNBR/dNVI surface. The vegetation sampled for unburned areas outside of the fire footprint must be similar in species composition, size, and density, as to what is contained within the fire footprint and have been subject to similar land management practices over a similar time period. It is also a good idea not to exceed over 20% of the samples for the unburned class outside of the fire footprint.

The use of CART and the custom python classification program in arcpy allows the rapid computation of preliminary burn severity results for daily inspection. For example, if field crews are collecting data for multiply days, preliminary results can be generate each day and errors by burn severity class can be quantified. This preliminary assessment can greatly facilitate the minimization of burn severity class errors and efficiently utilize field crew's time by focusing attention on classes with the highest errors. Once a sufficient number of field sample points are collected and the class errors are within acceptable levels a final burn severity map can be completed. The process is outlined in the flow chart below. The first two boxes in the flow chart below should be completed before field crews are deployed.



Using satellite imagery is beneficial in the fact that it is time and cost saving when classifying large landscapes. Conversely, satellite imagery can also present great challenges due to pixel infidelity to a particular severity class. Furthermore, the BAER soil burn severity method presents temporal image issues due to the fact that classification needs to be conducted immediately after the fire regardless of the time of year and the quality of the imagery available for the time period of interest. First and second order effects present yet different challenges in classification. That is, first and second order effects must deal with spectral anomalies due to vegetation regrowth, post-fire soil erosion, and delayed vegetation mortality.

When collecting imagery for bi-temporal analysis it is required to have one image pre-fire and one post-fire. Conducting first and second order fire effects allows some flexibility in image selection. That is collecting a single image that is cloud free and is plus or minus one or two months either pre or post-fire is acceptable. However, the BAER team requires imagery for the soil burn severity map as soon as the fire is extinguished. This may create a situation that requires mosaicking multi-images together from different time periods so that a single image is created that is cloud free and covers the entire fire footprint.

The LandSat and the WorldView-2 (multi-spectral) satellites acquire data using a passive data collection method. A passive data collection method requires no sensor energy output. That is, as the sun's light energy in the visible and non-visible spectrum hits the vegetation on the surface of the Earth, some of light energy is reflected back to the satellite sensor and some of the light energy is absorbed by the vegetation. The amount of reflected light energy and the associated band wavelength is subsequently partitioned by individual image bands and packaged into pixels. For details on the spectral reflectivity curve for vegetation see USDA Forest Service (2016).

It is widely known in a particular area during different months or seasons of the year changes in the sun's angle will occur. The passive satellite data collection method is sensitive to sun angle changes. Furthermore bi-temporal image analysis such as dNBR or dNVI is also sensitive to sun angle changes. Moreover, terrestrial vegetation is sensitive to the seasons of the year. That is, at different seasons of the year terrestrial vegetation may reflect different amounts of light energy in different spectral bands. Therefore, when mixing different sun angles, bi-temporal imagery, seasonal vegetation changes, cloud cover, and variable burn severity levels at the pixel level creates a difficult classification environment for the BAER team generating a soil burn severity map.

The WorldView-2 (multi-spectral) satellite has proven to be extremely useful for conducting first and second order effects. This is primarily due to the small pixel size (two-meters by two-meters). That is, when collecting field data it is easy to find areas that are at least four square meters in size and are uniform with respect to a single burn severity class. Unfortunately, WorldView-2 (multi-spectral) is very costly (e.g. $21 to $31 per square kilometer). Furthermore WorldView-2 (multi-spectral) imagery may not be available for the area of interest, time period of interest, or may be obscured by extensive cloud cover. Finally, WorldView-2 (multi-spectral) imagery is also sensitive to different sun angles and seasonal vegetation changes. Therefore, WorldView-2 (multi-spectral) data is unlikely to be used by the BAER team for soil burn severity mapping.

Conclusion

As stated creating an accurate soil burn severity map, a first order effects burn severity, or a second order effects burn severity map is an extremely challenging task. Bi-temporal imagery are subject to anomalies due to seasonal sun angles alterations, temporal vegetation changes, and post-fire soil erosion. Collecting field data on a large fire footprint in remote areas is costly and time consuming. Using the methods outline in this document may reduce overall field data collection costs and increase the accuracy and precision of the final product.

