Characterizing and Modeling Post-fire Vegetation Change in The Illilouette Creek Basin

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ABSTRACT

Fire is a key process influencing the composition and development of forests in western North America. As a result of an immense heritage of suppression, the Pacific Northwest is facing a crisis broadly known as the "western fire problem". Forest vegetation dynamics are intimately associated with this dilemma. In an effort to mitigate this problem, some parks such as the Illilouette Creek Basin in Yosemite National Park have implemented Wildland Fire Use. To investigate how post-fire vegetative landscape has transformed in this basin, I adapt a pre-existing vegetation map from 1997 and remotely sense three NAIP orthoimagery from 2005 to 2012 to create vegetation maps, representing major vegetation types on the landscape. I overlayed fire perimeter data, encapsulating small and large fires, from CALFRAP onto vegetation maps to generate pre-fire and successional post-fire vegetation. To evaluate post-fire vegetation change, two novel metrics were devised based on multitemporal remotely sensed data, indicating direct replacement and land cover shifts of particular vegetation types. Vegetation data, along with topographic variables and fire severity were additionally utilized as predictors in classification trees to model the future of vegetation change. The results presented here detail the decline of mixed conifer canopy and the expansion of sparse grassland and particularly shrubs. These trends are positively associated with elevation, slope, and RdNBR. TWI and hillshade have no significant on impact on vegetation change.

KEYWORDS

remote sensing, vegetation change, classification trees, shrub expansion, sierra nevada, long-term forest dynamics

INTRODUCTION

Fire is a key ecosystem process that influences the pattern, heterogeneity, fuel loads and development of forests in western North America (Agee 1998; Collins et. al 2009). Fire directly alters vegetation composition and density at numerous scales. At the landscape level, fire affects the size, arrangement, and age structure of vegetation patches (Turner et al. 1994). Widespread suppression policies (Skinner et. al. 1996) and the eradication of Native American burning practices (McKelvey et al. 1996) have disrupted these interactions and have transformed natural fire regime characteristics. As a result, composition and structure of forests in the western US have been altered significantly since Euro-American settlement (Taylor and Solem 2001, Heyerdahl et al. 2001). An immense accumulation of dry fuels has escalated burning potential in this region (Trouet et. al. 2006), reflecting a sharp decline in small recurring fires (Taylor and Solem 2001) and an increase in the risk of severe and catastrophic fire (Holden et al. 2007, Donovan and Brown 2007, Stephen et al. 2007, Miller et al. 2009). Reducing the risks associated with contemporary western fire regimes depends on landscape-scale vegetation distribution and abundance patterns.

While vegetation and species response is strongly influenced by variation in fire regime parameters such as the frequency, extent, return interval (Van Wagtendok et. al. 2012), severity (Collins and Stephens 2010), and seasonality of fires (Martin and Sapsis 1992, Bond and van Wilgen 1996), numerous variables affect vegetation patterns (and thus the fire regime). For example, invasive insect attacks (Swetnam and Lynch), windstorms (Taylor 1990a; Foster and Boose 1992), access to deep soil moisture (Thompson et al. 2011), and species life history (e.g. dispersal mechanisms, growth rates, etc.) all have been documented to affect vegetation patterns at landscape scales and contribute to the maintenance of species diversity (White 1979). In addition, topographic variables and particularly slope have been shown to have large influence on forest structure (Kane et al. 2014). Site water balance measured by evapotranspiration and climate water deficit, has been shown to be the most significant predictor in modeling forest structure (Kane et al. 2014). Annual actual evapotranspiration (AET) and annual climatic water deficit can be used to predict vegetation presence (McKenzie et al. 2003) and growth rates (Dyer 2004). Climate warming (Donovan and Brown 2007) is also anticipated to perturb other ecosystem responses such as vegetation development, which includes climate migration, substation and extinction (Weber and Flannigan 1997). Ultimately, wildfire is a disturbance that is sensitive to vegetation composition and structure and other spatially dependent variables (Clark 1993).

Because the National Park Service (NPS) policy states that it will protect natural resources, life and property from unnatural wildfires and restore and maintain natural fire regimes, an active non-repressive fire management program has been implemented within select western US parks. Fire management commenced using prescribed fire starting in 1968 when the first large prescribed burn on NPS lands (Kings Canyon and Sequoia) in the Western states was ignited (Kilgore 1971). Today, natural fire management programs are referred to as Wildland Fire Use (WFU), which is a long-term management program that allows naturally-lit fires to burn unhindered over a landscape. (Christensen 1991, Parsons and van Wagtendonk 1996). Since 1972, the Illilouette Creek basin in Yosemite is one of two areas where WFU has been implemented (the other is Sugarloaf Creek). Due to repeated burning, the Illilouette Creek basin has become one of the first restored natural fire regimes. As a result, determining what variables drive forest development patterns is key for identifying the essential role of disturbance in long-term dynamics of forest ecosystems (Collins et al. 2007). The Illilouette Creek Basin (ICB), within Yosemite National Park, provides a unique opportunity to study the process of post-fire vegetation development under relatively natural conditions.

To my knowledge, not one study in the ICB has yielded an exhaustive outlook at overall trends of vegetation development following a fire and what predictors influence them. Previous work in the Illilouette Creek basin have focused on the effects of fire suppression and fuel loads and succession (Van Wagtendonk 1985), the patterns of fire severity at the pixel level (Collins et al. 2007), the interactions among fires and the fire return interval as self-limiting mechanism of fire (Collins et al. 2009), stand-replacing patches (Collins et al. 2009), changes and trends of extreme fire weather (Collins et al. 2014). Major vegetation shifts as a function of the number of historic fire return intervals (or FRID) has also been characterized (Van Wagtendok et. al. 2012). Another study in Yosemite revealed that water changes in deficit over varying climate scenarios suggest that recent past changes in forest structure and composition will accelerate in the future, species varying individually to further declines in water availability (Lutz et al. 2010). In one of the most recent studies in Yosemite, environmental conditions, and particularly climate water deficit and slope, were shown to have strong relationship with fire and forest structure (Kane et al. 2014). While the previous two studies in particular utilized historic vegetation maps from 1937 and 1997 to quantify vegetation change, these maps may not capture the nuances of the dynamic forest structure for areas like the ICB, despite that both these studies quantified the interaction between individual species and variables to some extent.

Notwithstanding the immense contributions of previous research, studies addressing fine grain multi-spatial and -temporal trends and patterns of vegetation change within post-fire regions in the ICB are lacking. Although characterizing the larger vegetation trends and patterns in this basin would benefit fire disturbance ecology research by quantitatively evaluating the dynamism of the vegetative landscape within and apart from post-fire areas, I suspect current research has not taken on this project due to several reasons. Firstly, there is a limited amount of data within the ICB (e.g. Wieslander 1935). Secondly, acquiring data other than from pre-existing vegetation maps such as remote sensing is computationally intensive by nature. Thirdly, research using fine grain data may not have been considered favorable for an analysis. This is because numerous studies have neglected vegetation analysis for fire beneath 30 or 40 ha (e.g Collins et al. 2009, Kane et al 2014, etc), so if corresponding fire perimeter data were small, then a study would not have likely been conducted. Here, I reject the general consensus that large scale fire events are more valuable to evaluate and pursue an analysis of fires of varying spatial extents.

In this study I take advantage of fine grain aerial imagery to investigate the patterns and trends of vegetation development within recent fires of largely variable extents. The objective of this paper is the characterization of vegetation change in the Illilouette Creek Basin, Yosemite National Park, USA. Here I ask how has post-fire vegetation changed in the ICB due to fire over the past 15 years, from 1997-2012? To address this inquiry, I will determine (1) overall change of vegetation change (2) the dominant vegetation type that is emerging with greater frequency in fire-scarred areas, (3) the predictor variables with which vegetation change is positively associated, particularly assessing topographic variables and fire severity, and (4) the major vegetation transitions or departures from conifer species using two novel metrics of my design. As a means of quantification, I will classify vegetation types that are clearly articulated in the landscape using multitemporal remotely sensed orthoimagery, perform a statistical analysis on these vegetation data using two novel metrics, and lastly model vegetation change with classification trees. Due to the presence of WFU that has been in effect in and around the fires on which I will focus, the results from this study can serve as a proxy for understanding the effectiveness of natural fire programs. Ultimately, because the ICB is in the heart of the Sierra Nevada, I also intend for this work to provide managers in the Pacific Northwest with information on long term vegetation dynamics and possibly mimicking landscape development into the future.

METHODS

Study Area

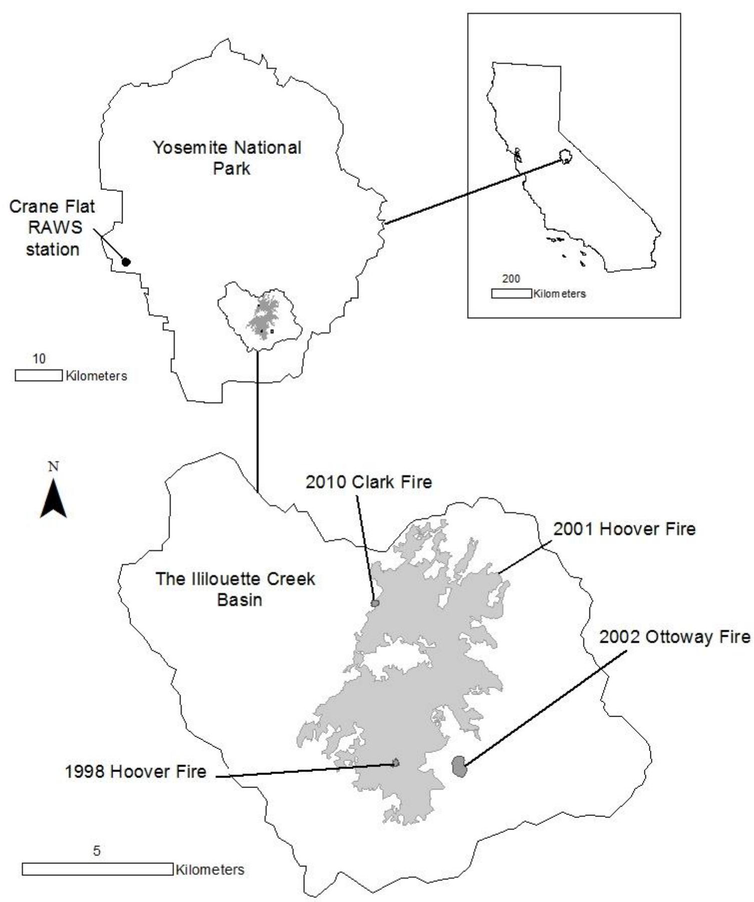

Fig. 1 The Illilouette Creek Basin and locations of the 1998 and 2001 Hoover fires, 2002 Ottoway fire and 2010 Clark fire in Yosemite National Park, California, USA.

The Illilouette Creek Basin (ICB) is located in Yosemite National Park, situated in the central Sierra Nevada, California, USA (Fig. 1). The basin is over 15,000 ha with elevations ranging from 1400 to 3000 meters for surrounding ridges. It has a Mediterranean climate with cool, moist winters, and warm, dry summers. The average January minimum temperatures range from -2 to 5 °C and the average July maximum temperature from 19 to 31 °C (1992-2009, Crane Flat Remote Automated Weather Station-RAWS). Precipitation varies with elevation and predominantly consists of snow, with an annual average of 62 cm (Collins and Stephens 2010).

