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Assessment of Vegetation Response to Wildfire at Bandelier National Monument, New Mexico: Case Study of the Las Conchas Fire

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ASSESSMENT OF VEGETATION RESPONSE TO WILDFIRE AT BANDELIER NATIONAL MONUMENT, NEW MEXICO: CASE STUDY OF THE LAS CONCHAS FIRE

BY

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2014

THESIS

To be Submitted in Partial Fulfillment of the
Requirements for the Degree of

Master of Science

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Dedication

To my beloved nieces and nephews,
my little beams of sunshine,
Mandy, Vanchi, Kike, Kini, Nico, Vivi and *x*
To my parents, Julian and Gladys,
and my siblings Vanessa, Julio E. and Julio.

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Abstract

In the past couple of decades, there has been an increase in the occurrence of wildfire events in the United States. The U.S. Forest Service estimates that over 73,000 wildfires on average occur annually in the U.S., burning about 7.3 million acres of land. Bandelier National Monument, in northern New Mexico, has been affected by several wildfires in the past 40 years, one of the most recent being the Las Conchas Fire in 2011, which burned over 60,700 hectaresin Bandelier National Monument and Valles Caldera National Preserve. This research explores a remote-sensing based assessment of vegetation response to and recovery from the 2011 Las Conchas Fire. Post-fire vegetation distribution was evaluated and analyzed to determine if fire severity and fire frequency were correlated with vegetation degradation or conversion. Analytical results, coupled with field observations, allow us to evaluate pre- and post-fire vegetation change at the community-type level. Classifications had varying levels of accuracy throughout the study area. Many areas that suffered vegetation mortality as a result of fire exposure have exhibited growth of New Mexico locust (*Robinia neomexicana*), gambel oak (*Quercus gambelii*), and quaking aspen (*Populus tremuloides*), which have been recorded in other forested areas affected by fire in the state. Based on cross-tabulation analysis results, nearly 75% of pixels suffered disturbance or vegetation type conversion, while 25% remained unchanged or recovered to the same type. Vegetation response related to fire variables based on amount of area per variable. This study is relevant for understanding and managing burned landscapes in arid and semi-arid regions. It contributes to a growing knowledge of the effects of large, high severity wildfires on vegetation distribution and resilience.

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Introduction and Background

1.1 Introduction

Historically, wildfires have been a natural phenomenon that influence the structure, nutrient availability, and life history of forest systems, characterized by high frequency, low severity surface fires that maintain habitat diversity, eliminate surface fuels, reduce competition for nutrients and promote optimal conditions for trees to thrive (Dewar, 2011). Fire suppression policies and practices implemented since the 1900s have transformed fire regimes by preventing these types of fires from occurring, resulting in a buildup of fuel materials, and fostering an increase in severe fire occurrence (Allen 2002; Dewar 2011). There has been an increase in the occurrence of wildfires in the western United States in recent decades, with longer fire seasons and increased fuel aridity (Abatzaglou and Williams, 2016; Cannon and DeGraff, 2009; Dennison et. al., 2014; Union of Concerned Scientists, 2013). Climate change projections estimate more frequent and intense drought events, as well as increasing temperatures, resulting in woody vegetation dieback and low fuel moisture (Williams et al., 2013). These conditions could increase fire frequency and/or severity in arid and semiarid regions such as the U.S. Southwest, which are already naturally characterized by warm and dry conditions (Garfin et. al., 2014). In the state of New Mexico, from 20002013, some 1,200,000 ha of land were burned (Johnston, 2013).

Remote Sensing and Geographic Information Systems (GIS) have been implemented to analyze and depict wildfire regimes and propagation, as well as post-fire impacts. The ability to study these phenomena remotely through aerial and satellite imagery, while integrating other variables (e.g., urban and natural features, topography, fire history, pre-fire vegetation condition, hydrography,) facilitate the description of past/active fire characteristics, modeling and assessing their behavior, their impacts, and post-fire recovery (Lentile et al., 2006). Image analysis techniques for post-fire vegetation recovery studies include classifications, spectral vegetation indices (SVIs) and Spectral Mixture Analysis (SMA) (Viedma et al., 1997; Gitas et al., 2012; Veraverbeke et al., 2012a, 2012b). The research seeks to assess and map vegetation change and recovery following wildfire in an arid forest landscape through remote sensing. High spatial resolution imagery, and evaluation of associations between recovery and recent fire history were incorporated. Variables include number of times burned, mean fire return interval, years elapsed since last fire, and fire severity. The 2011 Las Conchas Fire, which burned some 60,700 hectares in northern New Mexico, is used as a case study. Fires occurred in the past 40 years are included for the analysis of fire history.

1.2 Research Questions

1. How has vegetation responded to and recovered from the Las Conchas wildfire in Bandelier National Monument, New Mexico?
2. Is there a relationship between fire severity of the Las Conchas Fire and vegetation response post-fire?
3. What role has the occurrence of fire in recent history played in vegetation response and recovery post-Las Conchas Fire?

1.3 Background

1.3.1 Wildfire in Arid and Semiarid Regions

Charcoal deposits and fire-adapted vegetation suggest fires have been occurring in the U.S. Southwest region since around 8,000 to 11,000 years ago, when current vegetation patterns and climate conditions started to appear (Swetnam et. al., 2016). From 2002 to 2014, the U.S. Forest Service recorded the number of wildfires to be 28,552 in southwestern states (New Mexico, Arizona, Colorado, Utah, Nevada), burning some 2.5 million ha of land. Of those, 6,078 fires burned a total of 526,091 ha in New Mexico. (National Interagency Fire Center, n.d.). A digital fire dataset, depicting fire perimeters for the state of New Mexico (Earth Data Analysis Center, 2015) includes a total of 2,282 of the fires that occurred from 1911 to 2014, ranging from an area less than an acre to almost 122,000 ha.

Fire ignition can be naturally and human-induced. High lightning activity (Allen, 2002) provides a common natural source. Human-related sources include campfires, improperly disposed cigarettes, burning of debris, fireworks, and arson (U.S. National Park Service, n.d.).

Fire regimes at a regional scale are influenced by climatic conditions, especially their frequency, intensity, extent, and seasonality, while at the local scale, topographic and fuel characteristics play a key role. In general, precipitation patterns have been found to correlate with fire occurrence. Historically, wildfires have occurred in dry years following wet years, including areas comprised of ponderosa pine (*Pinus ponderosa*) forest (Swetman and Baisan, 1996). This hints to a possible association with abundant growth of vegetation during wet years, and its subsequent moisture decrease in dry years.

In other instances, lightning-ignited fires in record have had dry winter-spring seasons in both the year in which they took place, and the one immediately preceding it (Touchan et al., 1996). Topographic variables, including elevation and aspect, have been found to affect fire regimes. Higher fire frequencies have been reported on south-facing slopes, and south-facing slopes may burn earlier (compared to north-facing slopes) in fire seasons due to rapid snow meltdown with direct solar energy exposure. Elevation influences fuel moisture. Higher land has a longer exposure to snow due to decreased temperatures in comparison to low elevations. North-facing slopes and higher elevations have been linked to lower fire frequencies in dry forests (Heyerdhal et. al., 2001).

Post-wildfire conditions can precipitate the occurrence of secondary hazards. Flash floods and debris flow initiation has been linked to wildfire events, taking place due to the creation of impervious soils that can exacerbate water runoff after subsequent heavy rainfall, as well as water infiltration respectively. Areas previously burned have been subject to, and been identified as susceptible to, debris flows occurrence in the U.S. Southwest, more specifically in the states of states California, Arizona, Colorado and, New Mexico (Cannon et al., 2001, 2005, 2009; Tillery et al., 2011a, 2011b, 2014). Although flash floods and debris flows are not considered in the present research, they are an important aspect of post-fire conditions that can in turn affect vegetation response and change.

1.3.2 Vegetation Communities of Bandelier National Monument

The vegetation patterns observed at Bandelier National Monument are influenced by its elevational gradient. Elevation ranges from around 1,500 m near the Rio Grande to

3,100 m at Cerro Grande. Some of the dominant vegetation in the area, and more specifically in the portion affected by the Las Conchas Fire, include quaking aspen (*Populus tremuloides*), white fir (*Abies concolor)*, douglas fir (*Pseudotsuga menziesii*), ponderosa pine (*Pinus ponderosa*), one-seed juniper (*Juniperus monosperma*), common juniper (*Juniperus communis*), piñon pine (*Pinus Edulis*), gambel oak (*Quercus Gambelii*) and New Mexico locust (*Robinia Neomexicana*) (Muldavin et al., 2011; Carter, 2012).

White Fir and Douglas Fir are tree species of mixed-conifer forests, and are distributed in central and western New Mexico, as well as other southwest and northwest U.S. states. Both conifers reproduce by seed. White Fir seed production can begin at 40 years, usually in autumn, and germination can occur the following spring. It grows from 21 to 49 m, and growth rate is higher in sunlight. Douglas Fir starts reproducing at 12 to 15 years, and germination can occur in the first five months after seed dispersal. It can reach heights of 24 to 61 m at maturity. Douglas fir seedlings do better in partially shaded and dry areas (Zouhar, 2001; Steinberg, 2002; Little, 2016).

Ponderosa pine is another coniferous tree found throughout western U.S., whose height ranges from, 27 to 40 m, with a faster growth rate than Douglas fir. Ponderosa pine have been recorded to begin bearing cones at seven years of age. (Habeck, 1992). Piñon pine and one-seed juniper are small coniferous woodland trees that, although commonly found in the same locations, have different life history strategies. Piñon pine height ranges from 4.6 to 10.7 m; one-seed juniper grows from 3 to 7.6 m (Little, 2016). Piñon pine seed production can begin at 25 years of age, while One-seed Juniper seed production may begin between 10 and 30 years (Anderson, 2002; Johnson, 2002).

Gambel oak and New Mexico locust are both distributed in the in U.S. Southwest. Gambel oak can reproduce through seeds or vegetative sprouting, reaching heights of 6 to 21 m, and is often distributed in groves (Simonin, 2000; Little, 2016). New Mexico locust is a shrub which also reproduces through both seeds and sprouting. It can grow up to around 8 m tall (Pavek, 1993). Quaking aspen is a deciduous tree found across North America, distributed in mixed conifer forests populated areas in New Mexico. It can sprout from an underground root system, or germinate from seeds within a few days of dispersal. Its first flowers grow at two to three years of age. Quaking aspen can reach 61 cm in its first year, and grow up to around 24m in height (U.S. forest Service, n.d. b; Howard, 1996).

Wildfires have both positive and negative effects on forested ecosystems. Some vegetation communities, such as quaking aspen, rely on wildfire to create the optimal environment for regeneration and growth. Frequent low severity wildfires clear understory and densely vegetated areas, eliminating fuel materials, reducing competition for nutrients, adding nutrients such as calcium, potassium and magnesium, and potentially eliminating invasive species (Dewar, 2011; Pacific Biodiversity Institute, 2009; California Department of Forestry and Fire Protection, 2013; Northern Arizona University, n.d.). High-severity or high frequency wildfires pose a threat to vegetation communities in that large areas may be degraded or reduced to grasslands, shrublands and bare soil. In some instances, vegetation type conversion to other types of woody or herbaceous vegetation may occur (Lippitt et al., 2013; Coop et. al., 2016).

Different types of vegetation respond in varied ways to fire, depending on fire characteristics including fire frequency, fire return interval, and fire severity, as well as climate and topographic characteristics in their location. Fire frequency is the number of times the land has burned, while fire return interval refers to the time elapsed between fires. Fire severity refers to the degree of loss or change of organic matter due to fire impact (Keeley, 2009). As such, fire severity is a key indicator of vegetation change on a fire-impacted landscape. Some types of vegetation that inhabit areas previously affected by fire can exhibit higher resistance and/or resilience to subsequent fires (Fulé, 2002; Strom and Fulé, 2007; Larson et. al., 2013; Coop et. al., 2016). This includes both vegetation that has been impacted by fire but survived, and vegetation that has grown in areas that have been recently affected by fire. High fire severity has led to tree mortality and vegetation type conversion, limiting vegetation regrowth and promoting shifts to non-forested types (White et. al. 1996; Diaz-Delgado et. al., 2010; Coop et. al, 2016).

Quaking aspen, although sensitive to fire occurrence, can resprout quickly from undamaged underground root systems, dominating post-fire landscapes. In some regions with colder soil temperatures, the heat that fire provides is necessary to trigger sprouting. Even-aged stands can develop within the first ten years post-fire (Howard, 1996).

Younger stands of White Fir are susceptible to mortality following fire, while mature trees are more fire resistant due to their thick bark. Tree mortality occurs when the crown is affected. High heat can also affect shallow roots. Post-fire, seeds are dispersed by wind, and can germinate quickly, or more slowly, depending on canopy cover (Zouhar, 2001).