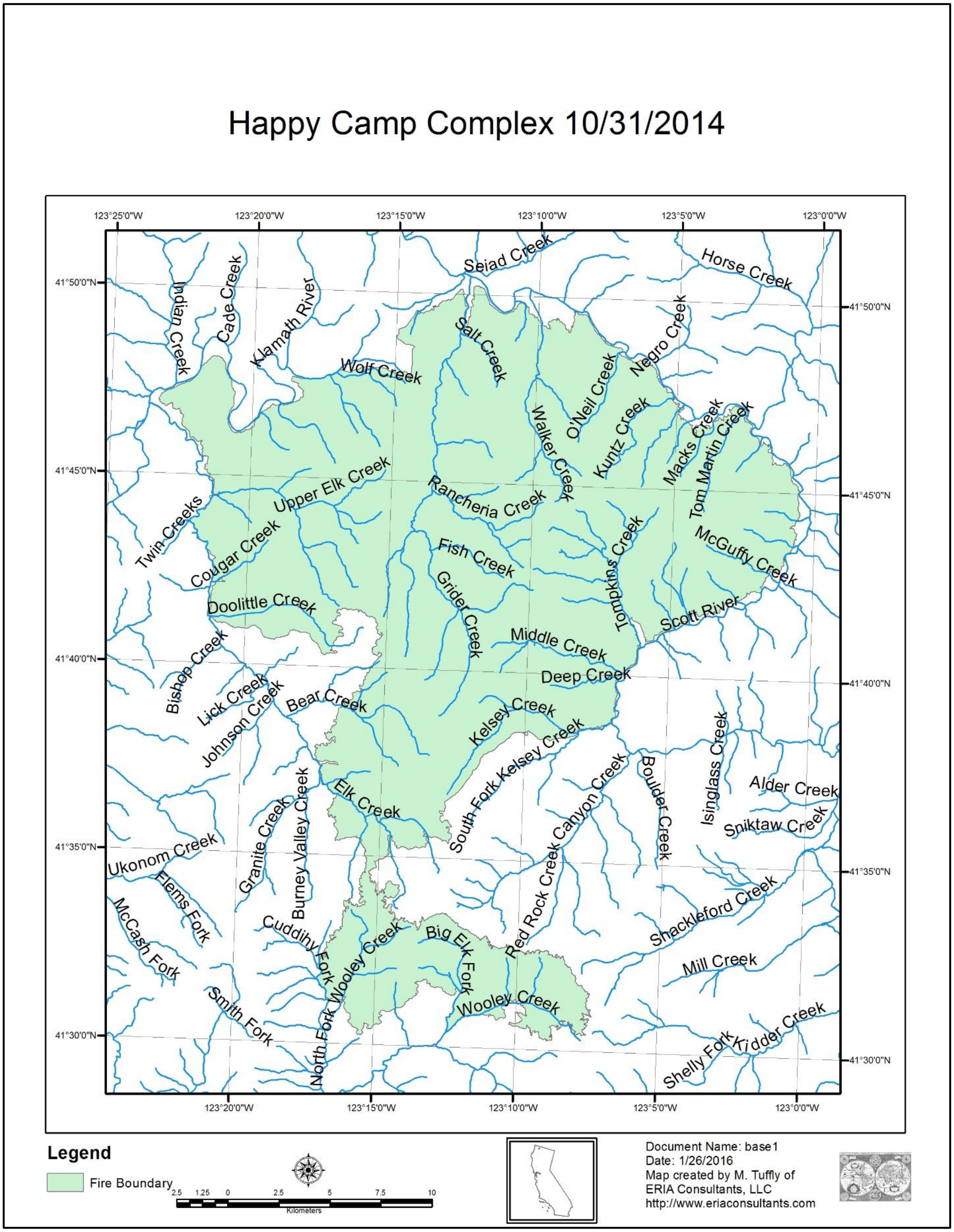


Figure 1. Fire Footprint.