Vegetation in the ICB varies with elevation (Collins et. al., 2007). The upper elevation mixed-conifer forest of the ICB are dominated by Jeffrey pine (*Pinus jeffreyi*), white fir (*Abies concolor*), red fir (*Abies magnifica*), and lodgepole (*Pinus contorta var. murrayana*), and are interspersed with meadows and shrublands. Shrublands are dominated by *Arcostaphylos* and *Ceanothus* (Personal Obs.). Along riverbanks and areas with high soil moisture in the lower montane forest, quaking aspen (*Populus tremuloides)* and red willow (*Salix laevigata*) commonly occur (Personal Obs.). Based on tree-ring analysis, the historical fire regime within Jeffrey pine-dominated stands predominantly consisted of frequent low-to-moderate-severity fires. The mean fire interval is approximately 6.3 years (Collins and Stephens 2007).

Numerous fires varying in severity and spatial extent have swept through the ICB from 1997-2012 (Fig. 2). Fires that burned the largest amount of ha occurred in 2001 and 2004, while the average is approximately 363 ha. The first Hoover fire (started in 1998), the second Hoover fire (started in July 26, 2001), and the Ottoway fire (started in July 11, 2002), with the exception of the Clark fire (started in August 8, 2010) were all fires that began as lightning-ignited fires that were allowed to burn under WFU programs in the Illilouette Creek Basin. These fires were selected because they were fires that burned variable spatial extents within the ICB and more importantly were encapsulated by the extent of my aerial imagery. The 1998 Hoover fire burned approximately 4 ha, the 2001 Hoover fire burned over 2100 ha, the 2002 Ottoway fire burned 25 ha and the 2010 Clark fire burned roughly 4.5 ha.

The methods I utilized comprised five main steps: 1) data collection, 2) remote sensing and construction of vegetation maps, 3) field validation, 4) statistical characterization of vegetation change and 5) environmental response modeling. Orthoimagery was gathered from a

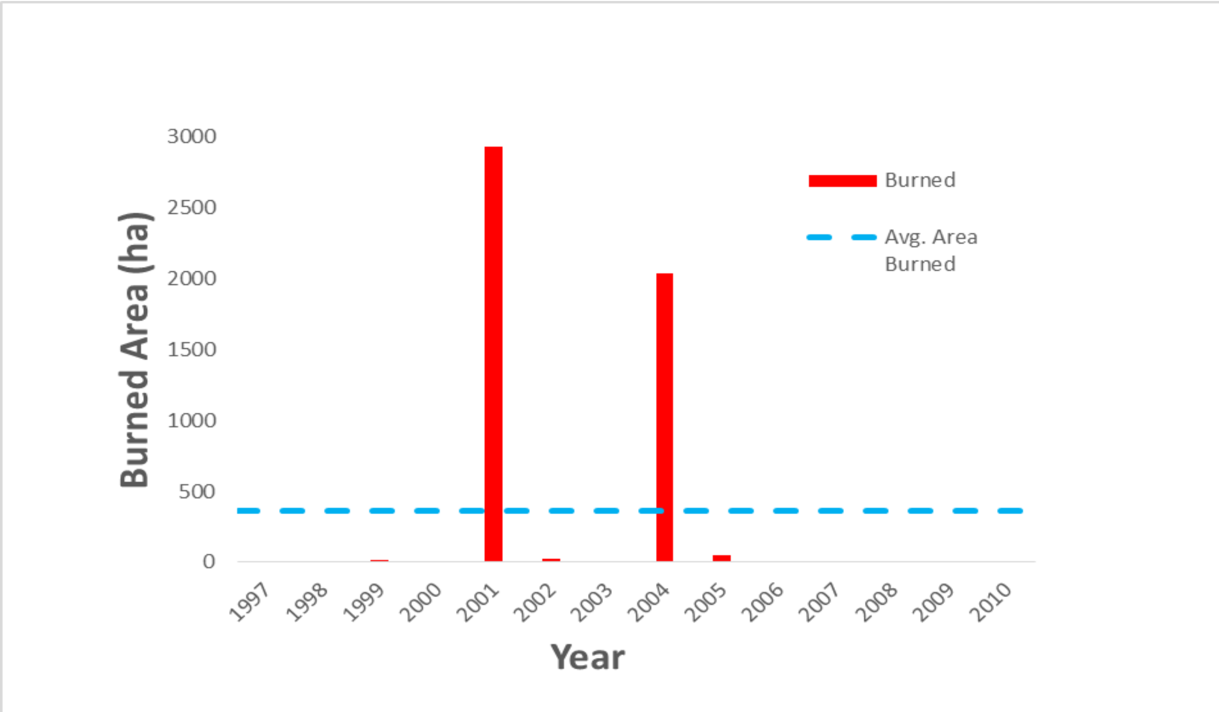

Fig. 2 Total area of vegetation burned (in ha) within the ICB from 1997-2012. 2012 not included along the x-axis because of the absence of fires that year.

variety of sources. Note that the spatial extent of my study site was larger than the area covered by a single photograph (Fig. 3). The extent of the aerial imagery clipped fires accordingly and produced vegetation maps with the same extent. For remote sensing and classification, I concentrated on obtaining five main vegetation types from the landscape; namely mixed conifer, shrubs, dense grassland, aspen, and sparse grassland. Using GPS data, I assessed the accuracy of one of the vegetation maps and assumed this accuracy over other maps. For statistical characterization, the variables I collected followed a certain logic; that is, initially looking at overall changes, then focusing on specific post-fire changes. To assess overall change, I found the total area (ha) of each vegetation type for all four vegetation maps. I then looked at percentages of vegetation cover vegetation transition ratios to assess vegetation change within fire-scarred areas by imparting vegetation data into fire perimeter data. I looked at vegetation change within these fires in terms of post-fire change and later post-fire change. Percent of vegetation cover change can broadly be understood as the percent of some post-fire vegetation area divided by its pre-fire vegetation area. A vegetation transition ratio can be conceptualized as the proportion of pixels classified as vegetation type A at time 1 classified as vegetation type B or A at time 2 [For formulaic details on these two metrics, see section on Statistical Characterization of Vegetation Change below]. With respect to environmental response modeling, I was concerned with further elaborating on vegetation change within fire-scarred areas on a pixel basis. To accomplish this, all predictor and response variables were rasterized to create a pixel-based, multivariate classification trees for each fire and then an ensemble for 1988, 2001 and 2002 fires. The predictors encompassed

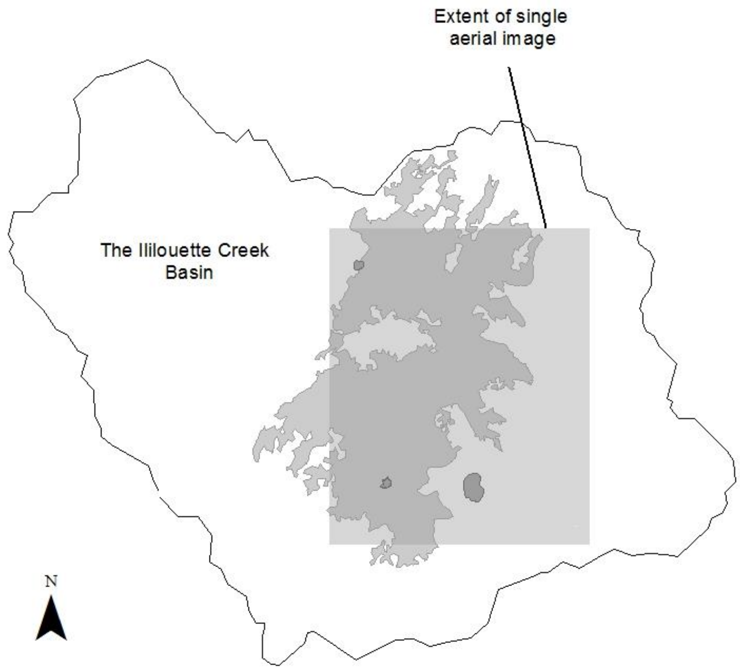

Fig. 3 Extent of aerial photography. Photograph depicted as grey rectangle.

five topographic features; namely, Topographic Wetness Index (TWI), elevation (meters), hillshade, slope (degrees), and aspect. Another predictor accounted for the fire severity or the Relative differenced Normalized Burn Ratio (RdNBR). The response variable was the vegetation type pixels within fire areas.

Data Source

I utilized three NAIP aerial images with 1-meter resolution and one coarse historic vegetation map when constructing my vegetation data. All aerial images were much smaller than the study site and were located within the eastern half of the ICB. Together these data spanned the years 1997-2012. The three aerial images encapsulated the years 2005, 2009, and 2012, (Fig. 4) while the vegetation map the year 1997. The three aerial images were compiled from DOQQ, Earth Explorer, NAIP, and NAPP and the vegetation map from the Yosemite National Park Service.

Remote Sensing and Construction of Vegetation Maps

To define the vegetation types in the ICB, I first constructed vegetation maps that synthesized and represented different vegetation types on the landscape using *eCognition Developer 9.0 (Trimble Navigation Ltd)*, a remote sensing software that integrates a development environment and a wealth of functions ranging from spectral to textural operators for object-based image analysis. The reason why this software was utilized was to have explicitly defined measurement procedures for vegetation map generation and therefore have an objective delineation of boundaries between vegetation types (Kadman et. al., 1999). Applying object-oriented supervised classification, as well as built-in functions specific to eCognition, I classified

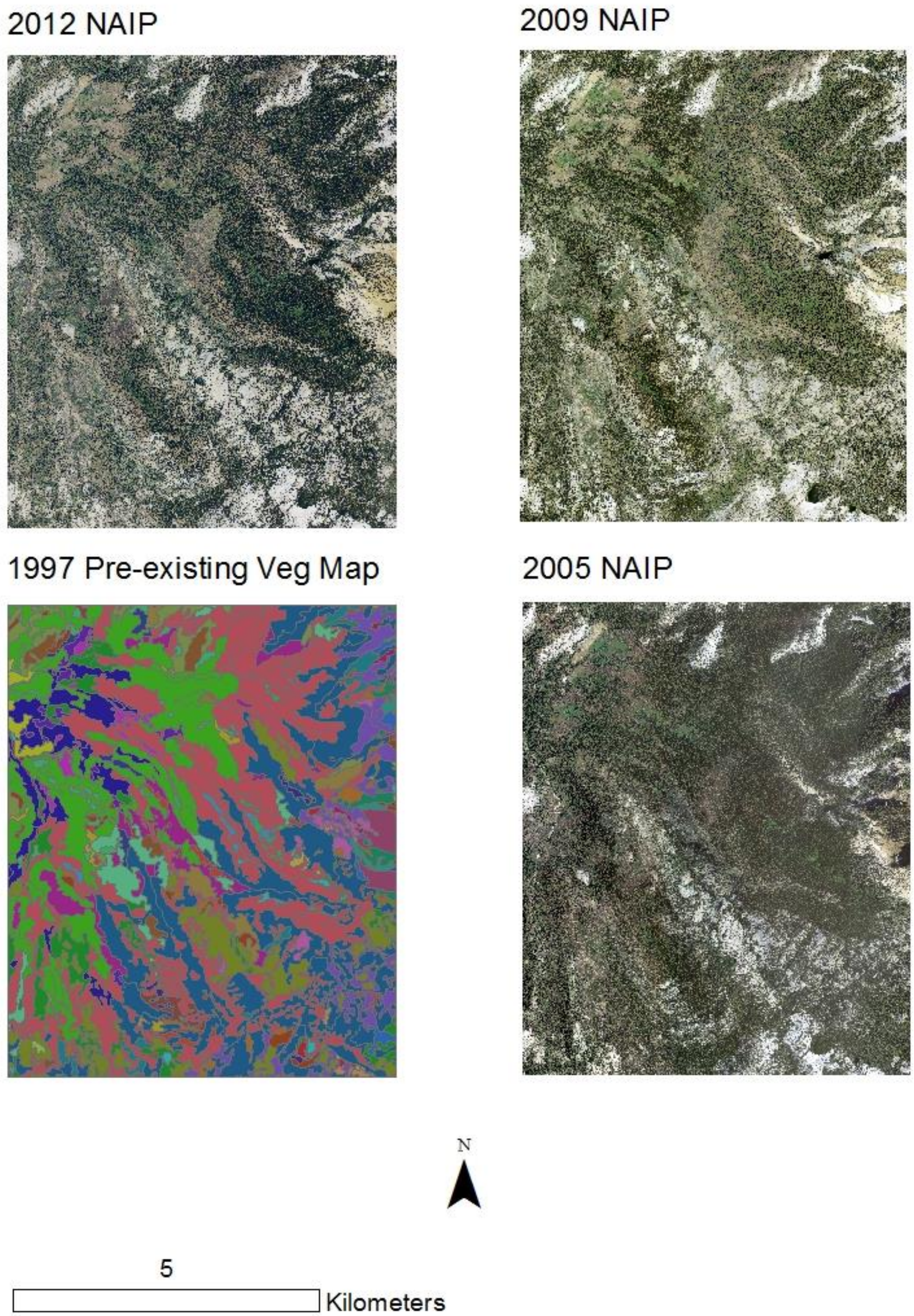

Fig. 4 2005, 2009 and 2012 NAIP images with 1-meter resolution taken in the eastern portion of the ICB, depicting a heterogeneous vegetative landscape.