Mature Douglas Fir are more resilient to low severity fires. Thick bark provides protection during surface fires, though mortality occurs when crown fires are experienced. Douglas Fir seeds are dispersed by wind, seedlings are often established within a few years post-fire (Steinberg, 2002).

Ponderosa pine has adapted to fire, with thick bark, an open crown structure, and thriving in fire-impacted soils. Mature trees are more resistant to fire, and mortality occurs when the crown is scorched. Ponderosa pine’s recovery from low and medium fire severities can be observed a year post-fire. Growth rates vary depending on location, weather, and fire severity (Habeck, 1992).

Both one-seed juniper and piñon pine respond similarly to fire. They have low fire resistance, especially trees with a height less than 1.2 m. Regrowth after fire occurs via seeds carried from other areas by fauna, and tends to be slow. Regrowth of piñon pine can begin before the post-fire one-year mark, but more often, considerable establishment of both tree types can take a few decades post-fire (Anderson, 2002; Johnson, 2002).

Gambel oak and New Mexico locust, although susceptible to immediate fire effects, both have rapid growth rates following fire from often abundant post-fire resprouts. Gambel oak can thrive in fire-impacted landscapes, with growth of new sprouts observed to begin as early as 10 days post-fire, from fire-promoted sprouting, or long-term through acorns carried by animals. Post-fire recovery can be faster on south-facing, warm slopes. In some New Mexico locust communities, considerable density has been observed two-years post-fire (Pavek, 1993; Simonin, 2000).

In summary, the vegetation types described exhibit two general patterns of recovery from fire. Most local conifers, including ponderosa pine, douglas fir, white fir, piñon pine, and one-seed juniper, reproduce only by seeds after fire, and thus depend upon local survival of some mature seed-bearing trees. Some of these species exhibit relatively high resistance to damage by fire low- to moderate-severity. In contrast, the broadleaf deciduous species of quaking aspen, gambel oak and New Mexico locust have a tendency to thrive in fire-impacted landscapes, with quicker regrowth and recovery rates post- fire due to their ability to regenerate immediately post-fire by vegetative root-sprouts. In this way, the broadleaf resprouters can dominate post-fire landscapes in a relatively short period of time, and can impede the regrowth, and potentially replace local non-sprouting conifer tree species that suffer severe fire impact, which show slower regeneration and recovery trajectories post-fire.

1.3.3 Remote Sensing of Vegetation

1.3.3.1 Image classifications

A common application of Remote Sensing is detecting different types of land cover (grass, asphalt, cement, water), or specific objects, which reflect light differently (Anderson, 1976). Remotely-sensed data can be used to classify different cover types based on the range of reflectance values of the images' pixels.

Supervised classification is a common approach used to distinguish differences in the spectral values of pixels. The identity and location of the different cover types are known, based on the analyst's personal expert knowledge and/or other ground or image-based data sources (Xie et al., 2008). In this case, the analyst trains the software with some form of calibration data: reflectance value samples of each class that the classifier then uses as input to classify other pixels with similar spectral values. Validation sets are equal to the calibration set in terms of format, but they are a separate set of samples used to assess classifications' accuracy once they have been created (Jensen, 2016).

Spectral separability between target classes in calibration sets dictates how well the classifier can distinguish between classes. Different land cover types have characteristic mean reflectance values, but in some cases, different cover types can have similar spectral values. Calibration and validation data should be spread throughout the area of interest, sampling a variety of ages and sizes of each class. Each cover type should be stratified over differing slopes and aspects to encompass a variety of illumination conditions to ensure the greatest range of reflectance values for each class.

An aspect that can vary spectral values within the same class is the presence of shadows, cast by clouds, trees, or topographic features, due to changes in light reflectance. Methods to deal with shadows and minimize their effects on the classification process include (1) restoring reflectance values through radiometric correction (Sarabandi, et. al., 2004; Yamazaki et. al., 2009), (2) classifying shadows by creating calibration data per class in shadowed areas (Exelis Visual Information Solutions Inc., 2015), (3) identifying shadow areas and masking them out, and (4) filling in missing pixel values with linear interpolation of adjacent pixels (Rossi et. al., 1994) or a majority filter. Depending on the overall research goal, some methods might be a better fit than others. Masking out shadowed areas represents a loss of data. For this research, shadowed pixels were classified as the cover types they belong to, which allows for a more comprehensive approach by accounting for the full range of reflectance values per class in the image.

One of the most commonly used supervised classification algorithms is the Maximum Likelihood decision rule, which classifies pixels based on their probability of belonging to a predefined class (Bossler et al., 2002). The probability that a pixel belongs to a certain class can be determined by providing different probabilities of occurrence per class, or assuming an equal probability of occurrence for all classes when there is no prior probability information (Jensen, 2016). When the probability of occurrence for each class are not know, maximum likelihood equation assumes equal probability of occurrence for all classes. Following Jensen (2016), the unknown measurement vector *X* is in class *i* if,

$$p_i \geq p_j \tag{1}$$

for all *i* and *j* classes out of *m* possible classes, and p_i is defined by the mean measurement vector for class *i* (M_i) and the covariance matrix of class *i* (V_i) for bands *k* through *l*, as follows:

$$p_i = -\frac{1}{2} log_e|V_i| - \left[\frac{1}{2}(X - M_i)^T {V_i}^{-1}(X - M_i)\right] \tag{2}$$

In the case where probability of occurrence for each class is known or can be estimated with confidence, a weight is applied for each class.

Vector *X* is in class *i* if,

$$p_i \times p(w_i) \geq p_j \times p(w_j) \tag{3}$$

for all *i* and *j* out of *m* possible classes, and

$$p_i \times p(w_i) = log_e\, p(w_i) - \frac{1}{2} log_e|V_i| - \left[\frac{1}{2}(X - M_i)^T {V_i}^{-1}(X - M_i)\right], \tag{4}$$

where p(w_i) is the *a priori* probability for each class (Jensen 2016).

1.3.3.2 Vegetation Indices

Remotely sensed data can be used to analyze vegetation and other phenomena through the creation of spectral vegetation indices and band ratios. SVIs can provide a variety of information, such as vegetation health and richness (Gould, 2000; Xie et al., 2008) and soil composition (Wulf et al., 2015). Prior studies have used vegetation indices to evaluate vegetation recovery/regeneration post-fire (Viedma et. al., 1997; White et. al., 1998; Diaz-Delgado et. al., 1998, 2002). The Normalized Difference Vegetation Index (NDVI), for instance, depicts photosynthetic activity by calculating the difference between near-infrared (Pnir) and red (Pred) spectral bands divided by their sum (Weier and Herring, 2000).

$$\boldsymbol{NDVI} = \frac{(Pnir-Pred)}{(Pnir+Pred)} \tag{5}$$

1.3.4 Post-classification Change Detection

There are different change detection algorithms that can be applied to time-series imagery to compare land cover or specific vegetation types. These include image differencing or band-ratioing, spectral vegetation indices, Principal Components Analysis, direct multidate classification, and post-classification differencing (Singh, 1989; Mas, 1999; Jensen, 2016).

Differencing or comparison of hard and fuzzy classifications is a commonly used method that allows the description of from-to change, quantifying change from one class to another on a comprehensive change matrix. The Per-Pixel Post-Classification Comparison is tailored to assess change between classification maps, provide information about the nature of change, and automatically generate an updated map of change classes (Cho, 1999; Alphan et al., 2009; Jensen, 2016). Spectral changes in forested landscapes following fire have been studied through vegetation index differencing, including NDVI (White, 1996; Lentile, 2006).

Change detection accuracy is dependent in great part on the use of comparable, accurately registered time-series imagery. Satellite imagery, such as Landsat, provide consistency in collection date, extent covered, radiometric and geometric resolutions, and image quality, minimizing differences in registration, sun angle and vegetation phenology (Singh, 1989). Aerial imagery can also be reasonably consistent throughout time, depending on collection methods and timing. The National Agriculture Imagery Program (NAIP) collects high resolution images for certain U.S. states every two years, with a horizontal accuracy of 6 meters and little variation in collection dates, using standardized image processing methods.

Chapter 2
Methodology

2.1 Overview

Remotes sensing and GIS techniques were implemented to assess vegetation response and recovery from the Las Conchas Fire of 2011 at Bandelier National Monument, New Mexico. Supervised vegetation classification of pre-fire (May 2011) and post- fire (June 2016) 1 meter spatial-resolution NAIP imagery provided maps of vegetation composition and distribution for eight target classes. Pre-existing vegetation plots (pre- and post-fire) and pre-fire vegetation classification data sets were used as reference for ground-based calibration and validation data. Calibration and validation data was used to train the software for supervised classifications, and assess their accuracy, respectively. The accuracy of the resulting classifications was assessed through confusion matrices. An analysis of vegetation change and recovery was produced by cross-tabulation, depicting from-to change by area. Relationship between vegetation change, fire frequency, mean fire return interval, years elapsed since last fire, and fire severity was assessed also through cross-tabulation.

2.2 Study Area

The study area covers the northern portion of Bandelier National Monument (Bandelier NM) in the counties of Los Alamos and Sandoval, New Mexico. Bandelier NM has an average annual precipitation of 427 mm, and low and high temperatures of -10 degrees C and 30 degrees C respectively (Muldavin et al., 2011). Elevation in the study area ranges from 1,767 m in the southeast, to 3,102 m in the northwest, with an average elevation of 2,485 m. This includes a majority of Frijoles Canyon down to the edge of the Las Conchas Fire perimeter, and extending south to the north edge of Alamo Canyon (Figure 1).

Fifty fires, including wildfires and prescribed fires, have been recorded in the study area from 1909 to 2014, 39 of which have taken place in the past 40 years (Figure 2; Chiverton et al., 2014). Prescribed fires form a key role in Bandelier NM's fire management efforts (Rodgers, 2005), and of those 39 most recent fires, 32 were prescribed or management ignited fires (MIF). In 1977, the La Mesa Fire burned 3,298 ha of the study area (Table 1). In 1992, the Cerro Grande Fire burned 316 ha, followed by a prescribed fire in 1993 that burned 101 ha. The Lummis Fire burned 653 ha in 1997, followed by three prescribed fires between 1997 and 1999, which burned a total of 1,241 ha. The Cerro Grande Fire (2000) burned 529 ha, a prescribed fire in 2007 burned 606 ha, and more recently, the Las Conchas Fire (2011) burned 5,459 ha of the study area.

2.3 Data

The research combined the use of remotely-sensed imagery, GIS data (historical fire perimeters, fire severity, pre-existing vegetation maps, and administrative boundaries) and field-based calibration and validation data for image classification (Table 2).

2.3.1 Imagery

National Agriculture Imagery Program (NAIP) from pre- and post-fire dates (May 2011 and June 2016, respectively) were acquired through the Earth Data Analysis Center in New Mexico. The NAIP images consist of four bands (G, B, R, NIR), have a spatial resolution of one meter and a co-registration of within six meters. A series of images from different sources were used as reference for creating calibration and validation data and observations. They include a 2011 15.2 cm spatial resolution image with three (RGB) bands, acquired by the U.S. National Park Service (2011a) immediately following the Las Conchas Fire. NAIP 2014 and Google Earth images (Google Earth, 2014).

2.3.2 Ancillary GIS Data

A fire history shapefile (Chiverton et al., 2014), containing New Mexico fire perimeters from 1909 to 2014, was used as a base for creating the fire frequency layer including number of burns and mean fire return interval. Fire severity data for the Las Conchas Fire was acquired from the Burned Area Reflectance Classification (BARC) (U.S. Forest Service, 2011). BARC utilizes near and mid infrared values from satellite imagery to depict post-fire vegetation conditions in four classes: unchanged, low, medium, and high change. Both layers were used to assess relationship with vegetation change/recovery.

A 2010 vegetation cover map depicting the different vegetation types present in Bandelier NM prior to the 2011 Las Conchas Fire was used to plan field work for data collection, as reference for creating calibration and validation data, and as a source of information for evaluation of the pre-fire classification and vegetation recovery. The 2010 vegetation map was generated by the USGS Vegetation Characterization Program (USGS-VCP) (USGS and National Park Service Inventory & Monitoring - Vegetation Mapping Program), following the National Vegetation Classification Standard. It combined field sampling methods and a supervised classification generated based on a two-m spatial resolution RGB orthophoto, coupled with 30-m Landsat Enhanced Thematic Mapper Plus (ETM+) images, and had an accuracy of over 80% for all target classes (Muldavin et al., 2011).

2.4 Pre-Processing

2.4.1 National Agriculture Imagery Program (NAIP) Imagery

Geometric accuracy of the 2011 and 2016 NAIP images was first assessed visually. Image co-registration is important when conducting analyzes that consider change in time. The images had a slight misregistration of 1 to 5 meters. The displacement was not consistent throughout the images, likely due to terrain factors. Geometric correction was not done to avoid introducing additional error to areas that registered well. Developed areas, including buildings and roads within the study area were digitized and then masked to exclude them from the classification process. Each image was coarsened to 3 m and 5 m, to generate and evaluate supervised classifications with multiple resolutions.