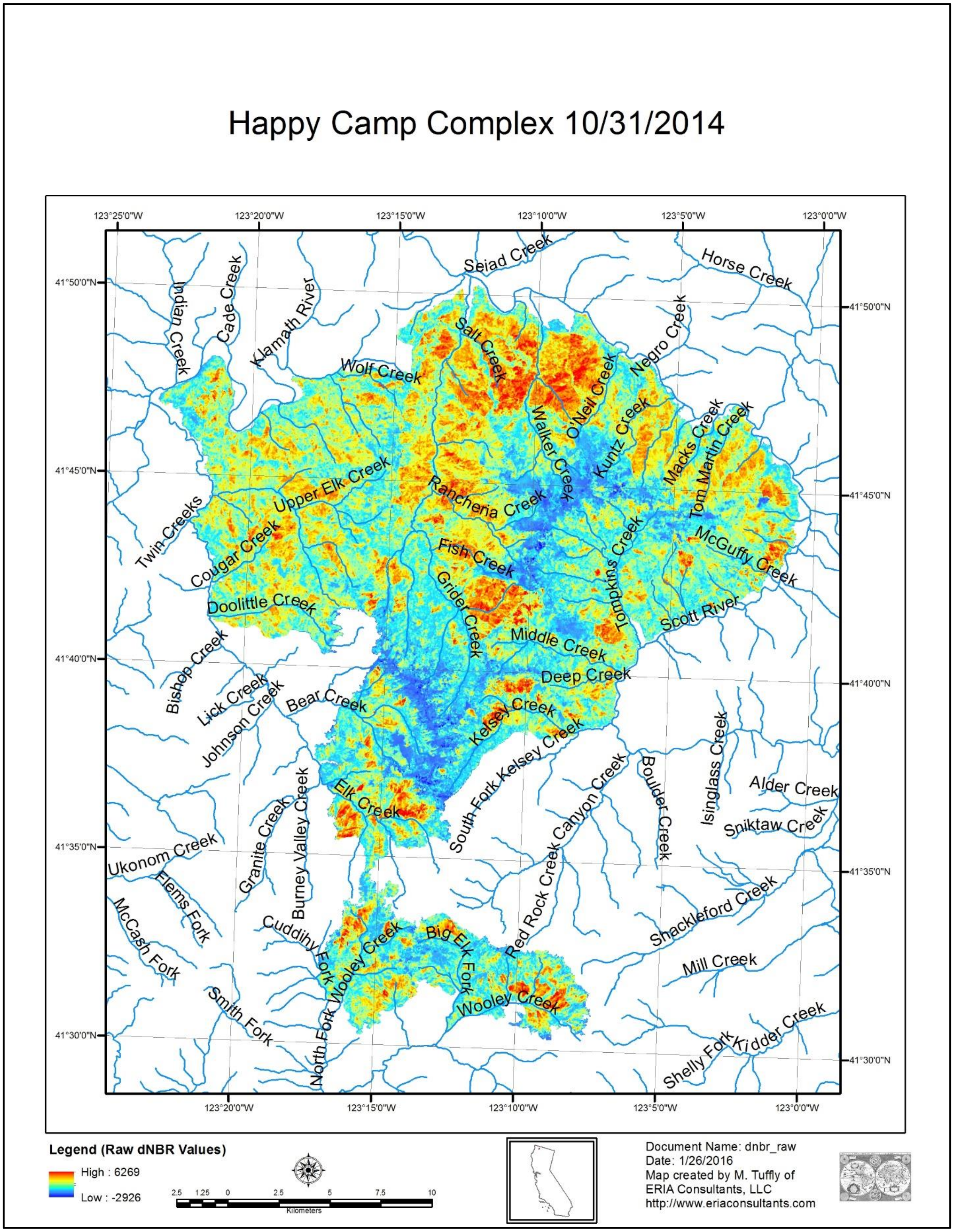


Figure 2. Raw dNBR values.