six vegetation types: 1) mixed conifer 2) sparse grassland 3) dense grassland 4) aspen 5) willows and 6) shrubs. There are two reasons for classifying these vegetation types as opposed to others: firstly, they were the clearest and most visible variables in aerial imagery and secondly, they have played large roles in altering the landscape when fires have swept through the ICB.

As input for *eCognition* I collected a total of 3 NAIP aerial images, with the earliest image from 2005 and the most recent 2012. Training data rule sets or programs for the five vegetation classes were constructed separately for each of the three aerial photos using a sub-extent of the entire photograph and then applying that completed ruleset to the entire photograph. All rulesets were based on thresholding and thus constructed on the basis of the assign class algorithm and various thresholding conditions. Assigning each vegetation type a class in the aerial images required a dissimilar combination of spectral conditions; namely, layer values. Rulesets were designed according to the following linear schema: 1) image object creation by segmentation, 2) classification of granite via thresholding, 3) classification of vegetation via thresholding, 3) corrections, and 4) merge. The merge function fuses image objects for selected vegetation type. Vegetation maps were created using the export vector layer algorithm.

A list of common ruleset parameters that appeared in 2005, 2009 and 2012 rulesets for each vegetation type will follow, where the term common signifies the parameters that appeared in all three rulesets [For more in-depth ruleset details, see Appendix 1, Table 1]. Across all rulesets, multiresolution segmentation was coupled with spectral difference segmentation to generate image objects from NAIP imagery. For granite, a mixture of Mean Red, Mean Green, and Rel. border to Granite was needed. There was only one requirement for sparse grassland demarcation and this consisted of indiscriminately assigning remaining unclassified objects after granite classification as sparse grassland using the assign class algorithm, no threshold conditions, and a sparse grassland class. Mixed conifer delineation required mode [Minimum] (Green) across all rulesets and Dense Grassland separation mode [Minimum] (Red). Aspen required mode [Minimum] (Red) range to distinguish it from other vegetation. Lastly, shrubs did not have any requirements common to all three rulesets. However, Standard deviation Green and HIS Transformation Saturation (R=Red, G=Green, B=Blue) did appear for both 2005 and 2009 rulesets. Shrub classification differed for 2012 differed largely.

Field Validation

To evaluate the accuracy and reliability of my vegetation maps generated from computerized analysis, I groundtruthed—or took independent field measurements in the study area, and created a confusion matrix. Accuracy is the percentage of groundtruth pixels that also appear as pixels in the classified vegetation maps. Reliability is the percentage of pixels in the classified image that actually represent pixels on the ground. To evaluate the actual distribution of the particular vegetation types remotely sensed and classified, three field excursions were taken to Yosemite National Park during the summer of 2014. These three trips took place May 27-29th, June 6-13th, and July 29-August 2nd. During the first trip I entered the ICB heading eastward from Glacier Point and the last trips from Mono Meadows. For each of these trips, groundtruthing was conducted using a *Garmin GPSMAP 62st*. The GPS points were recorded when sizeable vegetation stands indicating my five vegetation types were encountered. Descriptive text designating what vegetation we observed were linked to each GPS point. After these trips, on-site designations given to the GPS points were later summarized in *ArcGIS* to correspond to the major vegetation types being considered. They were finally compiled into a single shapefile of points called groundtruth. Given that the 2012 vegetation map was the closest year to when the field excursions occurred, a confusion matrix was made using the 2012 classified vegetation types and the 2014 referenced vegetation types.

Statistical Characterization of Vegetation Change

I defined the term vegetation change through three broad lenses: total area, percentage of vegetation cover change (VCC), and vegetation transition ratios (VTR). Total area was assessed to compare changes of the entire study area with post-fire vegetation change, represented by VCC and VTR. VCC is a value from 0 to infinity and can be interpreted as the percent of landcover change for some vegetation type from one year to another. VTR ranges from 0 to 1 and can be interpreted as the direct replacement or persistence of vegetation type cover from one year to another (for greater details on the interpretation of VCC and VTR, see Appendix 3). To analyze vegetation change specific to post-fire regions, I formulated these two metrics based on all vegetation maps and fire perimeter data that were either vectorized and rasterized (this will be explained soon). Rasterized data were further transformed into ASCII matrices of ones and/or zeros to facilitate the computation of VTR. Both VCC and VTR of vegetation types were based on three time intervals. The first interval is based on pre- and post-fire vegetation maps, whereas the two that follow are based on post-fire vegetation maps alone. This means for the 1998, 2001 and 2002 fires, the 1997 map acted as the pre-fire vegetation and 2005 map as the post-fire vegetation map used to compute VTRs and VCCs for all vegetation types. For the 2010 fire, the 2009 map will act as the pre-fire vegetation and the 2012 map the post-fire vegetation. The subsequent intervals will consider post-fire vegetation maps well after the fire. This means that for all fires except 2010, 2005 and 2009 maps will be the next interval analyzed for change. From here, 2009 and 2012 vegetation maps will follow as the last intervals to be analyzed. Given that the data only reached 2012, only one interval was analyzed for the 2010 fire. While numerous fires that fires considered were restricted to eastern portion of the ICB, only the 1998 and 2001 Hoovers fires, 2002 Ottoway fire and 2010 Clark fire were accounted for. GIS fire perimeter data for these years were acquired from CALFRAP.

I defined percent vegetation cover change as

$$VCC = \frac{A_{PostFireVeg}}{A_{PreFireVeg}} \times 100$$

Where $A_{PreFireVeg}$ is the vector area of some pre-fire some vegetation type A at year 1 and $A_{PostFireVeg}$ is the vector area the post-fire vegetation type A at year 2. I defined a vegetation transition ratio as

$$VTR = \frac{\sum[Fire_{year1} \times PreFireVeg(A)_{year1} \times PostFireVeg(B\ or\ A)_{year2}]}{\sum[PreFireVeg(A)_{year1} \times Fire_{year1}]}$$

Where $Fire_{year1}$ is a matrix of ones, ones indicating the spatial geography that the fire occupies. $PreFireVeg(A)_{year1}$ is a matrix of one and zeros, ones indicating the spatial geography occupied by vegetation type A at some year 1 and zeros all the remaining vegetation types and objects that comprise the vegetation map. $PostFireVeg(B\ or\ A)_{year2}$ is a matrix of ones and zeros, ones indicating the spatial geography occupied by vegetation type A or B (if the vegetation remained the same or changed) at some subsequent year 2. The zeros interpretation is the same as above. $\sum[Fire_{year1} \times PreFireVeg(A)_{year1} \times PostFireVeg(B\ or\ A)_{year2}]$ means the total number of pixels that changed to vegetation type B or remained as A, from year1 to year2, within the spatial geography of the fire. $\sum[PreFireVeg(A)_{year1} \times Fire_{year1}]$ means the total number of pixels of pre-fire vegetation type A in the year1 within the spatial geography of the fire. Together, the numerator and dominator form a single VTR, the proportion of pixels classified as vegetation type A at time 1 classified as vegetation type B or A at time 2 within some fire that occurred between time 1 and 2.

Environmental Response Modeling

To further articulate how my five vegetation types within fire-scarred areas are likely to alter in terms of post-fire change and regrowth at the pixel-level, I utilized multivariate classification trees capacities within *Matlab R2013a.* Classification Trees are a probabilistic method that disaggregate multivariate data based on a set of rules, where each rule is defined using a set of predictor variables. These predictors-based rules are represented by nodes on an inverted tree, from which response variables are ramified starting at a root node until ending at various leaf nodes. The topmost node represents the variable that explains the greatest variation in the data. Predictor variables range from numerical to categorical arrays and response variables are simply categorical. The predictor variables I selected to measure were aspect, slope, hillshade, elevation, RdNBR, TWI and pre- or post-fire vegetation types, depending on the interval I am assessing. RdBNR was a predictor factored for vegetation change within 1998 and 2001 fire perimeters. The response variable was post fire vegetation types. All predictor and response variables were rasterized. Predictor variables had variable grain-size, from 5-, 10-, to 30-meters resolution, whereas response variables a single grain size of 5-meters. Using the *sample* function in *ArcMAP 10.2.2*, all rasters and there grain sizes were consolidated, so that vegetation change within all fire perimeters could be analyzed at a 5-meter resolution.

TWI, hillshade, slope, and aspect were calculated using a Digital Elevation Model (DEM) in *ArcGIS version 10.2.2*. These topographic variables were assumed to have remained unchanged between 1997 and 2012. RdNBR was obtained from *Miller and Thode 2007*. TWI was calculated following *Sorenson et al. 2006*. The functions implemented in *ArcGIS version 10.2.2* for the four topographic features were the raster calculator, aspect, and slope. TWI is a measure of potential soil moisture controlled by the landscape (Beven and Kirkby 1979; Sorensen et al. 2006). It is defined as $\ln(a/\tan\beta)$ where a is the local upslope area draining through a certain point per unit contour length and $\tan\beta$ is the local slope. Given that upslope area and local slope can range widely, it theoretically has a range from 0<TWI<inf, where larger values generally signify a larger potential soil moisture. Hillshade is a shaded relief created by considering the illumination source angle and shadows, an integer value from 0-255, where 0 means shadow and 255 no shadow or sunlit. Slope is a measure of the gradient or rate of maximum change in z-value given in degrees from each cell of a raster surface, ranging from 0-90, where 0 indicates a plain slope and 90 a vertical slope. Aspect identifies the downslope direction of the maximum rate of change in value from each cell to its neighbors, a slope direction which shows in degrees whether or not slope is facing the sun. To avoid confusion between 0 and 360 degrees, I converted aspect into an aspect index which varies from 0 to 1 (see Moisen and Frescino 2002). RdNBR is an index that is computed by differencing reflectance in bands 4 and 7 in pre- and post-fire scenes from Landsat ETM+ imagery (see Miller and Thode 2007). This burn severity metric summarizes the effects of fire on the abiotic environment and vegetation, including impacts of the fire and ecosystem response up to a year. Higher RdNBR values signify a decrease in photosynthetic materials and surface materials holding water and an increase in ash, carbon, and exposed soil. RdNBR has been validated as a robust estimator of

burn severity in the field of the Sierra Nevada (Thode 2005. Thode 2011) Fire severity can be viewed as the loss of biomass caused by a fire, and vegetation productivity induced within a post-fire region (Ursino and Rulli 2010).