2.4.2 Calibration and Validation Data

Pre- and post-fire vegetation plots measuring 400 m^2, collected by Natural Heritage New Mexico (NHNM) between 2003 and 2008 (Muldavin et al., 2011) and 2012 respectively, were provided to serve as base for creating the calibration and validation data. Available in vector point format, 158 of them are within the study area and were visited pre- and post- Las Conchas Fire, providing valuable comparable information. Each point describes vegetation types present, notes from field observations, and other relevant data.

The pre-fire USGS-VCP vegetation classification (Muldavin et al., 2011) was incorporated to identify general areas that contained target classes. The 15.2 cm resolution image was acquired for Bandelier NM immediately post fire. The NAIP 2014 image, and several time-series Google images accessed through Google Earth Desktop were also used as reference for creating calibration and validation data. A Garmin eTrex GPS was used to navigate to existing NHNM plots and to record the location of additional calibration and validation points. GPS accuracy ranged from 1.8 to 4.6 m (6 to 15 feet).

Calibration and validation points were used to identify pixels that overlaid and represented each of the target classes. Sets of points were created for each class, from each image separately, and then divided into calibration and validation sets through random selection (Figure 3). Pixel clusters or ‘regions of interest’ (ROIs) were created based on those points, for each image (1 m, 3 m, and 5 m) per date, and were used as input for image classification and accuracy assessment. Ten to fifteen ROIs (each ROI averaging 4-5 pixels) were created for each class, per calibration and validation set (Table 3). A minimum of fifty pixels per class were selected for the 1 m images. For 3m and 5m images, each class had at least 20 pixels.

Spectral separability of the target classes was assessed by generating spectral profiles for pre- and post-fire ROIs (Figures 4, 5). Spectral profiles allowed for the assessment of the range of values for each class, and to evaluate if there was overlap in spectral signatures between particular classes.

2.4.3 Fire Frequency and Fire Severity Layers

A fire frequency layer was generated by overlaying individual fire perimeters from the fire history layer (Chiverton et al., 2014) in ArcGIS software (Esri, 2016). Individual fire perimeters from 1977 to 2011 were extracted and overlaid. The fire frequency layer includes the number of times burned, fire names, ignition years, time intervals between burns, mean return interval, and years elapsed since last fire for all areas burned from 1977 to 2011 within the study area, whose perimeters are available in digital form (Figure 6). The BARC layer depicting Las Conchas Fire severity was used as the input dataset for fire severity for this study (Figure 8). Both layers were rasterized to match the spatial resolution and extent of the vegetation classifications.

2.5 Processing

2.5.1 Supervised Classifications and Indices

Supervised classifications were created to classify pre- and post-fire imagery into eight target classes, (1) Bare Soil/Rock, (2) Quaking Aspen, (3) Ponderosa Pine, (4) Mixed Conifer (dominated by douglas fir and white fir), (5) Grassland/Herbaceous, (6) Gambel Oak, (7) New Mexico Locus, and (8*)* Piñon Pine-Juniper (PJ).

Shadows were present on both NAIP images, cast by trees and topographic features. Several methods to deal with shadows were considered, to minimize their impact on analyses and retain as much information as possible. Shadows were classified by creating ROIs that included both shadowed and non-shadowed pixels of each of the classes, for calibration and validation data.

ENVI image processing software (Harris Geospatial Solutions, 2015) was used to generate the supervised classifications with a Maximum Likelihood decision rule, utilizing calibration ROIs. A single probability threshold value of 0.2 was used for all classes. Values that fell under the threshold were categorized as “Unclassified”.

Once the classifications were generated, Gambel Oak, New Mexico Locust and Quaking Aspen were merged due to marked similarity in mean reflectance values (low spectral separability) of calibration and validation data (Figure 4, 5). Although other vegetation types also had similar values, it made sense to merge these three types together due to their tendency to thrive in fire-impacted landscapes and grow together in the same areas. (Foxx, 1984; Howard, 1996; Fulé, 2002). Patches of young gambel oak, New Mexico locust and quaking aspen together were observed during field work. The resulting classifications consisted of the following classes: (1) Bare Soil/Rock, (2) Ponderosa Pine, (3) Mixed Conifer (Douglas fir and White Fir), (4) Grassland/Herbaceous, (5*)* Piñon Pine-Juniper (PJ). (6) Disturbance vegetation (Gambel Oak, New Mexico Locust, and Quaking Aspen) (Figure 14, 15).

2.5.2 Accuracy Assessment

The accuracy of the supervised classifications was assessed using validation datasets. The result was a confusion matrix including overall accuracy, as well as User’s and Producer’s accuracy for each target class (Table 4, 5, 6, 7).

Supervised classifications generated with 1 m images were used to run the remaining analyses, due to their higher resolution compared with 3 m and 5 m classifications.

2.5.3 Classification Change Detection

Pre- and post-fire supervised classifications were evaluated to assess post-fire change. A cross-tabulation analysis ran in TerrSet software (Clark Labs, 2016) resulted in a map of from-to change, and a change matrix quantifying number of pixels on each new class of change (Table 8). The original from-to change raster was reclassified into three recovery classes: (1) Unchanged/Recovered, showing areas that did not change or recovered to the same class, (2) Disturbed, which refers to pixels that changed to Bare Soil/Rock, Grassland/Herbaceous, or a disturbance class (Quaking Aspen, Gambel Oak or New Mexico Locust), and (3) Undetermined, areas that were depicted as changed to Mixed Conifer, Ponderosa Pine or Piñon-Juniper, a conversion deemed improbable at 5 years post-fire(Figure 9).

2.6 Analytical Assessment

Cross-tabulation matrices were generated to compare vegetation recovery and change with fire characteristics. Each fire characteristic was evaluated separately (number of burns, mean fire return interval, years elapsed since the last fire occurred, and fire severity at the time of the 2011 Las Conchas Fire). The result was four separate matrices, showing area per recovery class that intersected with number of burns (Figure

10, Table 9), fire severity classes (Figure 11, Table 10), years elapsed since the last fire occurred (Figure 12, Table 11), and mean fire return interval (Figure 13, Table 12).

Chapter 3
Results

In this section, the accuracy of supervised classification results is described, and classification results are compared to pre-existing vegetation data. Post-fire recovery is assessed by quantifying change for each class and then evaluating changes with regard to fire frequency and severity.

3.1 Accuracy Assessment of One-Meter Resolution Classifications

Classification accuracy was assessed through confusion matrices (Tables 4a, 5a). The 1 m pre-fire classification had an overall accuracy of 63.1%, while the post-fire classification had an accuracy of 59.9%. Overall, User's and Producer's Accuracy, relating to omission and commission errors respectively, varied between classifications. For the pre-fire classification, User's Accuracy ranged from 38.4% (Gambel Oak) to 79.8% (Piñon-Juniper), while Producer's Accuracy ranged from 17.6% (Gambel Oak) to 86.5% (Bare Soil/Rock). Post-fire classification User's Accuracy ranged from 34.2% (New Mexico Locust) to 89.9% (Herbaceous), and a Producer's Accuracy of 91.6% (Herbaceous).

The classes with the highest accuracy (on both classifications) were Bare Soil/Rock and Herbaceous. Any confusion with these classes occurred between each other, and in a few instances, with New Mexico Locust. Piñon-Juniper also exhibited high accuracy. There was some confusion between Piñon-Juniper, Mixed Conifer and Ponderosa Pine and, although their presence resulted in an exaggerated distribution outside of their range, they were accurately depicted in areas coinciding with validation samples in most cases.

Certain classes tended to get confused between each other. Quaking Aspen, Gambel Oak and New Mexico Locust were confused with each other in several sections of the study area. In some instances, they were misclassified as Mixed Conifer or Ponderosa Pine. Mixed Conifer and Ponderosa Pine were confused with each other, and in some areas, as Piñon-Juniper. There was also confusion between Piñon-Juniper and the disturbance classes: Quaking Aspen, Gambel Oak and New Mexico Locust.

3.1.1 One-Meter Classifications with Merged Disturbance Classes

The pre- and post-fire classifications were reclassified in preparation for change detection and comparison with fire variables, based on observed class spectral separability. Quaking Aspen, Gambel Oak and New Mexico Locust were merged into one class, referred to as the Disturbance class. Similarities in spectral values for the disturbance classes meant that they presented considerable commission error amongst themselves. Once merged, classification accuracy increased. The resulting pre-fire classification had an overall accuracy of 70.8%, while post-fire had 73.6% accuracy (Table 4b, 5b). Pre-fire User's and Producer's Accuracy for the Disturbance class were 77.6% and 66.8%, respectively. On the post-fire classification User's Accuracy was 78.3% and Producer's Accuracy was 78.0%.

3.2 Accuracy of Three and Five Meter Classifications

Pre- and post-fire classifications were also generated utilizing aggregated NAIP images of 3 m and 5 m, to verify if coarser resolutions could result in higher accuracy than the one achieved with 1 m imagery. Overall, pixel aggregation resulted on a decrease of usable pixels as samples for calibration and validation. As image resolution decreased (from 1m to 5 m), so did the number of pixels available per ROI.

The highest overall accuracy achieved for 3 m pre-fire 8-class classification was 55.8%, while for 5 m, it was 55.2%. In the case of the 6-class pre-fire classification, 3 m resolution accuracy was 66%, and 5 m was 65.3% (Table 6). User's Accuracy for the 6-class 3m classification ranged from 27.8% (Mixed Conifer) to 96.8% (Herbaceous), while Producer's Accuracy for the 6-class 3m classification ranged from 29.6% (Ponderosa Pine) to 100% (Bare Soil-Rock). For 5 m, User's Accuracy ranged from 23.1% (Mixed Conifer) to 90.2% (Bare Soil-Rock). Producer's Accuracy went from 50.6% (Disturbance) to 100% (Bare Soil-Rock).

Post-fire, accuracy of 3 m classification was 60.7% for the 8-class classification, and 81.1% for the 6-class (Table 7a). In the case of the 5 m post-fire classification, the 8-class classification had an accuracy of 67.6%, while the 6-class classification had a 79.2% accuracy (Table 7b).

User's Accuracy for the post-fire 6-class 3m classification ranged from 42.9% (Ponderosa Pine) to 100% (Bare Soil-Rock), while Producer's Accuracy ranged from 48.4% (Ponderosa Pine) to 98.2% (Bare Soil-Rock). In the case of the 5m post-fire classification, User's Accuracy was 44.1% (Ponderosa Pine) to 96.9% (Herbaceous). Producer's Accuracy ranged from 68.2% (Ponderosa Pine) to 100% (Bare Soil-Rock).

For both dates, commission error was found to be similar to those from the 1 m resolution classifications, but mainly Disturbance class with coniferous trees, and Piñon-Juniper with Mixed Conifer and Ponderosa Pine.

One-meter 6-class classifications were used to run subsequent analyses.

3.3 Pre- and Post-Fire Vegetation Distribution

Vegetation classifications generated from this study were compared with existing pre-fire USGS-VCP vegetation map and post-fire field and image observations (Figure 14, 15). When vegetation classifications are compared to vegetation maps and observations, there are some classes and areas within the study regions with high agreement, and some classes and/or other locations with disagreement. Mixed Conifer and Ponderosa Pine distribution on the northwest portion of the study area, and along the Frijoles Canyon pre-fire compare well with USGS-VCP vegetation map. Patches of Quaking Aspen and Herbaceous match the USGS-VCP and observations on the northernmost section near Cerro Grande Trail, Alamo Boundary Trail, and the Apache Spring trail areas pre- and post-fire. In both classifications, Piñon-Juniper was accurately depicted in the southeast portion of the study area. Gambel Oak was accurately classified in areas including the south wall of the Frijoles Canyon in the pre-fire classification. Post-fire, patches of Gambel Oak were accurately classified in areas such as the Burnt Mesa Trail, when field observations confirmed its existence.

In other instances, lack of spectral separability between classes in calibration data limited the accuracy with which some vegetation cover types were classified (Figures 4 and 5). For instance, spectral similarities among Mixed Conifer, Ponderosa Pine and Piñon-Juniper, and among Quaking Aspen, Gambel Oak, and New Mexico Locust (disturbance classes) resulted in commission error. Piñon-Juniper Woodland has a mean elevation of 2000 m (Allen, 1989), but in the classifications, they were found in small clusters throughout the study area at higher altitudes. Areas that in reality were populated by Ponderosa Pine, including the Frijoles Canyon, Upper Frijoles and Lummis Canyon, exhibit inaccurate presence of Piñon-Juniper in the classifications.