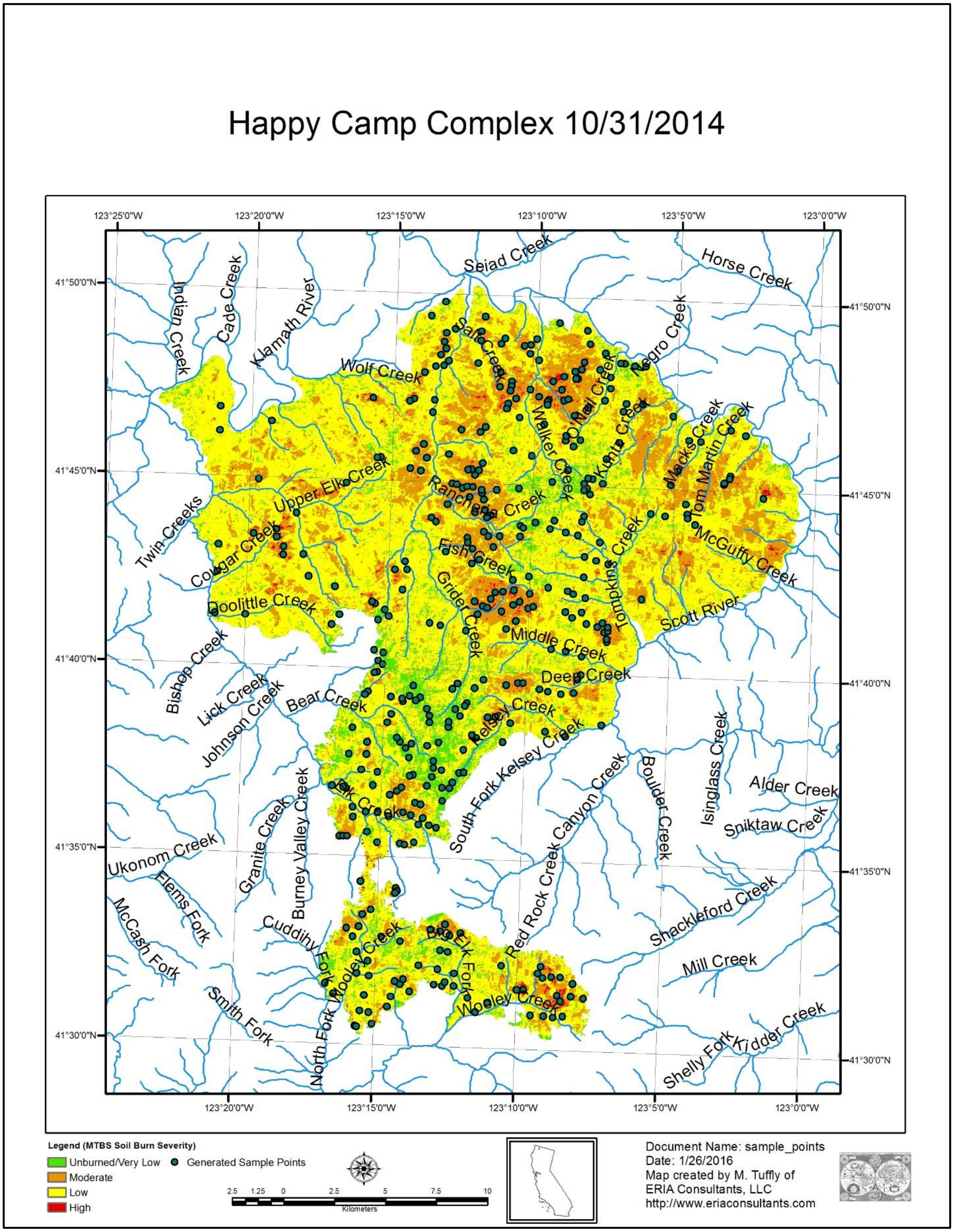


Figure 3. Generated Sample Points.