Using predictor variables associated with each fire-scarred area, I made a total of 13 classification trees. Nine trees stemmed from 1998, 2001 and 2002 fires, where each classification tree was based on one of three intervals in between 1997 and 2012 and elaborated on how vegetation types changed after the fire and how they changed some time later. Another can came the 2010 fire. The last three were ensembles of 1998, 2001 and 2002 fires. These ensemble classification trees are temporally and spatially heterogeneous, synthesizing vegetation change for all fires when and where they occurred.

RESULTS

Construction of Vegetation Maps

With a combination of remote sensing and classification, I generated a total of four vegetation maps that largely represent the eastern portion of the basin (Fig. 5). All maps, with the exception of 1997, considered only five vegetation types and one non-vegetation type — namely, mixed conifer, shrub, dense grassland, aspen, sparse grassland and granite. The 1997 vegetation map additionally classified water bodies on the landscape, such as small rivers and lakes. This is based on the original vegetation map made by the Yosemite National Park Service, which had various other classifications. These classifications detailed numerous individual tree species, such as ponderosa pine, red fire, which were not relevant to my analysis. Like remotely sensed NAIP imagery, these classifications were consolidated as five current vegetation types and granite classifications.

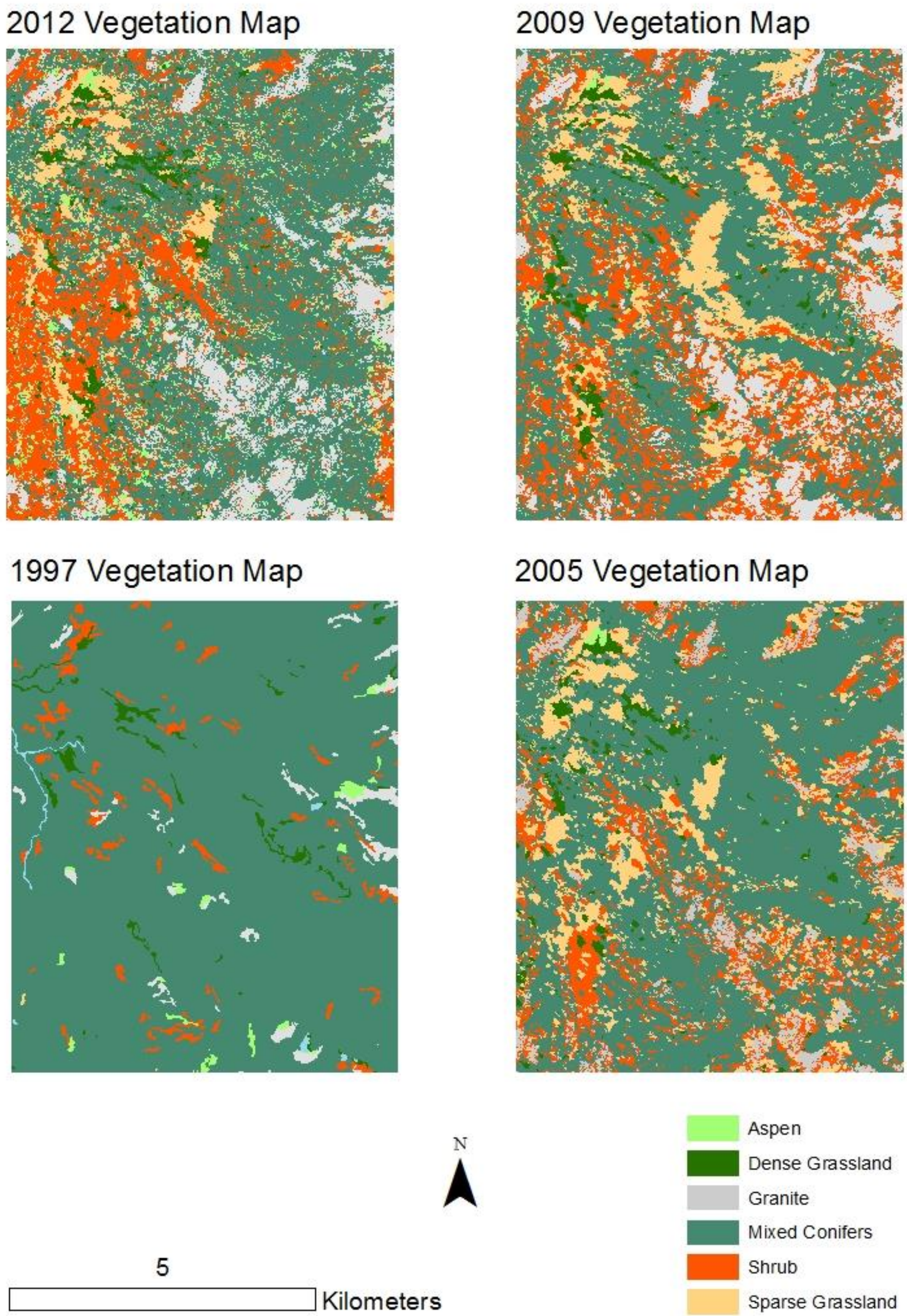

Fig. 5 1997, 2005, 2009 and 2012 vegetation maps from left to right and top to bottom. Vegetation types listed are aspen, dense grassland, mixed conifers, shrub and sparse grassland.

Field Validation

Applying a confusion matrix to the classified 2012 vegetation map revealed a high accuracy and reliability, as well as overall accuracy (Table 2). These resulted after excluding and manually shifting 4-5 GPS points of a 90-point sample. Points were removed when the vegetation type they represented were miniscule in comparison to a surrounding vegetation type as shown in the aerial image and classification. One example would be an unrecognizable shrub patch in the midst of large sparse grassland. Other points were shifted to account for error in the GPS and particularly moments when a vegetation type was recorded outside the vegetation patch, such as in the case of shrubs. Accuracy turned out to be 92.4 % and reliability 93.2%. A computation concerning overall accuracy, or the total number of pixels whose GPS data corresponded with classified pixels divided by total pixel sample, yielded 92.9%.

Table 2 Confusion Matrix detailing the accuracy (producer's accuracy) and reliability (user's accuracy) of the remotely sensed 2012 NAIP image classification. Average accuracy and reliability are 92.4% and 93.2%, respectively. Overall accuracy is 92.9%

	Reference data						
Classified data	Dense Grassland	Sparse Grassland	Mixed Conifer	Shrub	Aspen	Row total	Reliability
Dense Grassland	18	0	0	1	0	19	0.95
Sparse Grassland	0	12	0	1	0	13	0.92
Mixed Conifer	0	1	22	0	1	24	0.92
Shrub	0	0	1	14	1	16	0.88
Aspen	0	0	0	0	13	13	1
Column total	18	13	23	16	15	85	
Accuracy	1	0.92	0.96	0.88	0.87		

Statistical Characterization of Vegetation Change

An analysis of vegetation change with respect to total area and post-fire vegetation change through VTRs and VCCs revealed related trends regarding the vegetation cover and direct transitions of particular vegetation types on the landscape. In terms of all vegetation maps, including burned and unburned areas, mixed conifer canopy had significantly decreased from 1997 to 2012, from approximately 4,500 ha to 2,500 ha (Fig. 6), while shrub and sparse grassland canopy had significantly increased, from 180 to 1000 ha and virtually no land cover to 500 ha, respectively (Fig. 7).

VCCs and VTRs elaborated vegetation trends. From 1997 to 2005 (Table 3), all fires had mixed conifer VCCs were < 1, indicating a decrease in mixed conifer cover. VCCs of shrub and particularly sparse grassland were >>1, indicating significant increases in shrubs and sparse Grassland cover. The only exception to this trend is the 2010 fire, which has a VCC <, 1 indicating a decrease in shrub cover. Spanning into 2009 from 2005 for 1998, 2001 and 2002 fires (Table 4), the VCCs of mixed conifer continue to be < 1, indicating a continued decrease in mixed conifer cover. The majority of shrub and sparse grassland VCCs are still > 1, indicating an increase in shrub and sparse grassland cover. The only exception to this trend is the 1998 fire for shrub. From 2009 to 2012 for the same fires (Table 5), the majority of mixed conifer VCCs continue to be <1, evincing a persistent decrease in mixed conifer cover. The 2002 Fire is the only exception to this trend. In this interval, the VCCs of shrub and conifer begin to alter. While the majority of shrub VCCs continue to be >1, sparse grassland VTRs become < 1, indicating that while shrub cover on whole continues to increase, sparse grassland cover decreases. The 2002 fire yields the only exception to general VCC shrub trends.

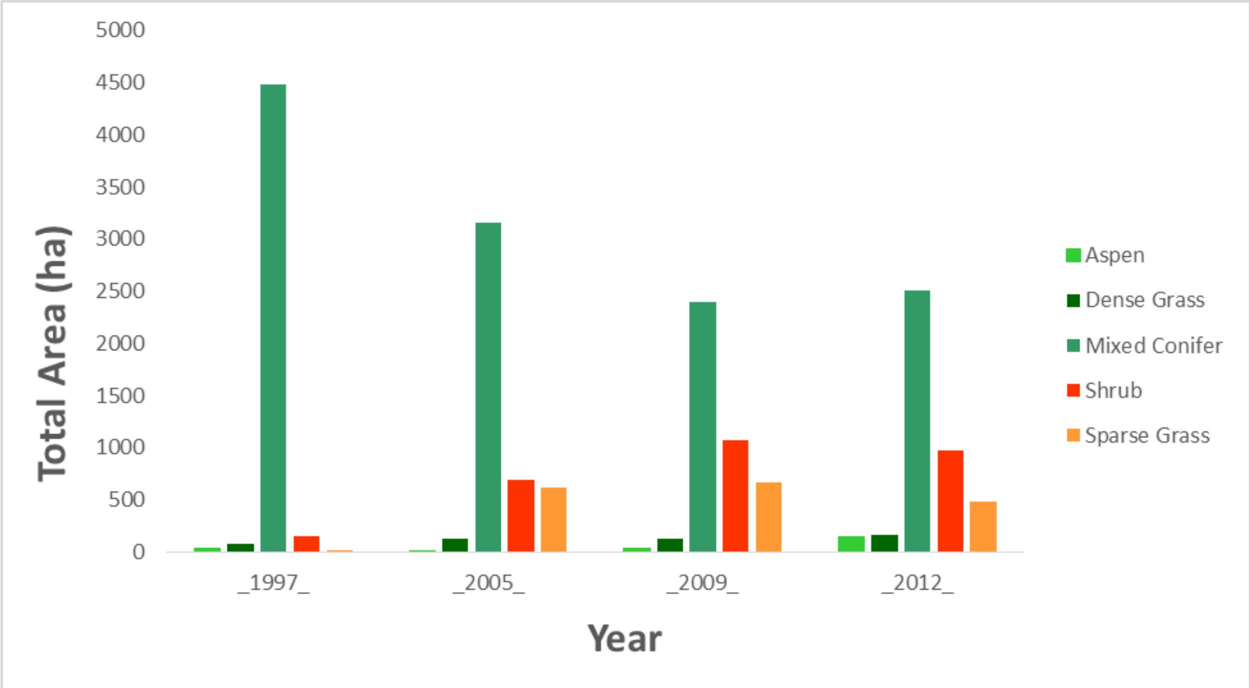

Fig. 6 Total area of each vegetation type derived from 1997, 2005, 2009 and 2012 vegetation maps.