Differences in the reflectance of live and senescent vegetation between the NAIP images played a role in how certain classes were distributed. Areas dominated by Herbaceous vegetation pre-fire, such as the Burnt Mesa Trail area and north of Alamo Canyon, were classified as Bare Soil/Rock. Dry months prior the collection of the 2011 NAIP image (PRISM Climate Group, 2017; Table 13, Figure 17) may have resulted in senescent herbaceous vegetation, and attenuated pixel reflectance values with digital numbers (DNs) of above 140, resembling those of Bare Soil/Rock. This may have created confusion between the two classes. The opposite was true for the post-fire classification, where wetter conditions in the months prior to the 2016 image collection resulted in herbaceous plants being in leaf out and reflectance values more characteristic of photosynthetic plants. In some areas, this resulted in over-estimation of Herbaceous, including areas north of Frijoles Canyon and around the northwest portion of the study area. The differences in reflectance values for the Herbaceous class between images is visible through an NDVI comparison (Figure 18).

Based on classification observations, post- fire Herbaceous, although overestimated on the northwest section, was more accurately classified on the Upper

Frijoles area. Bare Soil/Rock was accurately classified at Upper Frijoles and northwestern portions of the study area. Loss of mature trees at the bottom of the Frijoles Canyon due to fire impact and post-fire flash floods is evident by the presence of Bare Soil/Rock class on the Frijoles Creek drainage area (Figure 15, inset a).

Gambel Oak, New Mexico Locust and Quaking Aspen had the least spectral separability on calibration and validation data amongst the classes, and were found together throughout the study area on both classifications. This dynamic was observed during field work (Figure 21). Areas adjacent to St. Peters Dome Road, as well as the Blue, Cerro Grande and Apache Springs trails were observed to have abundant young quaking aspen, gambel oak and New Mexico locust, mainly in the understory of burned/dead conifers or open areas surrounded by dead conifers. In those same areas, the post-fire classification shows a shift from Mixed Conifer and Ponderosa Pine to other classes, including Quaking Aspen and Herbaceous. Although field observations attest to substantial growth of disturbance vegetation types in areas previously populated by Mixed Conifer and Ponderosa Pine, their presence on the post-fire classification was amplified. Post-fire, Mixed Conifer was also found on canyon walls on the southeast portion of the study area, which agrees in some areas with the depiction of this class in the USGS-VCP map.

Calibration and validation data included shadowed pixels for each class except Bare Soil/Rock and Herbaceous. In some areas, shadowed pixels were classified following the pattern of adjacent cover types. Others, including canyon walls or steep cliffs, tended to get classified as Piñon-Juniper. This hints to a marked similarity between spectral values of other classes in shadowed areas, and those of Piñon-Juniper in general.

3.4 Post-fire Change Detection

Change detection on the post- Las Conchas Fire landscape was assessed through cross-tabulation of pre- and post-fire classifications. As a result, a raster depicting from-to change classes, and a change matrix enumerating the number of pixels that changed per class were generated (Table 8). Results in this section are described for individual vegetation classes, and for overall recovery classes.

Changes of individual classes can be addressed from two standpoints: the changes from one class into others, or changes from other classes into a target class. Not counting area that did not change or that recovered, per class, the cross-tabulation results indicate that 15% of pixels changed into Bare Soil/Rock, 10.5% into Herbaceous, and 13.2% changed into a disturbance class (Table 8b). A total of 35.9% changed into Mixed Conifer, Ponderosa Pine, and Piñon-Juniper. Slow growth trajectories and a relatively short time elapsed since the Las Conchas Fire (5 years up to June 2016, when NAIP image was collected), provide limited time for enough growth from seeds of these types of trees to be identified through 1 m resolution imagery. This makes the high change percentage increase of new conifer cover not possible. .

Cover types with the highest percentage of change into other classes begin with Herbaceous, Piñon-Juniper and Disturbance (Table 8b). Herbaceous converted mainly to Bare Soil/Rock. Piñon-Juniper and Disturbance’s highest percentage of change were both into Ponderosa Pine, which again, is unlikely. Herbaceous, Mixed Conifer and Ponderosa Pine had a similar percentage of total change into other classes

Finally, the overall distribution of recovery classes (Unchanged/Recovered, Disturbed, and Undetermined) was assessed (Figure 9). Percent areas per recovery class was: 38.5% Disturbed, 36.2% Undetermined, and 25.3% Unchanged/Recovered. This means that nearly 75% of pixels experienced change into another vegetation/cover type.

The Disturbed class is dispersed throughout the study area, but was mostly found on the northwest side, on the Friojles Canyon walls located at Upper Frijoles, and along Apache Springs trail (Figure 20). Pre-fire, these areas were populated by mixed conifer, ponderosa pine and sparse patches of quaking aspen. To this day, dense areas of these trees can be observed along the St. Peters Dome road and the Blue trail, while areas adjacent to the Alamo Boundary Trail and Rabbit Mountain Road were severely degraded by the fire. Undetermined change showed a tendency of covering walls of topographic gullies or natural ditches.

3.4.1 Fire History

Mapped fire occurrence in the study area ranged from one to five times for the 1977-2014 time period (Figure 6), with15.6% of the area burned once in the time period, 40.9% burned twice, 39.5% burned three times, and 4.3% burned four and five times (Table 9b). Areas with the greatest number of burns include the northernmost portion of the study area, north of the Frijoles Canyon between W Jemez Road and 3.5 km west of and Entrance Road, and the southernmost section, down to Alamo Canyon. When assessing type change per class with regards to number of times burned, the greatest amount of area per number of burns coincided with the Disturbed class (Table 9b). All recovery classes intersected primarily with areas that were burned two or three times prior to the Las Conchas Fire, which amount to 80.4% of the study area, followed by areas burned once. Areas burned four and five times amounted to less than 5% of the study area.

Mean fire return interval (MFRI) ranged from three to thirty-four years (Figure 7). Lower MFRI indicate more frequent fire occurrence. MFRIs of 17 and 34 years accounted for the majority of study area, due to the 1977 La Mesa Fire, fires that occurred in the 1990s, and the 2011 Las Conchas Fire (Table 12b). 51.2% of Unchanged/Recovered areas experienced a 17-year mean interval between fires, and another 21% had been burned in 1977 by the La Mesa Fire. 13% of the study area had an MFRI of three to five years. Out of that percentage, 42% were Disturbed areas, 39% Undetermined, and 19% Unchanged/Recovered.

The number of years that had elapsed since the last fire prior to the Las Conchas Fire occurred was compared to each recovery class (Table 11b). 53% of the study area was burned last 11 to 15 years prior to the Las Conchas Fire. Disturbed areas largely intersected with areas that had burned last 11 to 15, or 31 to 35 years before.

3.4.2 Las Conchas Fire Severity

The study area presented all four fire severity classes, in varying percentages. 46.2% of the area had a low severity impact, 16.03% medium impact, 15.89% high impact, and 21.88% was classified in the BARC layer as ‘Unchanged.’ Based on a comparison with the pre-fire classification and USGS-VCP map, high fire severity occurred in places mostly populated by Mixed Conifer and Ponderosa Pine tree types. High severity also occurred on the northwest section and on the south wall of Upper Frijoles where patches of quaking aspen were distributed. These areas were characterized by tree mortality and growth of disturbance vegetation types post-fire. On the southeast, where piñon-juniper is known to exist, the landscape experienced low severity fire. Patches of gambel oak were affected by high severity at Upper Frijoles, and by low and medium severities on the east.

Chapter 4
Discussion

This study sought to assess vegetation response to wildfire in Bandelier National Monument, by answering three target questions, focused on the five years elapsed since the Las Conchas Fire occurred, in 2011. First, vegetation response to and recovery from the Las Conchas Fire was assessed by creating Maximum Likelihood supervised classifications of immediately pre- and five years post- fire imagery. They provided the means to observe and compare vegetation distribution at both dates, and study the types of changes that took place. Potential relationships between areas with differing fire frequencies, return intervals, and severities were evaluated with respect to vegetation recovery and change.

4.1 Accuracy Comparison Between Different Resolutions

Classification accuracy varied between different image resolutions: 1, 3 and 5 meters. Although the accuracy of the 6-class classifications for 3 m and 5 m resolutions was higher than the 73.6% achieved with 1 m resolution, visual inspection of the classification shows higher discrepancy with actual vegetation/cover type distribution. User's and Producer's Accuracy varied per vegetation/cover type, increasing, or decreasing with coarser resolution, or increasing for one of the resolutions.

Some vegetation/cover types show an accuracy pattern for both pre- and post-fire Classifications, and User's and Producer's Accuracy. For instance, Ponderosa Pine and Piñon-Juniper both had higher accuracy for 1m and 5m, than for 3m. On the other classes, User's and Producer's Accuracy per date does not show a trend or pattern of increase or decrease as the images coarsen. Producer’s Accuracy for Mixed Conifer is highest at 3 m on both classifications, while User’s Accuracy is highest at 1 m pre-fire and 3 m post-fire. For the Disturbance class on the pre-fire classification, accuracy decreased as resolution coarsened, while User’s Accuracy increased with lower resolution. Post-fire, User’s and Producer’s Accuracy was highest at 3 m. In the case of the Herbaceous class, Producer’s Accuracy for both dates decreased with lower resolution. User’s Accuracy pre-fire was highest at 3 m, while post-fire, it was lowest at 3 m and highest at 5 m. Lastly, Bare Soil-Rock Producer’s and User’s Accuracy on the pre-fire classification increased as resolution decreased. For post-fire, Producer’s Accuracy was lowest at 3 m, while User’s Accuracy was highest at 3 m.

Reasons for the variation in accuracy between classes lies on the size of tree crown and cover type patches from which calibration and validation data was selected. Bare Soil/Rock and Herbaceous areas where ROIs were selected tended to be broad. For those classes, User’s and Producer’s Accuracy was found to be highest on all three resolutions. For Piñon-Juniper, Mixed Conifer, and Disturbance classes (especially Gambel Oak and Quaking Aspen), pixels selected as samples belonged to relatively small crowns. As resolution decreased (pixels became larger), aggregation of pixel values changed the pureness of the samples. At 1 m, pixels selected fell fully within tree crowns, while at 3 m and 5 m, although the majority of the pixel represented the intended class, slight aggregation with Bare Soil-Rock and Herbaceous may have occurred. Lastly, conditions of Ponderosa Pine calibration and validation data resemble those of Mixed Conifer: relatively small crown. The pattern observed, where high accuracy was achieved with 5 m resolution images, is unclear. one reason could be commission with Mixed Conifer.

4.2 Post-fire Vegetation Response and Recovery

The supervised classifications (Figure 12) presented vegetation cover distribution with varying degrees of accuracy. All classes had instances of being classified correctly, but also were classified as mixed, reduced or exaggerated in extent, or misplaced in distribution in different sections of the study area. Minimal spectral separability between particular classes limited the accuracy with which class types were distinguished and portrayed.

The ground-referenced samples for calibration and validation were collected in a robust manner, which provides confidence that classification inputs accurately represent the intended vegetation cover type. NAIP images were prepared in the same manner, which decreases the probability of misclassification due to differences in image processing. It is possible, however, that the one-month difference in image collection date (May 2011 and June 2016), and differences in precipitation in the months prior to image collection (Table 13, Figure 17), may have played into differences in spectral values between images, impacting the way different vegetation cover types were classified.

In terms of vegetation change, 75.1% of the total study area changed to another vegetation/cover class. While field observations attest to vegetation degradation and conversion in several portions of the study area, it is believed that this high percentage of change was likely due to class confusion due to limited spectral separability, and from slight NAIP image misregistration. A recent study conducted at Bandelier NM post-Las Conchas Fire (Coop et. al., 2016) suggests that there has been considerable conversion, mainly from forested to alternate states, as a result of recent fires including the Las Conchas Fire.

Field observations and classification results indicate that quaking aspen, gambel oak, and New Mexico locust have grown in several sections of the study area post-Las Conchas Fire. This includes areas that were previously populated by conifer trees (mainly mixed conifer and ponderosa pine). This coincides with previous studies that have observed their growth in fire-impacted areas, both at Bandelier NM and other sites. The La Mesa Fire in 1977 has been linked to gambel oak and New Mexico locust growth, which came to dominate areas that had a range of fire severities at that time (Foxx, 1984, Fulé, 2002). Quaking aspen has been observed as a dominant species in fire-impacted landscapes, sprouting from undamaged root systems, and in some regions necessitating fire to grow (Howard, 1996).

Based on the change detection analysis, around 36% of the study area changed into Mixed Conifer, Ponderosa Pine, and Piñon-Juniper. Slow post-fire growth trajectories of these tree types (Zouhar, 2001; Anderson, 2002; Habeck, 2002; Johnson, 2002; Steinberg, 2002), indicate there should have not been any growth from these tree types (i.e. 0%) that could be visible in 1 m resolution images 5 years post-fire. Growth trajectories have been observed to range from one to two years for ponderosa pine, to over 40 years in the case of piñon-juniper. This high increase is attributed to poor spectral separability between these classes and the disturbance classes, especially on the post-fire calibration and validation data sets (Figure 5). This limits the precision with which the actual presence of these classes is depicted. Thus, there is uncertainty regarding recovery class distribution.