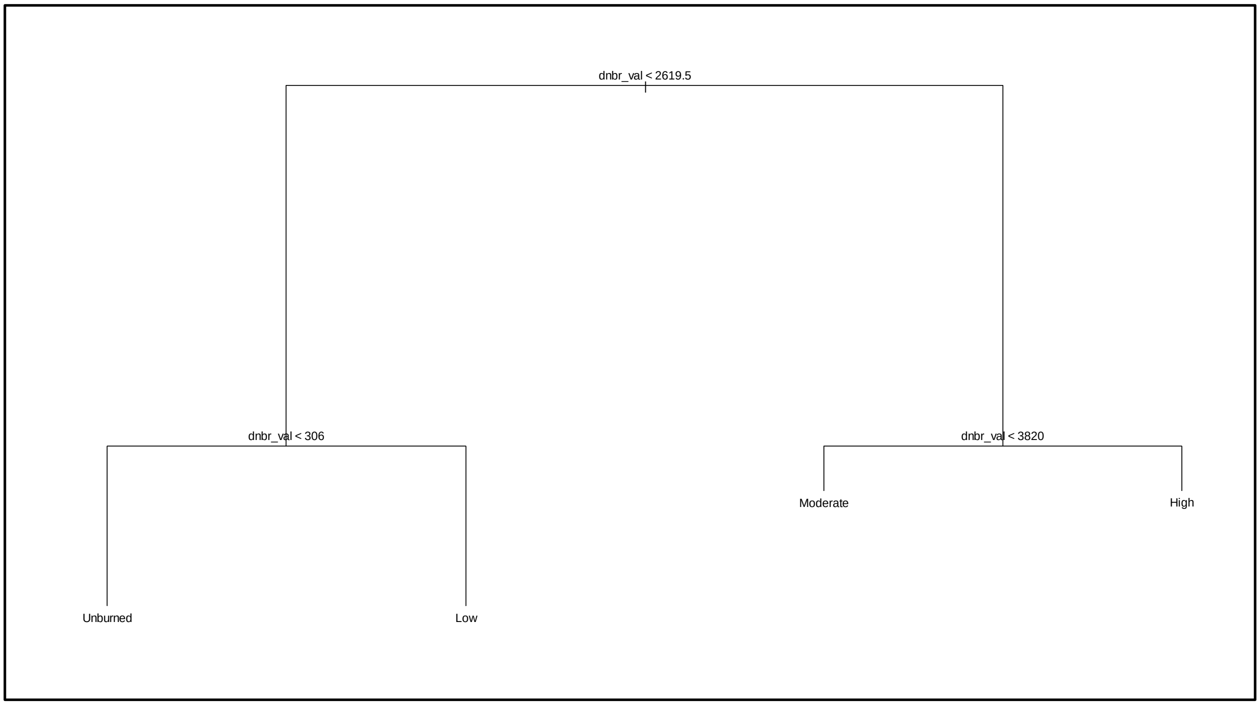


Figure 4. Results of the CART. Shown here are the break points for the raw dNBR values.