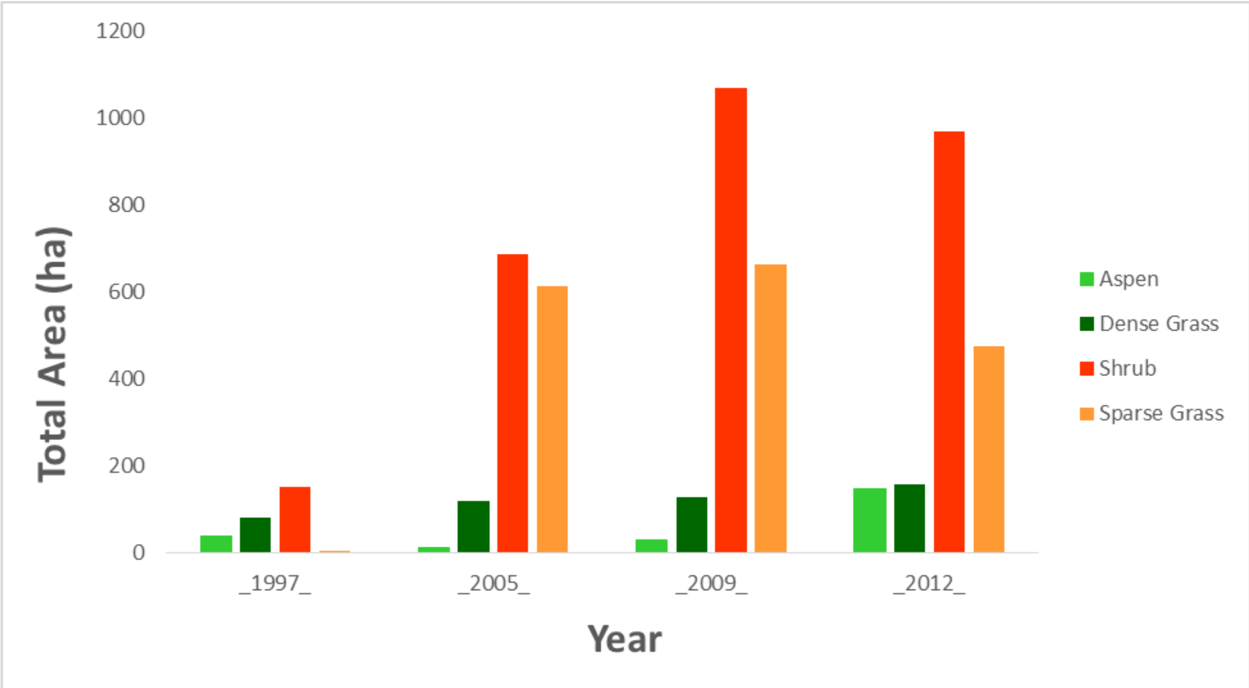

Fig. 7 Total area of aspen, dense grassland, shrub and sparse grassland from 1997, 2005, 2009 and 2012 vegetation maps.

Table 3 Percent of Vegetation Cover Change for All Fires derived from 1997 and 2005 and 2009 and 2012 vegetation maps.

Percent of Vegetation Cover Change 1997-2005, 2009-2012					
	Vegetation Types				
Fire Year	Aspen	Dense Grassland	Mixed Conifer	Shrub	Sparse Grassland
1998	NaN ^a	NaN	0.63	Inf^b	Inf
2001	0.97	2.05	0.7	3.12	449.85
2002	NaN	0	0.7	6.09	Inf
2010	NaN	NaN	0.91	0.37	38.504

a^NaN = Not a Number. This symbol arises when 0 is divided by 0.

b^Inf = Infinity. This value arise any whole number is divided by 0.

Table 4 Percent of Vegetation Cover Change for 1998, 2001 and 2002 Fires derived from 2005 and 2009 vegetation maps.

Percent of Vegetation Cover Change 2005-2009					
	Vegetation Types				
Fire Year	Aspen	Dense Grassland	Mixed Conifer	Shrub	Sparse Grassland
1998	NaN	Inf	0.87	0.85	1.43
2001	2.54	1.29	0.8	1.63	1.16
2002	NaN	NaN	0.18	1.37	5.7

Table 5 Percent of Vegetation Cover Change for 1998, 2001 and 2002 Fires between 2009 and 2012.

Percent of Vegetation Cover Change 2009-2012					
	Vegetation Types				
Fire Year	Aspen	Dense Grassland	Mixed Conifer	Shrub	Sparse Grassland
1998	NaN	0	0.58	3.1	0.82
2001	4.33	1.27	0.83	1.38	0.82
2002	Inf	NaN	5.2	0.3	0.14

VTRs for 3 vegetation intervals analyzed reveal similar and different vegetation trends occurring at the pixel level. For brevity, both here and within the tables, I will remark on mixed conifer as MC, aspen as A, dense grassland as DG, shrub as S, and sparse grassland as SG.

Arrows found in the tables 6-8 under vegetation transitions (->) indicate a transition from a set of pixels of one vegetation type to another. From 1997 to 2005 for all fires (Table 6), the majority of MC->A and MC->DG VTRs are zero, indicating no MC pixel transitions to A or DG occurred. The 2001 fire is the single exception to these trends. MC->MC VTRs are < 1, revealing a transition of pixels that were once mixed conifer to other vegetation types and a decrease in mixed conifer pixels. Relative to MC-MC VTRs, MC-S and MC-SG VTRs <<1, representing transition of small number of pixels that were once MC to S and SG. From 2005 to 2009 for 1998, 2001 and 2002 fires (Table 7), MC->A and MC->DG VTRs largely continue to be zero, indicating no transition of MC pixels to aspen or dense grassland pixels. The exception to these trends is the 2001 fire. MC->MC VTRs continue to be <1, indicating a continued loss MC pixels. MC->S and MC->SG VTRs continue to be <1, evincing a continued transition from MC pixels to S and SG pixels. From 2009 to 2012 for the same fires (Table 8), the majority of MC->A VTRs are now greater than zero, indicating an increase in A pixels. The exception is the 1998 fire. MC->DG VTRs continue to be 0 on the whole, with an exception in 2001, Relative to previous MC->MC VTRs, within this span VTRs are much less than 1, indicating more loss of MC pixels. Compared to previous MC->S VTRs, VTRs here are closer to 1, indicating a relative increase S pixels. In contrast, MC->SG VTRs relative to past VTRs are much less than one, indicating a relative decline in SG pixels.

Environmental Response Modeling

The multivariate classification tree analysis indicates differences and similarities in the relative importance of topographic variables, RdNBR and pre- and post-fire vegetation in explaining trends in post-fire vegetation change between fires of varying fire severity, extent, seasonality and location (see Appendix 2). The reason for the lopsided shape of the majority of classification trees are the N/A values, which arose from ascii matrix multiplication. These values indicate the logical zeros that were not clipped correctly by *ArcMAP* when performing raster calculations.

Table 6 VTRs for all fires derived using 1997 and 2005 maps for 1998, 2001 and 2002 fires and 2009 and 2012 maps for 2010 fire.

	VTRs, 1997 to 2005, and 2009 to 2012				
	Vegetation Transitions				
Fires Year	MC->A	MC->DG	MC->MC	MC->S	MC->SG
1998	0	0	0.62	0.17	0.21
2001	0.0017	0.025	0.68	0.12	0.16
2002	0	0	0.68	0.19	0.077
2010	0	0	0.75	0.15	0.08

Table 7 VTRs for 1998, 2001 and 2002 fires derived using 2005 and 2009 maps.

	VTRs, 2005 to 2009				
	Vegetation Transitions				
Fires Year	MC->A	MC->DG	MC->MC	MC->S	MC->SG
1998	0	0	0.72	0.15	0.13
2001	0.0052	0.017	0.7	0.14	0.13
2002	0	0	0.18	0.23	0.54

Table 8 VTRs for 1998, 2001 and 2002 fires derived using 2009 and 2012 maps.

	VTRs, 2009 to 2012				
	Vegetation Transitions				
Fires Year	MC->A	MC->DG	MC->MC	MC->S	MC->SG
1998	0	0	0.49	0.42	0.093
2001	0.025	0.032	0.62	0.25	0.071
2002	0.046	0	0.83	0.1	0.0017

What follows is a description of all classification trees for each fire and finally a description of the ensemble classification trees, joining fires from 1998, 2001 and 2002. All of these with the exception of the 2002 fire, were derived from 1997-2005, 2005-2009 and 2009-2012 intervals.

1998 Hoover Fire

RdNBR explained the greatest variation in vegetation types from 1997 to 2005 [Fig. 9 (a)]. Higher RdNBR values corresponded to shrub, while lower to slope, the second important variable in terms of predictive power. Large slope corresponded to shrub and small continued to elevation. For remaining two time intervals, RdNBR continued to show up, but diminished as the main explanatory variable. From 2005 to 2009, **elevation** explained the greatest variation in vegetation types [Fig. 9 (b)]. Larger elevation corresponded with mixed conifer and smaller corresponded to elevation once again. For this elevation, larger values were associated with the RdNBR, the third predictor within this interval. From 2009 to 2012, **aspect** became the variable that explained the largest variation in vegetation types [Fig. 9 (c)]. Larger aspect values corresponded to elevation and smaller with 2009 vegetation types. Larger elevation is associated with shrubs and smaller with sparse grassland. On the other hand, all 2009 mixed conifer is associated with sparse grassland and all other 2009 vegetation types with yet another aspect. RdNBR follows aspect as the variable with the least explanatory power. Large RdNBR values were associated with shrub, while smaller values with sparse grassland.

2001 Hoover Fire

No predictor variables explained variation in vegetation types spanning 1997 to 2005. This is because vegetation types largely remained as mixed conifer. From 2005 to 2009**, RdNBR**

was the predictor variable with the greatest explanatory power. Large RdNBR values corresponded with aspect and small values with slope. From 2009 to 2012, **2009 vegetation types** explained the largest variation in vegetation change. Aspect and 2009 vegetation types follow as the second-most important predictor. TWI, RdNBR, and hillshade have least explanatory power.

2002 Ottoway Fire

Elevation explained the largest variation in vegetation types from 1997 to 2005. Large elevation values corresponded to hillshade and small values to slope, both of which were second in terms of importance in explaining vegetation type variation. Large slope values corresponded to aspect and small values to elevation. Ramifying from these variables are predictors including TWI, aspect, slope and elevation. These lead to mixed conifer, shrub sparse grassland. Large hillshade values were associated with elevation and small values with slope. From these predictors numerous applications of TWI, aspect and slope arise. This branching leads to mixed conifer and shrub.

Spanning 2005 to 2009, **elevation** once again proved to explain the greatest variation in vegetation types. Large elevation values were associated with slope and small with elevation. With respect to slope, large values corresponded with elevation and small with 2005 vegetation. While there were many other predictors underneath this 2005 vegetation, the results were sparse grassland, shrub and mixed conifer. Large elevation corresponded to hillshade and following many other variables, sparse grassland, shrub and mixed conifer arose. Small elevation corresponded to aspect and after many branches, resulted as shrub and sparse grassland.

From 2009 to 2012, **slope** explained the largest variation in vegetation types. Large and small slope values were both associated with aspect, the second-most important explanatory variable. The first aspect, the one following from large slope, had large and small values associated with elevation. Following other predictors (mainly TWI), aspen was largely associated with elevation values that came from large aspect values, whereas mixed conifer, sparse grassland and shrub with smaller values. Elevation values related small aspect values after some branching were associated with mixed conifer, shrub and sparse grassland. The second aspect, the one following from the first slope, had small values extendedly associated with mixed conifer and sparse grassland.