4.3 Fire History and Vegetation Response and Recovery

In general terms, the distribution of recovery classes per number of burns related directly to the amount of area both variables comprise of the study area. Since 80.4% of the study area was burned either two or three times prior to the Las Conchas Fire, it makes sense that all recovery classes mainly intersected with those fire frequencies (Table 9a). Disturbed areas covered the largest portion of study area, and most of the area per number of burns intersected with Disturbed areas.

The same relationship was found with mean fire return interval and years elapsed since the last fire prior to the Las Conchas Fire. In both cases, most of the area per mean return interval and years elapse intersected with Disturbed areas. Sections with short fire return interval, of 3 to 5.5 years between fires, summed 13% of the study area. Pre-fire, almost 80% of those areas were populated mainly by mixed conifers and ponderosa pine, based on the USGS-VCP vegetation map. The largest portion of short return interval areas also coincides with areas that were Disturbed post-Las Conchas Fire, based on the pre-fire classification.

Coop et. al. (2016) found that vegetation showed higher resistance to burning in areas that had been previously affected by fire. Vegetation change patterns in areas that had not been burned until the Las Conchas Fire (since 1977), were similar to the patterns observed previously in other areas after fire impact. Their findings coincide with studies from other locations, considering both wildfires and prescribed fire history (Fulé, 2002; Strom and Fulé, 2007; Larson et. al., 2013)

Impacts of fire frequency, mean fire return interval, and years elapsed since last fire could be assessed again in future research, once more time has passed since the Las Conchas Fire and regrowth and change patterns become more prominent in the landscape.

4.4 Effects of Fire Severity on Vegetation Response and Recovery

Dry months prior to ignition of the Las Conchas-fire (Figure 17) allowed for its rapid spread and extensive impact. The majority of the study area extent had a low fire severity impact (Table 10), which intersected with the highest amount of area for each recovery class. High fire severity affected areas populated by mixed conifer and ponderosa pine on the northwest section, as well as areas where Disturbance classes were distributed.

Frequent fire occurrence has been linked to reduced fire severity in subsequent fires (Coop et. al., 2016), but results of this study indicate that areas impacted by high severity fire in the northwest also had short mean fire return interval since 1977. It is important to note that most of the fires that had short intervals in between in that area were prescribed fires. Fire severity of previous fires was not considered in this study, but based on image and field observations, tree mortality was not prominent in those areas pre-Las Conchas Fire.

Although frequent high severity fires have been found to increase vegetation resilience to subsequent high severity fires (Donato et. al., 2009), high fire severity has also been linked to tree mortality and vegetation type conversion (White et. al. 1996; Diaz-Delgado et. al., 2010; Coop et. al, 2016). Field observations in the study area confirmed a loss of woody vegetation types on the northwestern area affected by high severity fire. Dense patches of quaking aspen, gambel oak and New Mexico locust (sometimes mixed), were found during field work in the understory of dead mixed conifer and ponderosa pine in those areas (Figure 21b).

Chapter 5
Conclusions

5.1 Conclusions

Wildfire is a natural phenomenon that has played a key role in forested landscapes, positively impacting forest structure and nutrient availability, periodically eliminating surface fuel materials, and providing ideal conditions for healthy trees to flourish without substantial competition (Dewar, 2011). Changes in fire regimes have fostered the occurrence of less frequent, higher severity fires that consume forests and promote vegetation type conversion.

A changing and warming climate is expected to increase the number of wildfire events (Williams et. al., 2013). Fire regimes are controlled by climatic conditions, in addition to forest structure, such as fire frequency, intensity, size and seasonality (Touchan et. al., 1996, Dale et. al., 2001). Studying the response of different types of vegetation to such events is crucial for outlining best practices for mitigation and management efforts in fire-prone environments.

Maximum Likelihood supervised classifications were created for pre- (2011) and post-fire (2016) 1 m NAIP imagery using ENVI software, and for their aggregated versions of 3 m and 5 m. Calibration and validation data were generated from the collection of ground-reference points, pre-existing vegetation plots and maps, and image-reference points. Limited spectral separability between certain target classes resulted in mixed or misplaced distribution of vegetation cover on both dates, although accurate display of classes was found in several sections of the study area. Overall accuracy of the

1 m vegetation classifications used for change detection and correlation with fire variables was 70.8% and 73.6% for pre- and post-fire, respectively.

A change detection analysis was conducted through cross-tabulation, to assess types of change post-Las Conchas Fire. 75% five percent of pixels changed to a different cover type. The class with the least change was Bare Soil/Rock. There was a 35.9% increase in Mixed Conifer, Ponderosa Pine and Piñon-Juniper, which contrasts with the 0% increase expected due to slow growth trajectories and misplacement of Piñon-Juniper outside of its life zone. Considering only areas that were classified as one of the recovery classes, 38.5% percent of the study area was disturbed to some degree (changed to Bare Soil/Rock, Herbaceous or Disturbance). Another 36.2% of the area was experienced change into Mixed Conifer, Ponderosa Pine or Piñon-Juniper (categorized as Undetermined change), while 25.3% were unchanged or recovered.

The relationship between fire variables and vegetation response and recovery was assessed through cross-tabulation. The majority of the study area (40.9%) was burned two times prior to Las Conchas Fire, while 39.5% was burned three times. Nearly 70% of the study area had a mean fire return interval of 17 or 34 years. Based on growth trajectories, immature coniferous trees from Piñon-Juniper, and Mixed Conifers to Ponderosa Pine, might be at risk with these return intervals. In terms of fire severity, the majority of the study area (46.2%) had a fire low severity, followed by 16% medium severity, 15.9% high severity, and 22.9% unchanged. In general, recovery classes mostly experienced low severity impact, followed by areas unchanged by fire, with the exception of the Disturbance class, for which the second highest occurred in high severity areas (Table 10).

Overlapping spectral signatures in calibration and validation data limited the accuracy with which they were classified and portrayed in both pre- and post- fire classifications. Similarities in spectral values and weather conditions in the months preceding image collection may have impacted class separability. Future research could include additional calibration and validation data and high-resolution imagery from other seasons to take advantage of differences in vegetation phenology.

This research explores the utility and accuracy of using Maximum Likelihood supervised classification applied to high spatial resolution NAIP imagery and for mapping pre- and post-fire vegetation distribution and change. Although there were discrepancies in vegetation distribution between the classifications generated and pre-existing vegetation data and field observations, the results of this study provide a view of general patterns of distribution and change. It also provides a record of vegetation changes visible in aerial imagery five-years post-fire in an arid, semi-arid forest. Methods demonstrated in this study can be implemented in other U.S. southwestern states, as well as arid/ semi-arid regions with similar vegetation types, elevation ranges and climatic conditions.

5.2 Limitations

Research limitations can be divided into three main sections: data limitations, processing limitations, and replicability in future research. The minimum mapping unit (MMU) of the USGS-VCP 2011 vegetation map (Muldavin et. al., 2011) and BARC fire severity map did not match the spatial resolution of the NAIP imagery used for supervised classifications and subsequent analyses. This poses a limitation with evaluating vegetation classifications and fire characteristics, particularly along edges of polygon lines. The BARC fire severity data has been known to misclassify high severity areas as low severity in some sections of the study area. Although this limitation could have added some error into the assessment of the relationship between vegetation distribution and fire severity, this data set was found to be the best option available.

The NAIP images used for classifications, had a misregistration of one to five m in different sections, which impacted the precision with which change detection analysis portrayed class change. The high, 1 m resolution of the NAIP imagery may have introduced some error to image classifications in areas where different vegetation communities grow together naturally. Aggregating the images to 3 m and 5 m may have alleviated this impact, but also resulted in a loss of calibration and validation data, by aggregating and decreasing number of pixel samples per ROI. NAIP and other images used as reference for interpretation and creation of calibration and validation data sets had different collection dates (NAIP: May 2011, and June 2016; 15.2 cm Bandelier NM aerial image: September 2011, and Google images with varied dates). This represents a limitation when visually comparing images, conducting comparison analyses (in the case of NAIP imagery), and comparing pre- and post-fire NDVI, as differences in illumination and vegetation phenology may occur. For NAIP imagery specifically, it is known that considerable difference in precipitation patterns prior to the 2011 and 2016 collection dates took place. This may have influenced reflectance values, playing a role in class distribution and change detection.

Field work for observing vegetation conditions and gathering geo-located calibration and validation data was affected by limitations in accessibility to some sections of the study area. Portions of the northwest side, at Upper Frijoles and along the Frijoles Canyon down the southeast edge, experienced high fire severity and considerable post-fire tree mortality. With standing dead trees, danger of falling trees during strong winds create hazardous conditions in these areas. Thus, they were not visited during field work. Ground reference data were located adjacent to access roads and along trails.

Replicability of this research is dependent upon the accessibility of vegetation and fire history data similar to those used in this study. This research benefited from availability of several existing data sets, such as the NHNM vegetation plots collected during the decade preceding the Las Conchas Fire and a year post-fire, and the detailed USGS-VCP pre-fire vegetation map. Well-timed high-resolution imagery were available for the study area, consisting of a pre-fire NAIP image collected immediately pre-fire, and another collected five years post-fire, around the time when this research began. Future research that intend to re-create the methods used here will depend upon available data necessary to follow the steps taken.

5.3 Future Research

Future research to enhance the understanding of current results would include the use of additional color-infrared images. NAIP 2018, and other high-resolution images collected during other seasons could be added to take advantage of more pronounced vegetation response, and differences in vegetation phenology based on seasonality, respectively.

Collection of additional field data in areas that had not been visited during this study, including areas in Upper Frijoles, would increase samples per class and potentially increase spectral separability of calibration and validation data sets, thus enhancing distinction of vegetation cover. Areas that presented inconclusive vegetation distribution could be visited to observe vegetation types and state, and collect additional field data. Other environmental variables could be integrated into the study, such as elevation, slope, aspect, and precipitation. A decision tree classifier could be incorporated, taking advantage of a variety of variables to distinguish between and more accurately map vegetation cover.

In this study, fire severity was only considered for the Las Conchas Fire. Future research could address fire severities of previous fires, to assess relationships between vegetation response and varied fire severities in the same areas. Finally, different types of statistical analyzes could be applied as an addition to cross-tabulations between vegetation distribution and fire variables, to quantify the degree of correlation between variables. These may include multiple linear regression, logistical regression, and bivariate correlations, providing relationship values and level of significance.

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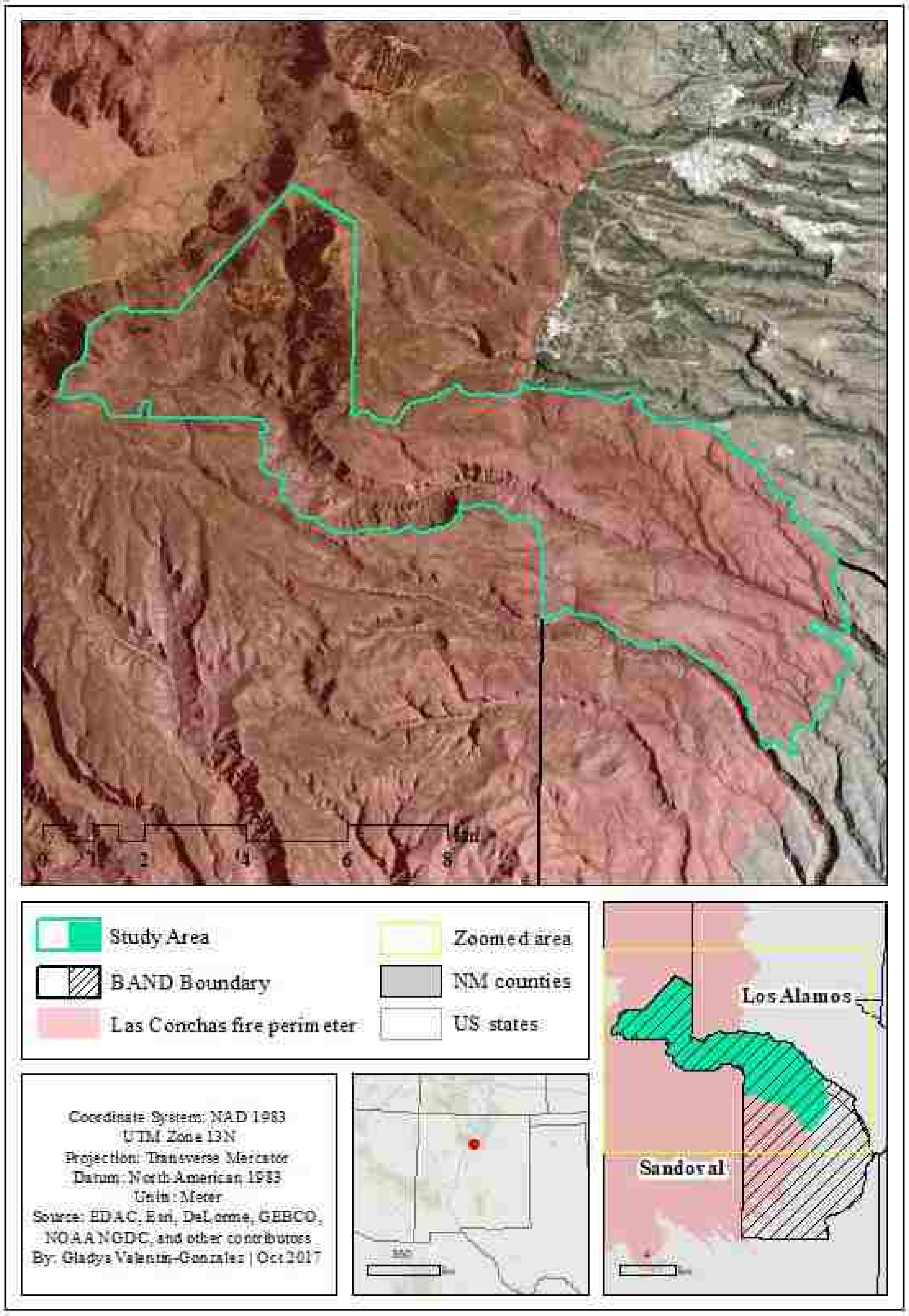
Figures