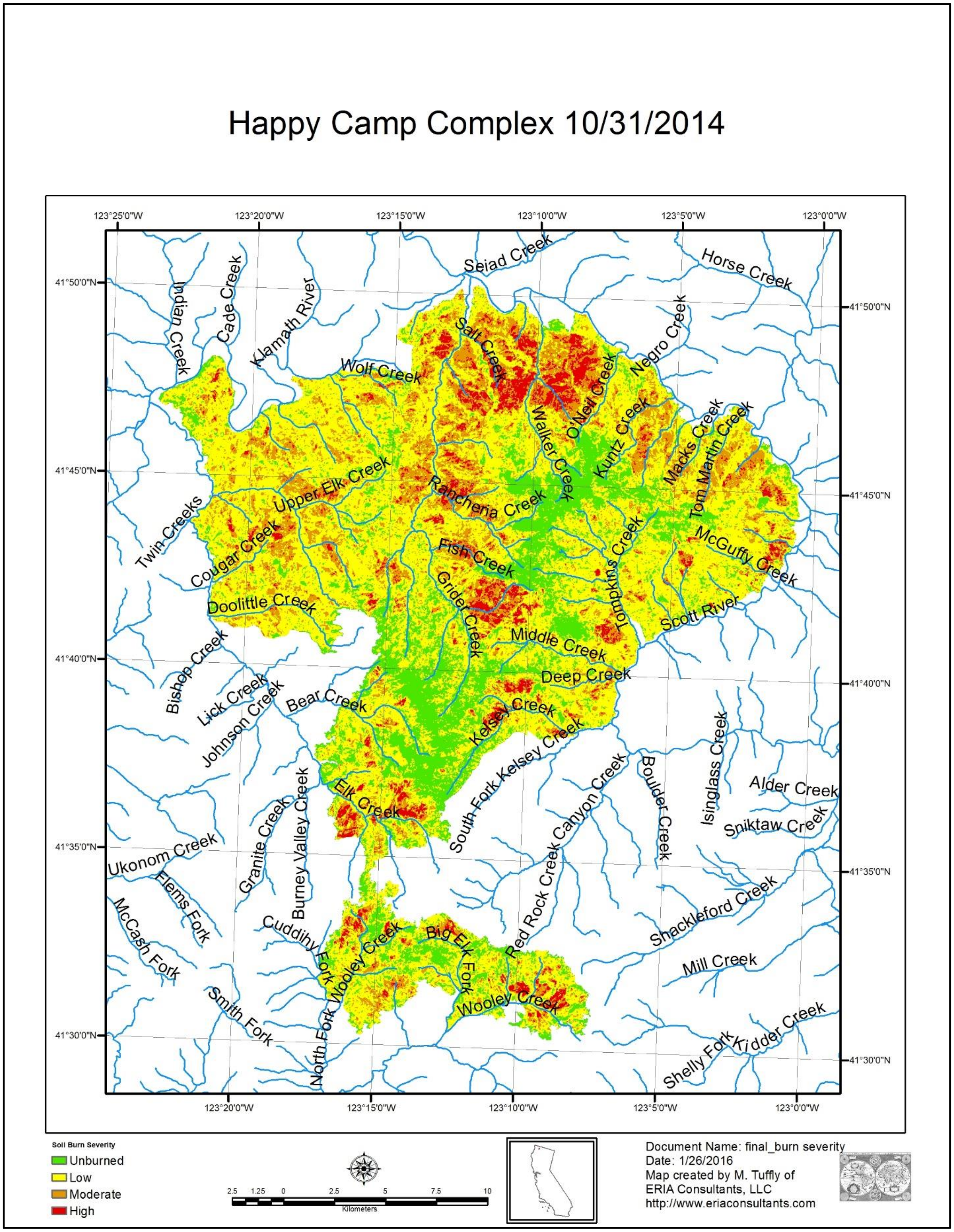


Figure 5. Final Burn Severity Map using Generated Points.

Table 1. Field Sample methods for implementing burn severity.

Burn severity	Sample within Fire Footprint	% crown fire	% area burned by pixel size	% mortality of late seral stage vegetation	% surface fuels consumed
Unburned	No (< 20%) & Yes (80%)	0	0	0	0
Low	Yes	0	< 25	0	<25
Moderate-Low	Yes	<20	>25 and <50	<25	>10 and<25
Moderate	Yes	> 20 and <50	>25 and <50	>25 and <50	>25 and < 50
High-Low	Yes	>50 and <75	>50 and <75	>50 and <75	> 50 and <75
High	Yes	>75	> 75	>75	>75

Table 2. Generate sample points by class.

Class	Number of Points
Unburned	85
Low	123
Moderate	110
High	80
Total	**398**

Table 3. CART Break Points

Class	Break Points
Unburned	< 306
Low	> 306 and < 2619.5
Moderate	> 2619.5 and < 3820
High	> 3820

Table 4. Acres partitioned by burn severity class using generated points.

Class	Acres	Percent
Unburned	24,290.94	18.84
Low	75,900.11	58.86
Moderate	22,244.67	17.25
High	6,516.28	5.05
Total	**128,952.01**	

Table 5. Confusion Matrix

				Modeled					
		Unburned	Low Burned	Moderate Burned	High Burned	Total	Omission Error (%)	Commission Errors (%)	Accuracy (%)
	Unburned	**71**	13	1	0	85	16.47	20.22	83.53
	Low Burned	14	**101**	7	1	123	17.89	29.37	82.11
	Moderate Burn	0	14	**58**	38	110	47.27	24.68	52.73
Field	High Burn	4	15	11	**50**	80	37.50	43.82	62.50
	Total	89	143	77	89	398			**70.35**

Appendix 1

Difference in Normalized Burn Reflectance dNBR Process.