2010 Clark Fire

Elevation and **hillshade** explained the largest variation in vegetation types from 2009 to 2012. Large elevation values corresponded to slope and small values with elevation. After branching off to other predictors, slope was extendedly associated with mixed conifer, sparse grassland and shrub. Small elevation, again after some branching, corresponded with shrubs and mixed conifers. Large hillshade, on the other hand, was associated with mixed conifer. Small hillshade corresponded with 2009 vegetation. After 2009 vegetation ramified to other predictors, it was extendedly associated with mixed conifer, sparse grassland and shrub.

1998, 2001 and 2002 Fire Ensemble

Elevation explained the greatest variation in vegetation type from 1997 to 2005. Large and small elevation values corresponded to another elevation. Elevation from previous large elevation values had large values that corresponded to slope and small values to yet another elevation. Slope, after a large degree of branching, is extendedly associated with shrub and mixed conifer, while elevation is extendedly associated with mixed conifer. Elevation from previous small elevation values had large values that corresponded to hillshade and small values to slope. Hillshade after a large degree of branching, is extendedly associated with mixed conifer and shrub. Slope corresponded to elevation and aspect. Elevation extendedly corresponded to mixed conifer, shrub and sparse grassland, whereas aspect to shrub and mixed conifer.

From 2005 to 2009, **slope** explained the greatest variation in vegetation change. Large and small slope values were associated with elevation. From 2009 to 2012, **2009 vegetation** and aspect explained the largest variation in vegetation types.

DISCUSSION

The main objective of this study was to evaluate the extent to which post-fire vegetation has changed in the Illilouette Creek Basin from 1997 to 2012. My results indicate that over the past 15 years, landscape vegetation and particularly post-fire vegetation in the basin has undergone significant change in structure and composition. Overall, the forested landscape is gradually disappearing as sparse grassland and shrubs emerge. An analysis of the development of post-fire vegetation change has revealed that mixed conifer in particular has been subject to direct replacement or colonization often by vegetation types such as sparse grassland and shrubs, inasmuch as conifers persist. Mixed conifer within these fire-scarred areas has additionally experienced a sharp decline in canopy cover. Under the influence of topographic variables and RdNBR, aspen, wet meadows, and particularly ceanothus and willows have emerged and flourished in this Sierra Nevadan landscape. These findings are important for two reasons: firstly, because mechanics of vegetation change have been so far largely been neglected in forest disturbance ecology studies, despite drier vegetation being more susceptible to fire and extreme fire weather. And secondly, because forests provide numerous controls for hydrological output (Jung et al. 2008). Thus conifer decline could have immense implications on water availability for dependent regions (Smith et al. 2011). It should be noted that because the metrics utilized in this analysis are novel and have not been subject to critical evaluation, that this study has some limitations which should be taken into account when interpreting the results. Below I will discuss the main methodological components of this analysis and elaborate on main considerations, particularly limitations and relevance to other studies where applicable.

Vegetation Maps and Validation

While the overall accuracy of the 2012 vegetation map exceeded 90 %, assuming that this value extends to other vegetation maps by virtue of its objective computer-aided classification, should not be confused with attributing this very same accuracy to these maps. I could not evaluate the accuracy of the 1997, 2005 and 2009 vegetation maps. There is a large degree of uncertainty related to historic and even recently older aerial imagery whose landscape can no longer be groundtruthed due to the dynamism of an environment. Because of this, the overall accuracy of 92.3 % is considered a maximum bound in relation to other vegetation maps. It is additionally worth recalling that the accuracy assessment used groundtruth data that were collected in 2014. However, given that the 2012 map is at most only two years apart from the 2014 summer field survey and that no large-scale fires occurred during this period, it is reasonable to assume that there were no significant differences in the vegetative landscape.

When interpreting the results of the confusion matrix, it should be taken into account that groundtruthing data had its own errors associated with the GPS device utilized in this study.

This is why some points were manually shifted or omitted from the accuracy assessment. It should also be noted that even with an appropriate sample of GPS points, there is still a positional uncertainty inherent in pixel coordinates which makes it nearly impossible to identify or register any pixel on a landscape. A common approach to control for this uncertainty and avoid misregristration is to restrict GPS data to the center of preselected NxN pixel blocks (e.g. Elmore et al. 2000). However, this approach has been noted to introduce bias into classification accuracy by favoring heterogenous areas (Hammond and Verbyla 1996). It also assumes that the heterogeneity within the N m by N m area is representive of the heterogeneity of the sampled landscape (Elmore et al. 2000) As a corrective, groundtruthing was conducted overall in large-scale and identifiable patch stands.

Furthermore, the objectivity of supervised remote sensing software is obscured when aerial images utilized as input have varying spectral signatures, tone, resolution, or darkness. For example, the 2005 NAIP integrated in this study was exceptionally darker than the other orthoimages. The presence of numerous shadows in the landscape indicate that this image was taken late in the afternoon, most likely during sunset. While image processing and orthorectification stand as viable options to minimize error associated with spectral variability (Kadman et. al. 1999), these methods are temporally and computationally costly. Provided that vegetation maps were generated using 1) thresholding, a methodology that accounts for the particularities of spectral variability and 2) a non-differentiable ruleset schema, I do not suspect any differences in accuracy.

Moreover, the pre-existing 1997 vegetation map provided by the national park service clearly underestimates rock outcrop, providing a possible bias in conifer decline. Acknowledging this difficulty did not come at the expense of potential data. To correct this, I assumed that certain species of conifer were more prevalent on rock outcrop in previous years.

Characterization of Vegetation Change

My results point to a significant increase in shrub and sparse grassland land cover and a simultaneously significant decrease in conifer for the overall landscape and post-fire regions between 1997 and 2012. The results further indicate that over time sparse grassland land cover begins to decrease as shrub continues to grow. Given that over time, shrubs have also been shown to directly replace sparse grassland, competition between these two vegetation types is evident. I relate these observed patterns of sparse-grassland-shrub growth and competition to fire severity and to the effects of topography on solar radiation and thus, water availability. Although I was able to detect distinct patterns of change in the ICB between 1997 and 2012, it is apparent that the metrics I constructed and hence equations I utilized were not without error.

There are some basic difficulties in using remotely sensed data to study vegetation change, especially in relation to the pixel data comprising an image. It has been noted, for example, that the materials in a given pixel in remotely sensed data are rarely represented by a single physical component or a uniform spectral signature. In measuring vegetation abundance, for instance, a leading method, Spectral Mixture Analysis, is based on the concept of a mixed pixel, that is, that the relative proportion of a few spectrally distinct components is what dominates the variance across a given remotely scene. The SMA method has been applied by many (Adams and Adams 1984, Pech et al. 1986) within a linear modeling framework, where the spectral properties of a pixel are modeled as a linear combination of endmember spectra weighted by the percent of ground coverage of each endmember. Endmembers can be viewed as fundamental physical components of a scene that that themselves are not mixtures of other components. Linear models assume that components be arranged in spatially separate areas of the pixel, thereby reducing the number of spectral signatures or reflectances (Singer and McCord 1979).

This type of modeling however is only distantly related to my study for three reasons. Firstly, most arrangements of physical material will produce nonlinear component (Mustard and Pieters 1989, Elmore et al 2000). Secondly, SMA is primarily used for measuring vegetation abundance, even though it has been used to measure percent landcover (%LC) in semiarid regions (Sohn and McCoy 1997), a value conceptually similar to VCC. Lastly, mixed pixels usually arise more often in arid and semi-arid regions when viewed with coarse aerial imagery (see Elmore et al. 2000). My study area is not arid or semi-arid. Nor did I utilize coarse aerial imagery when quantifying vegetation change, but rather fine grain.

In using remotely sensed data to track vegetation change in forests, another problem arises. That is, when measuring conifers, we are only capturing the canopy and not the understory that has been shown to contain numerous species and increasing error. But in during field excursion to the ICB, there was very little understory underneath the tree canopy (Personal Obs).

While there are numerous other equations detailing how to quantify vegetation change (e.g. Elmore et. al., Kadman et. al., 2006, Dial et al., 2007, Baker 1989, Keane and Finney 2003), there are several reasons why I decided to create two new metrics. As opposed to existing equations considering vegetation change, these metrics account for direct replacement or persistence (VTR) and land cover change (VCC) of vegetation types from one year to another. Furthermore, the calculations of these metrics are straight-forward and can be systematized and facilitated within *ArcMAP* and *Excel*, without making recourse of computationally-intensive statistical software. Lastly, the interpretations easily follow from the raster and vector data-forms utilized for their computation.

Environmental Response Modeling

The importance of predictor variables in explaining vegetation type variation largely depended on the allocation of predictors, fire size, and therefore sample size. Recall that RdNBR was only applied to 1998 and 2001 fires. For the small 1998 fire RdNBR initially played the largest role for developing vegetation patterns on the landscape but subsided in later years to elevation and aspect as the next two important variables. In contrast the larger 2001, did not have any strong predictors at the outset. However, RdNBR soon became the leading predictor in the following years. As with the 1998 fire, it subsided to another predictor in later years; namely, 2009 vegetation types. The other small fire in 2002, also had elevation as the leading variable for a majority of years, but then it changed to slope. In the 2010 fire, elevation and hillshade were the leading variables. The ensemble classification, synthesizing 1998, 2001, and 2002 fires, had elevation as the first, followed by slope and 2009 vegetation. All in all, while variable fire severity seems to affect post-fire vegetation shifts initially, after some time the fire-induced change diminishing as the influence of topographic variables rises. This suggest limits that can help us understand the magnitude of vegetation change that may result from fire and and to infer the sensitivity of vegetation types within a particular location, and set of topographic variables.

The presence of elevation as a key predictor across all studies suggest that vegetation is greatly influenced by topography. This is consistent with previous studies in Yosemite dealing with individual species change (Kean et al. 2014, Kane et al. 2014). Mountain topography creates fine-scale mosaics that vary in precipitation, temperature and related environmental conditions which influence forest structure (Kane et al. 2014).

The Caribou Wilderness, a mesic upper montane forest, in northern California is controlled more by topographic variables than by regional temperature gradients. This is because topographic variables influence local patterns of soil moisture and cold air drainage, two variables which determine the location of lodge pole stands (Taylor et. al.; 2001). Similar to lower montane forests like the ICB, recent increases in fire-intolerant fir and decreases in fire-resistant pines suggest continued fire suppression will cause shifts in species composition and changes in landscape vegetation patterns. Moreover, future of upper and lower montane forests will additionally be determined by the drought and water deficit in the state of California.

In Yosemite National Park, while response to water availability (evapotranspiration and deficit) will differ by tree species, forest structure and composition may accelerate in the future due to climatic changes (Lutz et. al.; 2010). On a regional scale, dry forests as compared to mesic forest burned twice as frequently and earlier in growing season in southern water sheds than in northern watersheds in the Blue Mountains of northeastern Oregon and southeastern Washington. At a local scale, fire frequency varied with different parameters of topography in watersheds with steep terrain (Heyerdahl et. al.; 2001). In Sequoia and Kings Canyon National Parks, two parks also known to practice WFU and prescribed burns, burn programs effort to reduce fuels and restore fire as an ecological process exacerbated fire frequency and fire extent for areas with greatest ecological need for conflagration (Caprio and Graber; 2000).

The importance of predictively modeling relationships between species and the environment has long been recognized (e.g. De'ath 2002). If used routinely as a method of statistical modeling, it can replace repeated hypothesis tests, circumventing spurious explanatory variables and deficiencies that accompany such tests. Classification trees are great for exploration, description, and prediction.