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UTM Zone 13N
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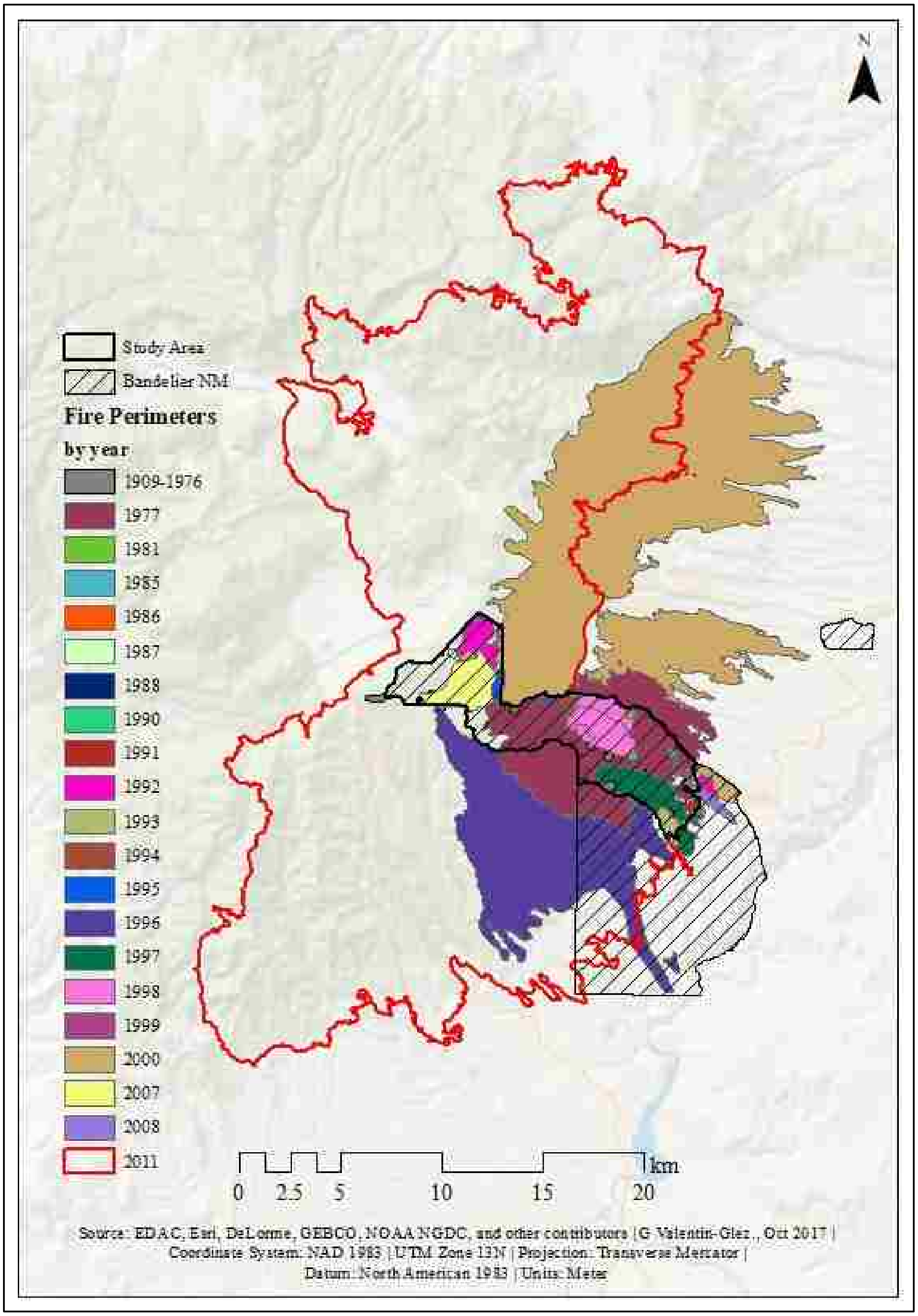
Datum: North American 1983
Units: Meter
Source: EDAC, Esri, DeLorme, GEBCO, NOAA NGDC, and other contributors
By: Gladys Valentin-Gonzalez | Oct 2017

Figure 1: Study Area at Bandelier National Monument, New Mexico.



Source: EDAC, Esri, DeLorme, GEBCO, NOAA NGDC, and other contributors | G Valentin-Glez., Oct 2017 | Coordinate System: NAD 1983 | UTM Zone 13N | Projection: Transverse Mercator | Datum: North American 1983 | Units: Meter

Figure 2: Historical fire perimeters within Bandelier National Monument, from 1909 to 2014.

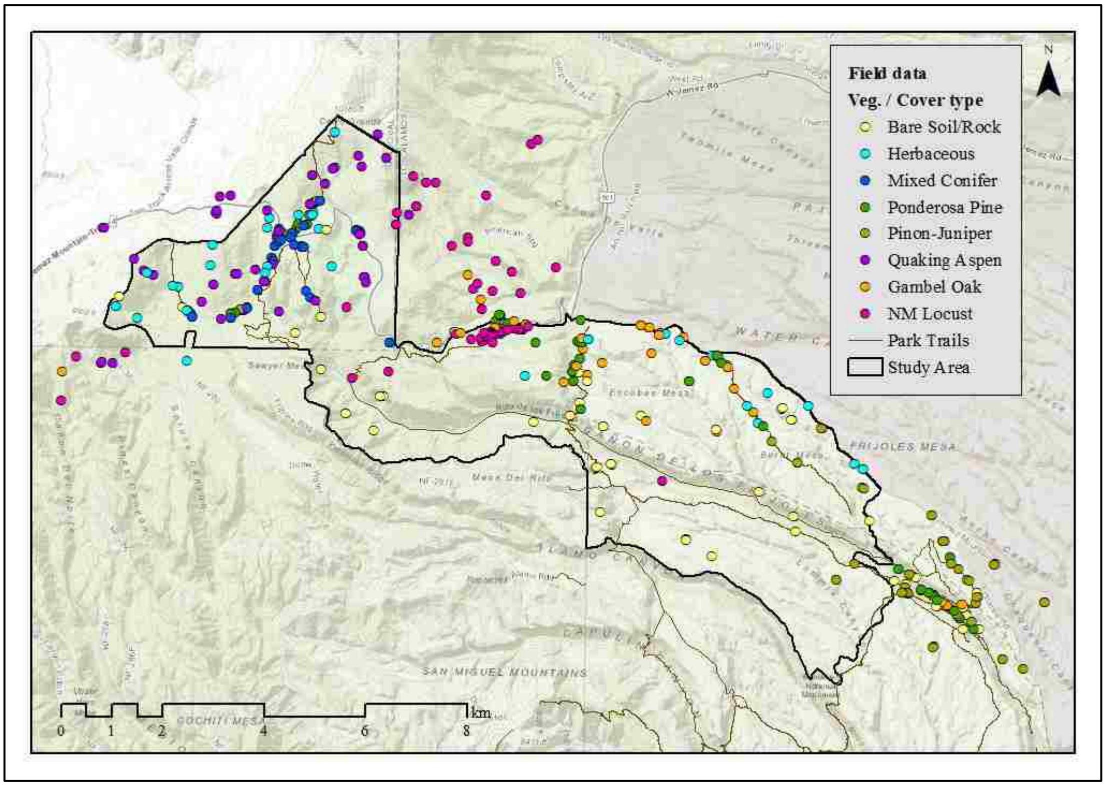
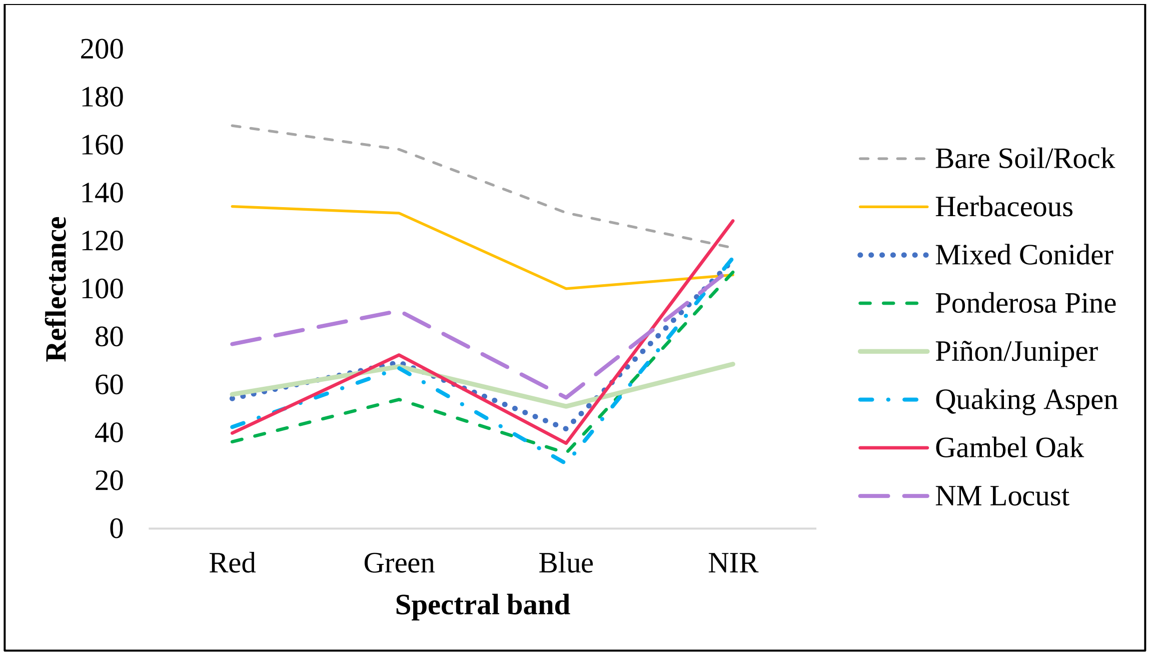
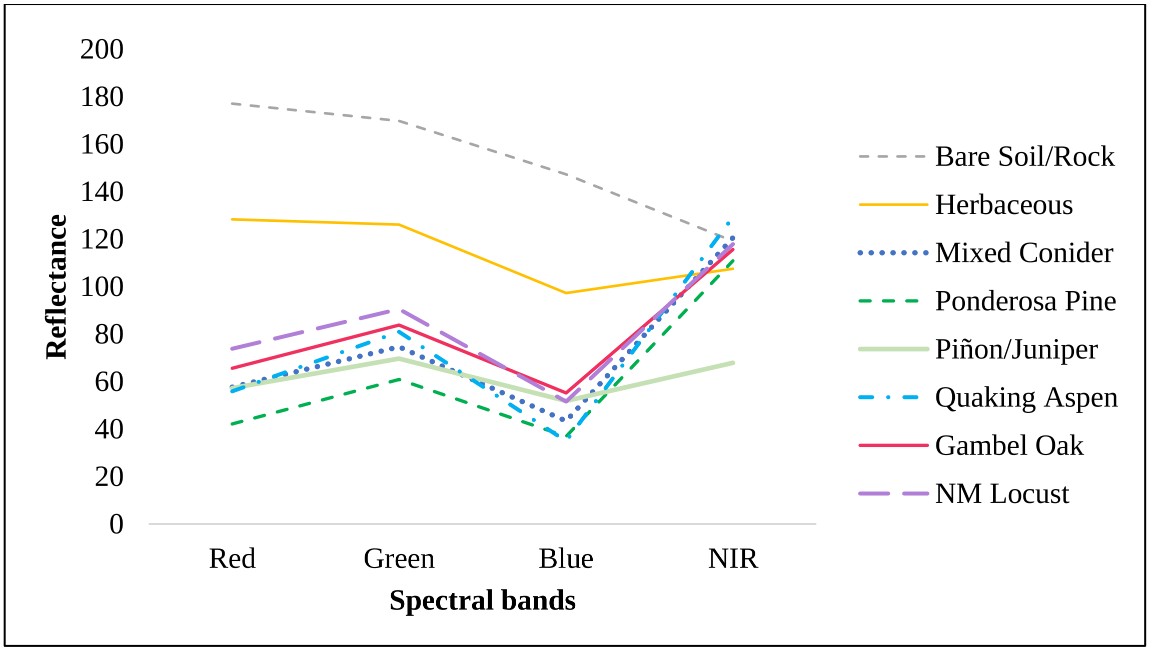


Figure 3: Calibration and validation data for pre- and post-fire classifications. There was a total of 430 points reference points, used as base to create "regions of interest" (ROIs): 258 pre- fire and 277 post-fire. Some points work for both pre- and post-fire images.