If using LandSat8-OLI use Band-5 and Band-7. First a Normalized Burn Reflectance (NBR) needs to be created.

$$NBR = \frac{\text{Band5} - \text{Band7}}{\text{Band5} + \text{Band7}}$$

If using LandSat7-ETM+ use Band-4 and Band-7 (Key and Benson 2006)

$$NBR = \frac{\text{Band4} - \text{Band7}}{\text{Band4} + \text{Band7}}$$

If using WorldView -2® (WV-2) multi-spectral a Difference in Normalize Vegetation Index (dNVI) needs to be computed (Thompson, Pauli et al. 2015) to detect vegetation changes. Red visible Band (630 – 690 nm) and Near-IR1 Band (770 – 895 nm).

If using WV-2 use Near_IR1 and Visible Red. First a Normalized Vegetation Index needs to be created (NVI).

$$NVI = \frac{\text{NEAR\_IR1} - \text{Red}}{\text{NEAR\_IR1} + \text{Red}}$$

Two images are needed that are at least one year apart and as close to the same anniversary (bi-temporal). This will capture initial or first order effects (Chen, Zhu. et al. 2008). One image should to be as close to the time of the fire as possible without exceeding the ignition date. The second image should be at least one year post-fire. This will capture initial or first order effects (Chen, Zhu. et al. 2008). In order to capture second order effects the post-fire image should be two years post-fire (Chen, Zhu. et al. 2008). It is optimum to collect imagery as close to the summer solstice as possible. That is, when using bi-temporal imagery in a band ratio computation the summer solstice (Northern hemisphere only) time period for image collection will reduce shadows (Reeves, Anson et al. 1974, Jenson 1986).

Furthermore went computing the soil burn severity for a Burn Area Emergency Response (BAER) team time is of the essence. Post-fire images are needed as soon after the fire is extinguished regardless of the time of the year. Therefore compromises for a particular image selection are exercised.

$dNBR = NBR_{pre} - NBR_{post}$ (LandSat)

$dNVI = NVI_{pre} - NVI_{post}$ (WV-2)

WV-2 imagery does not contain parameters for atmosphere correction or solar zenith adjustments. However, it is advised not to use any WV-2 imagery that is greater than 30° off Nadar.

Processing LandSat imagery for dNBR

1) Download the LandSat imagery from the USGS
2) Correct for Top of Atmosphere (TOP) and solar zenith
    a. Using ERDAS 2015 model maker extracting and apply the parameters for the TOP (regression equation) and solar zenith angle contained in the in the imagery metadata.
    b. Multiply by 10000
3) Rescale values to go from 1 – 15000 (or whatever is needed) in ERDAS 2015
4) Use python or ArcGIS model Builder to computer the following
    a. Pre NBR (float)
    b. Post NBR (float)
    c. Final dNBR (int). To get the final dNBR multiply the float dNBR by 10000 and convert to integer.
5) Once the final dNBR is computed (raw dNBR values)
    a. Partitioned potential field samples using preliminary dNBR break points outline by Key and Benson (2006)
    b. Field data should be driven by Burn Severity classes descriptions contained in Table 1.
6) Using the statistical program R (R Development Core Team 2008) coupled with the Tree library (Ripley 2014) a Classification and Regression Tree (CART) is implemented on the raw dNBR values. This particular step is designed to capture either the soil burn severity, first order, or second order fire effects (Chen, Zhu. et al. 2008). CART is the ideal statistical method to use to classify the raw dNBR values because it is a non-parametric data classification technique. Moreover, CART can accommodate both continuous and categorical data in the same model. Furthermore, CART is not influenced by data that are spatially autocorrelation.

Processing WV-2 imagery for dNVI

1) WV-2 data can be orthorectified when purchased from the vendor for an additional cost (approximately $5/sq km)
    a. Or orthorectified can be done by an in house analyst that is familiar with the process.
2) The same methodology used to generating the dNBR using LandSat will apply for generating the WV-2 dNVI except:
    a. WV-2 needs no TOP or solar zenith correction.
    b. Different image bands are used in the computation.

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