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Appendix 1. *eCognition* Ruleset Parameters

Table 1 Ruleset Parameters. Listed below are the specific segmentation algorithms and layer values for 2005, 2009 and 2012 Vegetation Maps used for image object generation and delineation of granite, sparse grassland, mixed conifer, dense grassland, aspen, and shrub. R = Red, G = Green and B = Blue.

2005 Vegetation Map Ruleset						
Segmentation	Granite	Sparse Grassland	Mixed Conifer	Dense Grassland	Apsen	Shrub
Multiresolution	Mean R	unclassified ^b	mode [Min] (G)	mode [Min] (R)	Mean B	Std. dev.(^d) G
Spectral difference	Mean G	HSI Trans. Sat.^c		HSI Trans. Sat.	mode [Min] (R)	HSI Trans. Sat.
	Custom Feature	(R = R, G = G, B=B)		(R = R, G = G, B=B)		(R = R, G = G, B=B)
	Rel. border to Gr^a					
	mode [Min] (G)					
2009 Vegetation Map Ruleset						
Multiresolution	Mean R	unclassified	mode [Min] (G)	Mean Brightness	mode [Min] (R)	Mean Brightness
Spectral difference	Mean G			mode [Min] (R)	Std. dev. B	Max. diff (custom)
	Mean NDVI^e					Std. dev. G
	Custom Feature					HSI Trans. Sat.
	Rel. border to Gr					
	mode [Max] (NDVI)					
2012 Vegetation Map Ruleset						
Multiresolution	Mean R	Mean NDVI	mode [Min] (G)	mode [Min] (R)	Mean G	Mean Brightness
Spectral difference	Mean G	unclassified	Std. dev. G	HSI Trans. Sat.	mode [Min] R	Std. dev. R
	Rel. border to Granite			(R = R, G = G, B=B)		
	mode [Min] (G)					
	mode [Max] (NDVI)					

a^Gr = Granite
b^unclassified. This parameter follows granite classification and means to classify everything expect granite as sparse grassland using the asign class algorithm. This ensures that all image objects do not remain

unclassified and also that other vegetation will have a class filter defined as sparse grassland

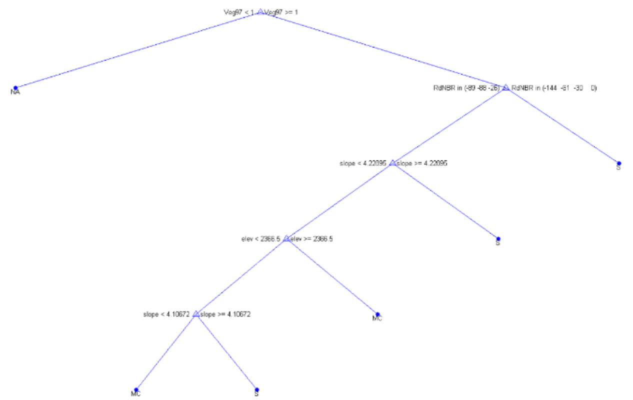
c^HSI Trans. Sat. = HIS Transformation Saturation

d^Std. dev. = Standard deviation

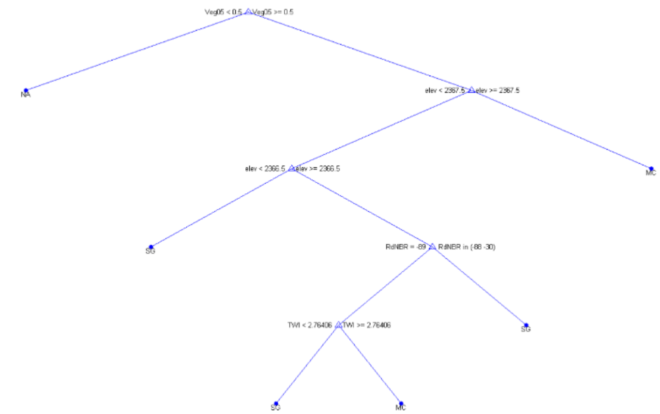
e^NDVI = Normalized Difference Vegetation Index

Appendix 2. Classification Trees

(a)



(b)



(c)

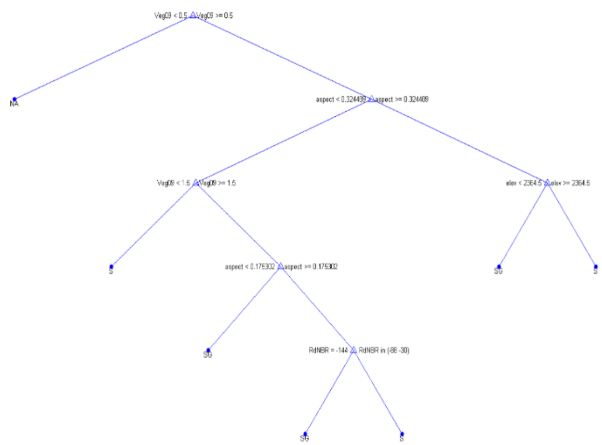


Fig. 9 Classification Trees for the 1998 fire. From top to bottom (a)-(c). (a) comprises the first post-fire analysis, with 1997 vegetation, topographic variables and RdNBR as predictors and 2005 veg as the response variable. (b) is a subsequent post-fire analysis, with the same variables, but with 2005 vegetation as predictor and 2009 as response. (c) is the last post-fire analysis with 2009 vegetation as a predictor and 2012 as a response.

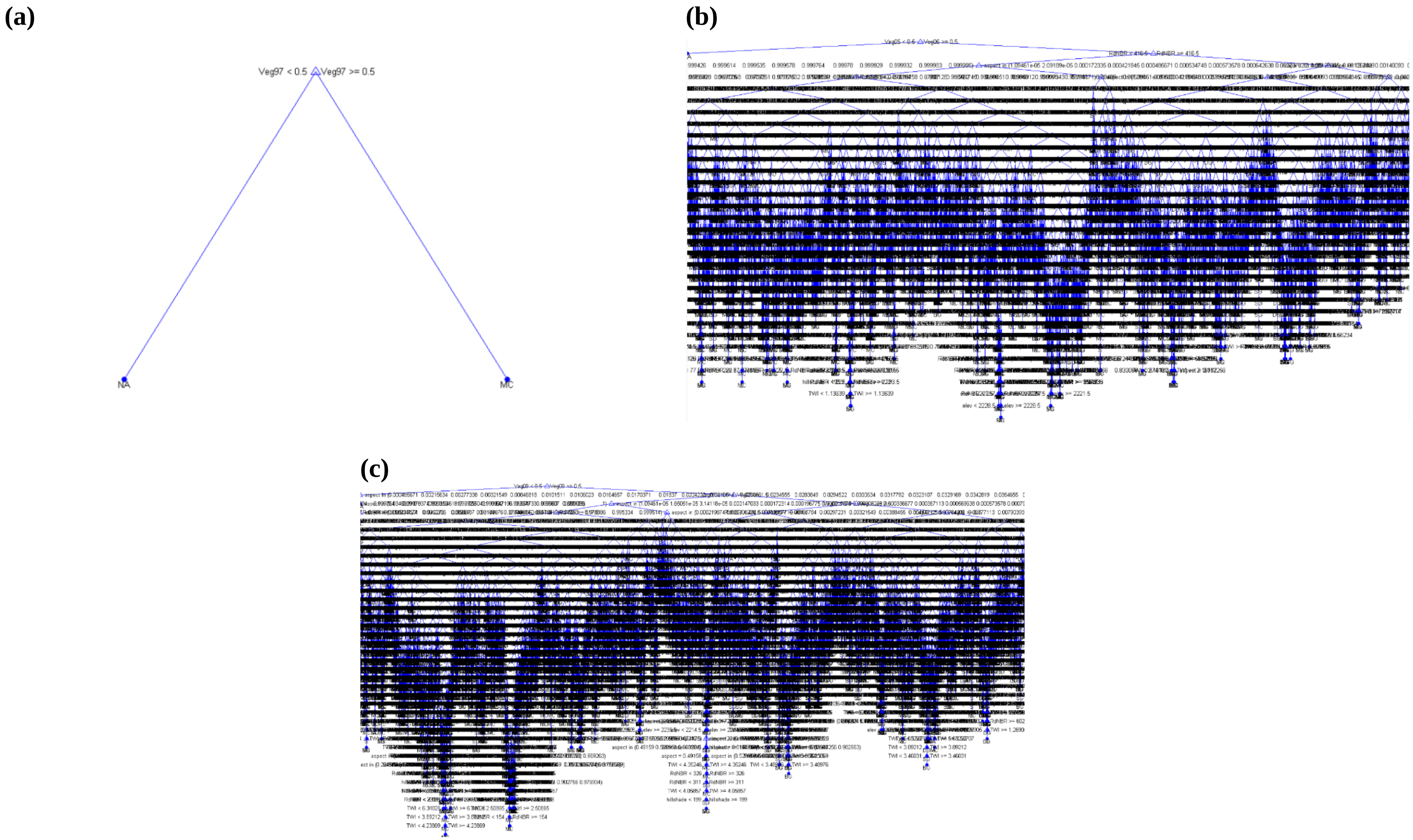


Fig. 10 Classification Trees for the 2001 fire. From top to bottom (a)-(c). (a) comprises the first post-fire analysis, with 1997 vegetation, topographic variables and RdNBR as predictors and 2005 veg as the response variable. (b) is a subsequent post-fire analysis, with the same variables, but with 2005 vegetation as predictor and 2009 as response. (c) is the last post-fire analysis with 2009 vegetation as a predictor and 2012 as a response.