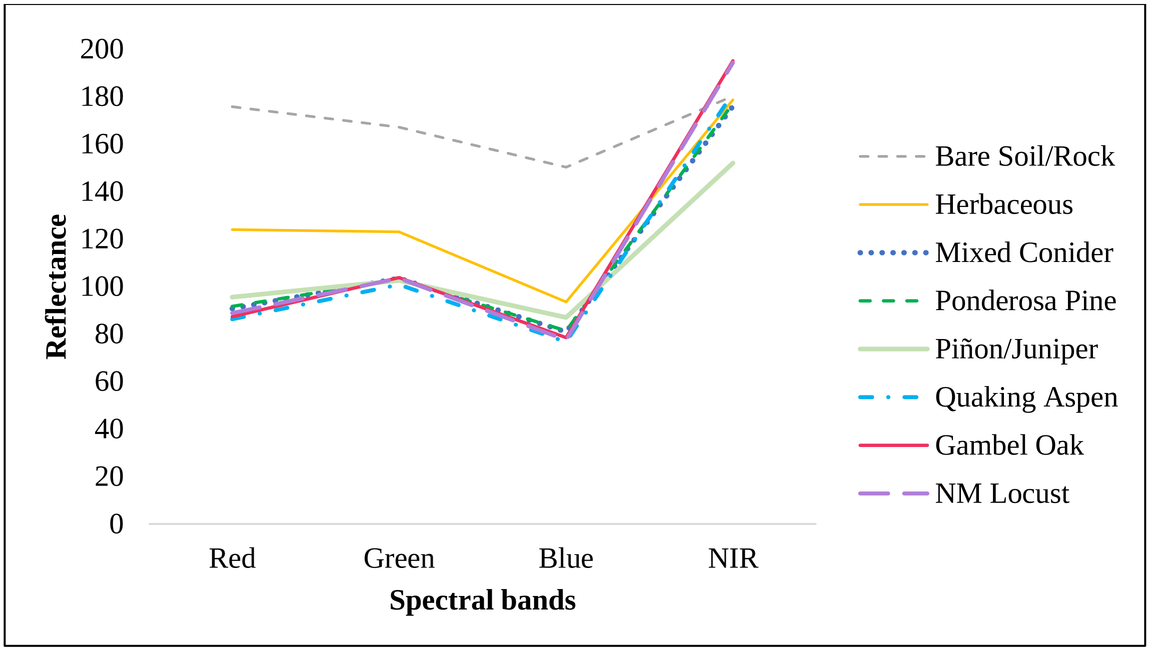


a)

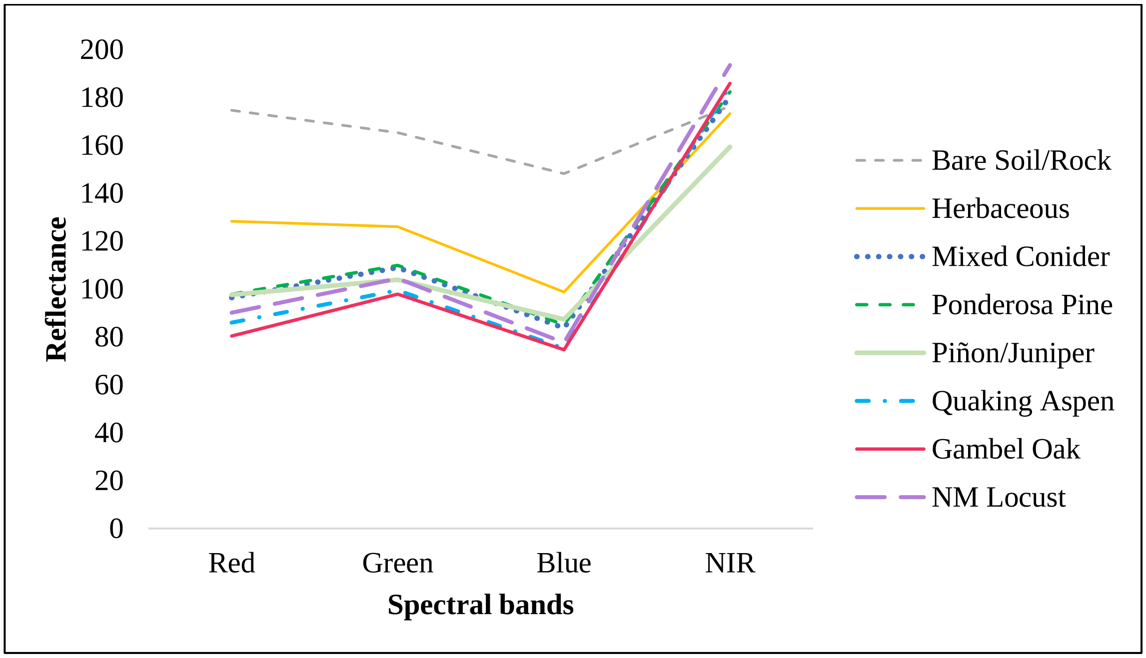


b)

Figure 4: Spectral separability of vegetation/cover classes used to a) calibrate and b) validate pre-fire (2011) supervised classification.



a)



b)

Figure 5: Spectral separability of vegetation/cover classes used to a) calibrate and b) validate post-fire (2011) supervised classification.

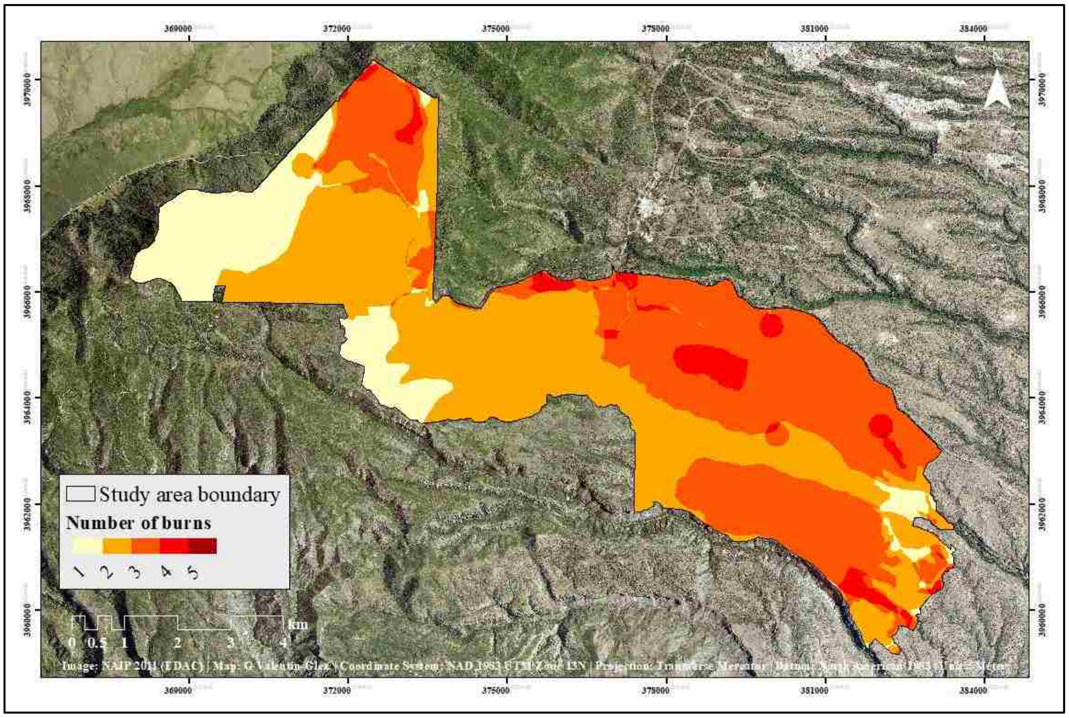


Figure 6: Number of burns in the study area from 1977 to 2014.

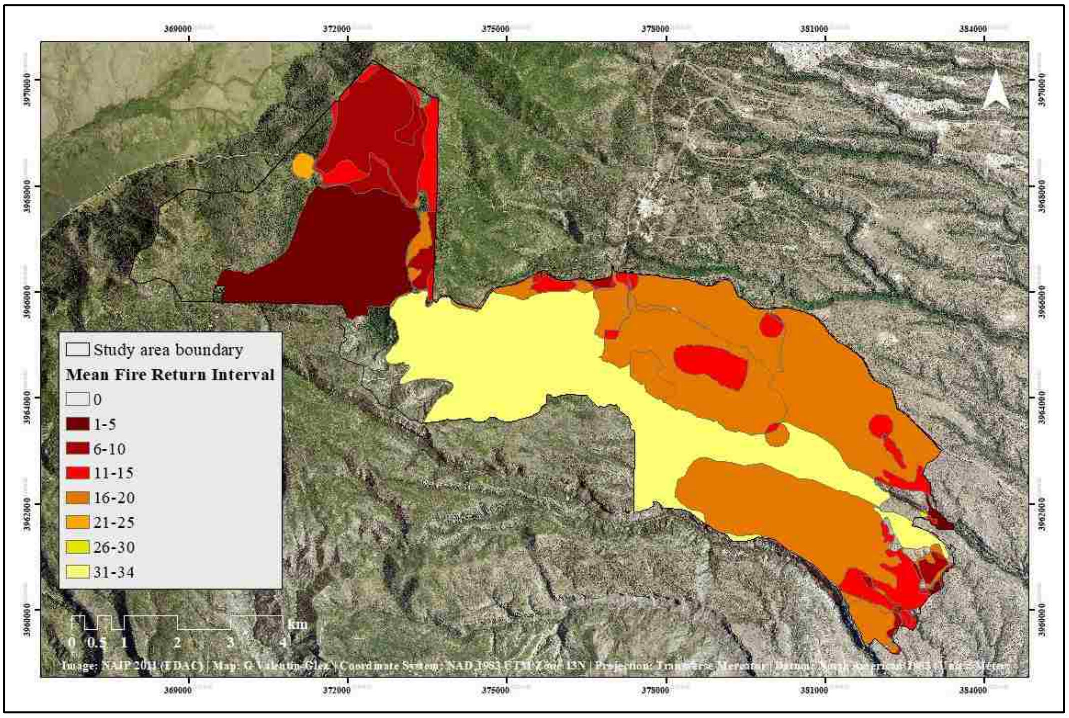


Figure 7: Mean Fire Return Interval in the study area, considering fires from 1977 to 2014.

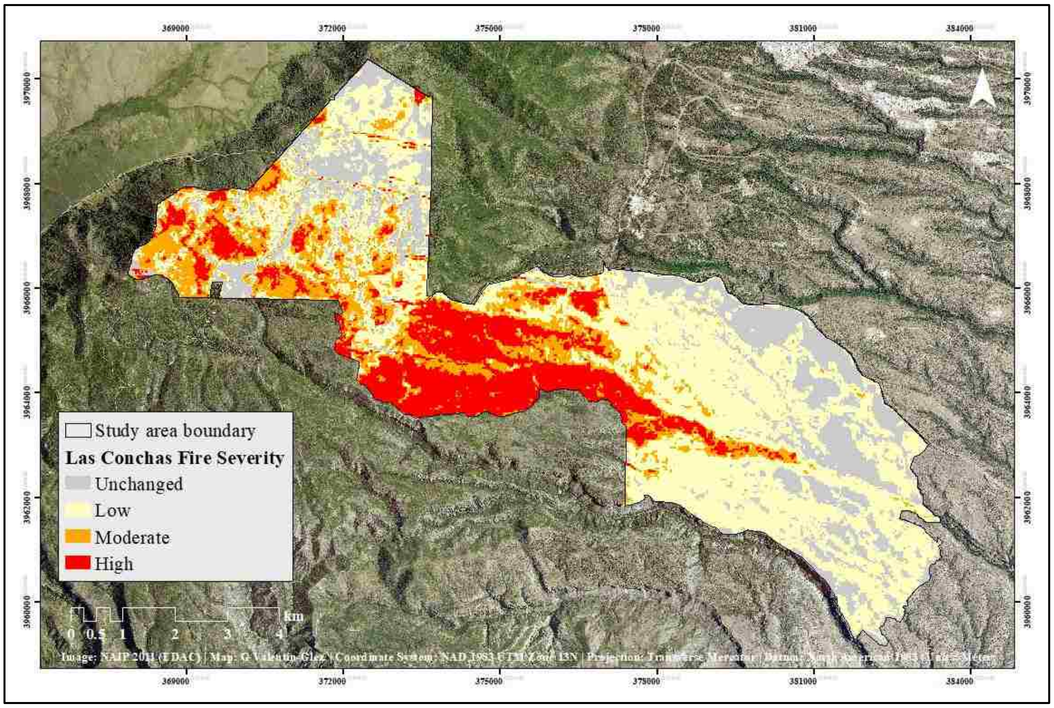


Figure 8: Burned Area Reflectance Classification (BARC) fire severity map of the Las Conchas Fire.