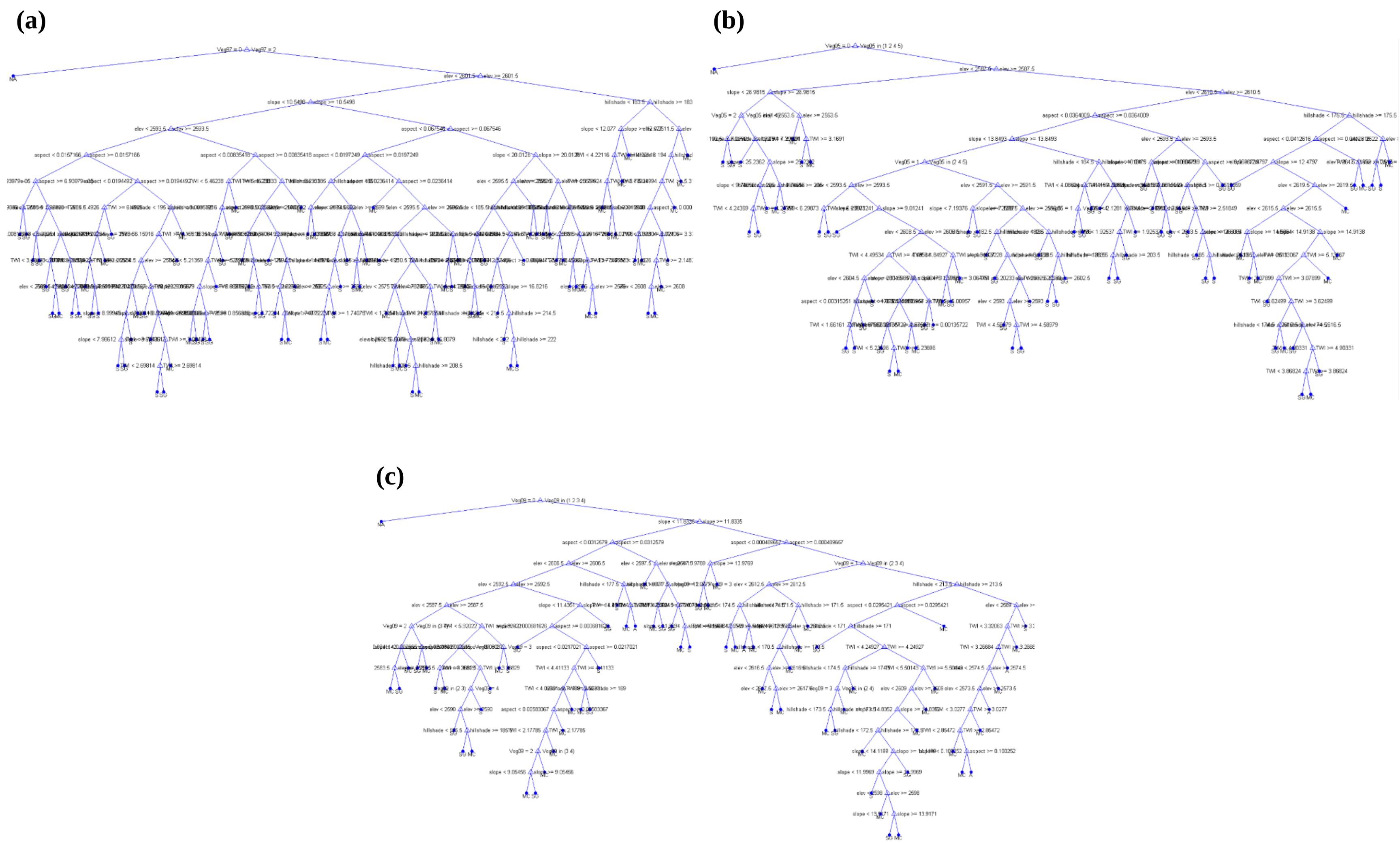


Fig. 11 Classification Trees for the 2002 fire. From top to bottom, (a)-(c). (a) comprises the first post-fire analysis, with 1997 vegetation and topographic variables as predictors and 2005 veg as the response variable. (b) is a subsequent post-fire analysis, with the same variables, but with 2005 vegetation as predictor and 2009 as response. (c) is the last post-fire analysis with 2009 vegetation as a predictor and 2012 as a response.

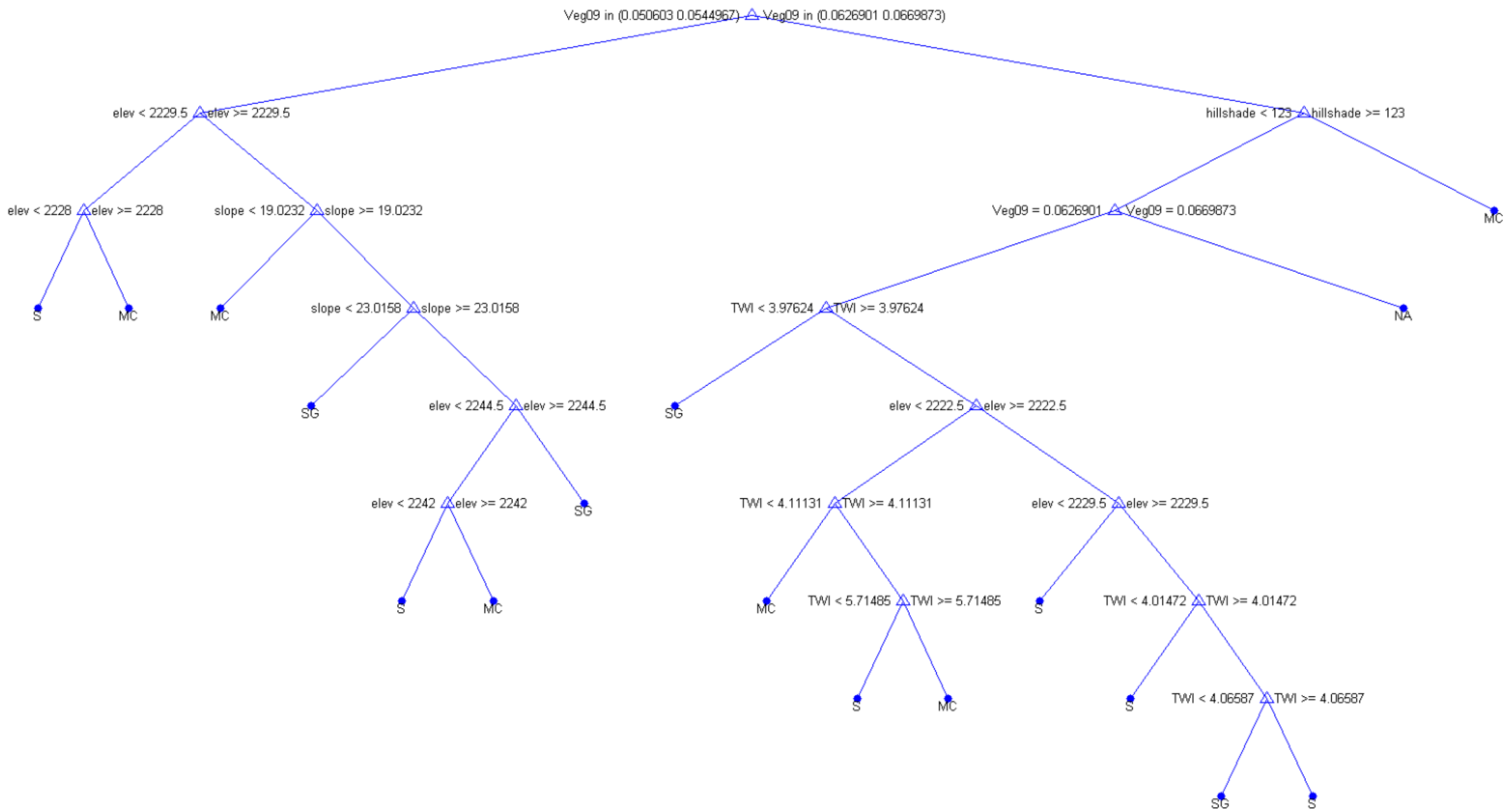


Fig. 12 Classification Tree for the 2010 fire. This tree comprises the first post-fire analysis, with 1997 vegetation and topographic variables as predictors and 2005 veg as the response variable.

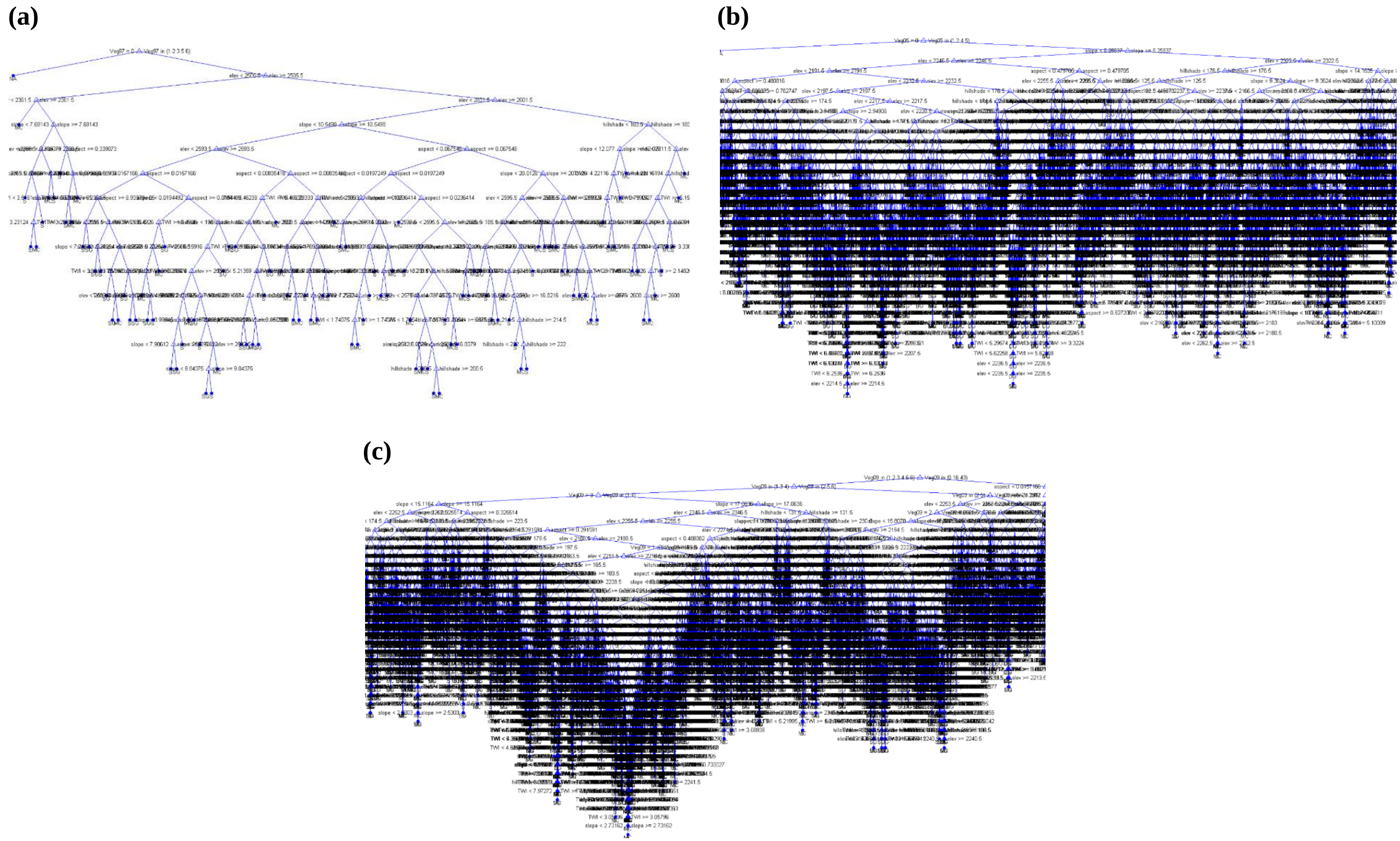


Fig. 13 Classification Trees for the 1998, 2001 and 2002 fire ensemble. From top to bottom, (a)-(c). (a) comprises the first temporally and spatially heterogeneous post-fire analysis, with 1997 vegetation and topographic variables as predictors and 2005 veg as the response variable. (b) is a subsequent post-fire analysis, with the same variables, but with 2005 vegetation as predictor and 2009 as response. (c) is the last post-fire analysis with 2009 vegetation as a predictor and 2012 as a response.

Appendix 3. An Explanation of VCC and VTR

VCC = 0 indicates that the vegetation type no longer occupies an area and 1 indicates that vegetation area did not change; 0<VCC<1 means a decrease in area and VCC>1 an increase. In effect, the closer to VCC is to 0, the more vegetation canopy is vanishing and larger than 1 the more it is growing. Note that the growth or decline of this canopy is not spatially specific, the area may have shifted with the fire perimeter, but this metric does not take that into account. VTR, on the other hand, is a value that accounts for shifts or transition. The word direct is used here to signify that this metric is spatially specific and takes into account the original set of pixels in which the shift occurs from year to year. VTR = 0 indicates no pixels representing some original veg type transitioned to another veg type. If one tracks the same veg type from year to year, this can be interpreted as persistence, whereas is one tracks a shift from one type to another, this means no direct replacement. 0<VTR<1 indicates that some pixels representing an original veg type transitioned to another veg type. If one tracks the same veg type of shifts, this simply means a direct replacement.