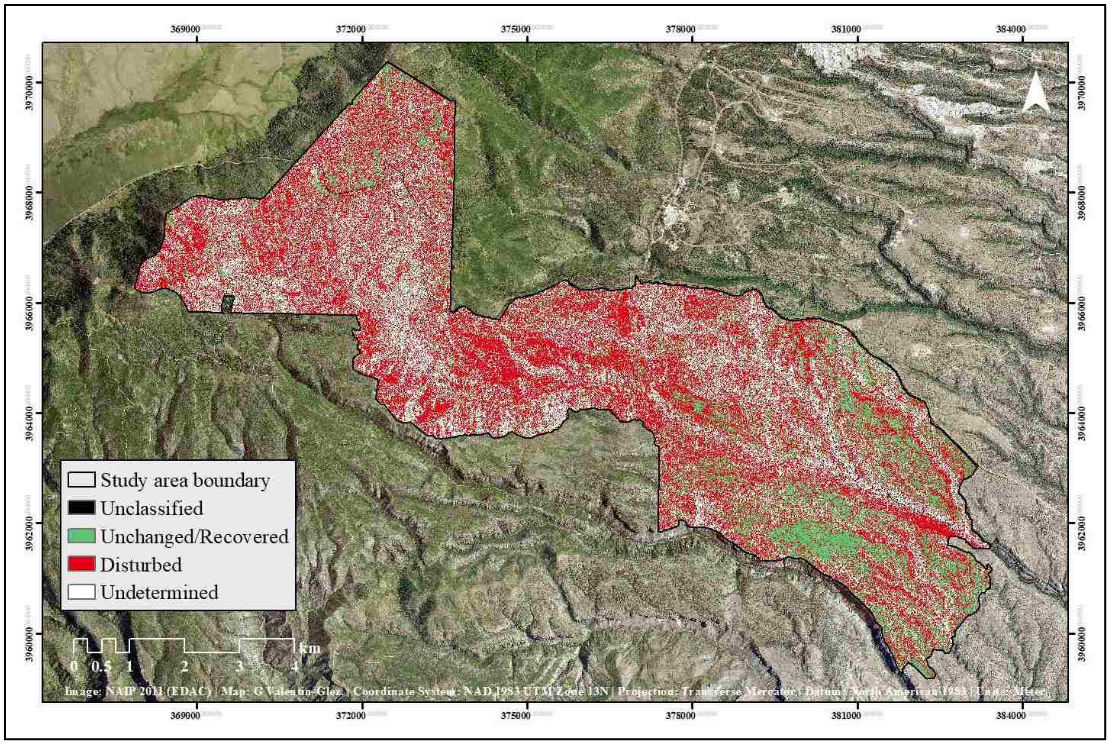


Figure 9: Recovery map depicting recovery classes: (1) Unchanged/Recovered to the same vegetation or class type, (2) Disturbed: changed to Bare Soil/Rock, Herbaceous, or Disturbance class; and (3) Undetermined (modeled change to Mixed Conifer, Ponderosa Pine or Piñon-Juniper).

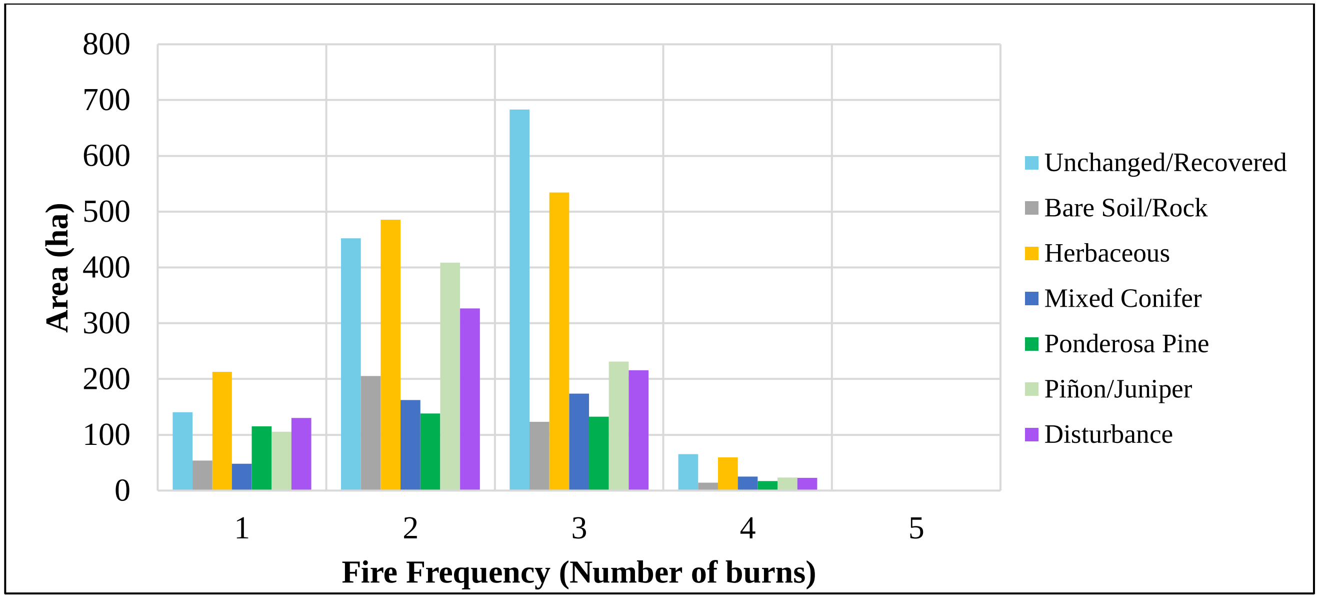


Figure 10: Area (ha) per change class (post-fire cover type) by number of fires.

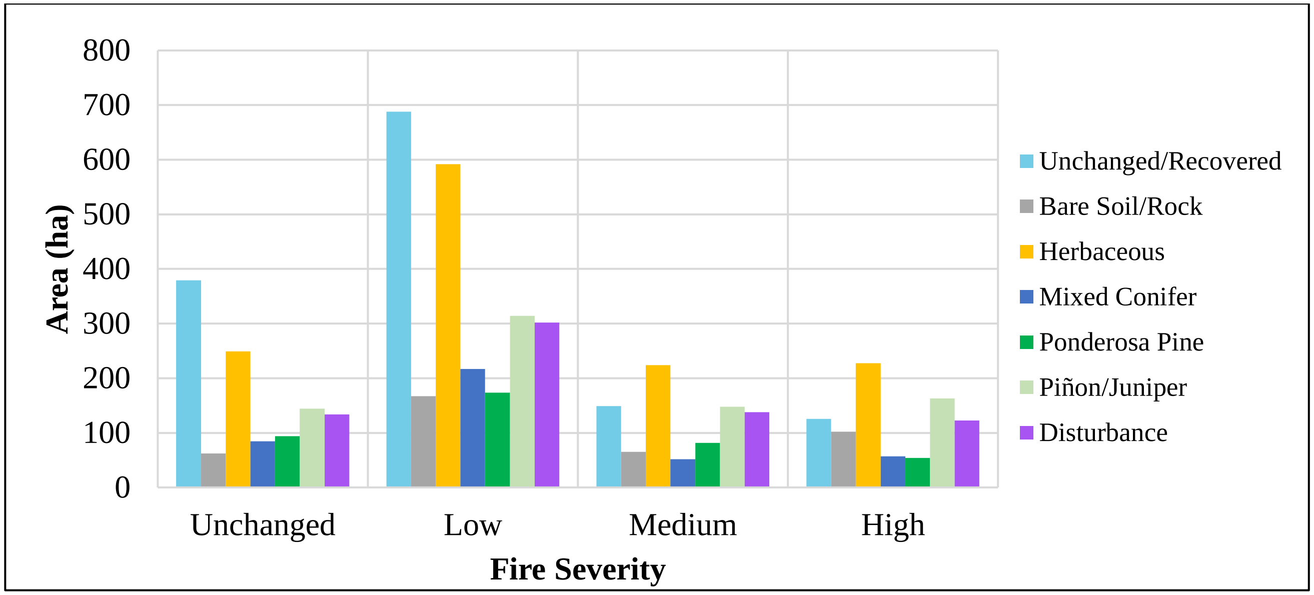


Figure 11: Area per change class (post-fire cover type) intersecting with areas of different Las Conchas Fire severities.

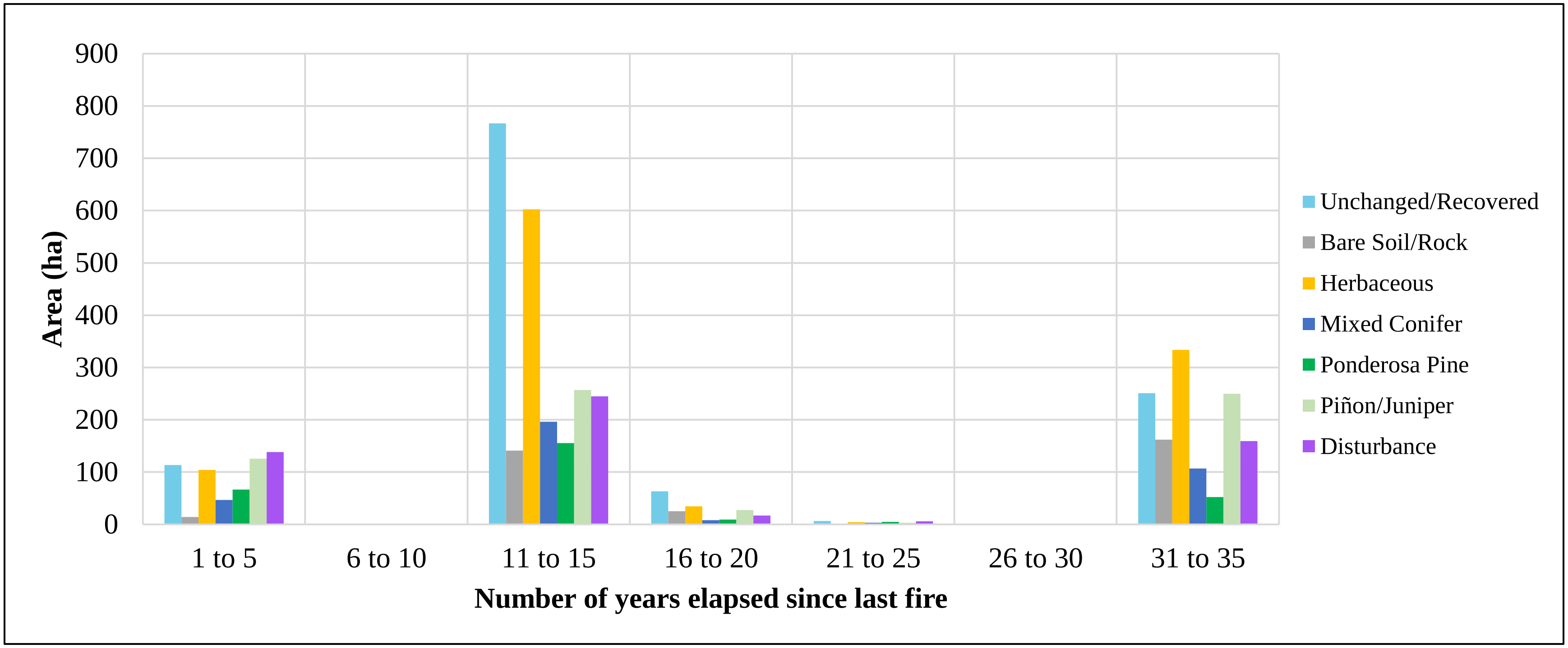


Figure 12: Area per change class (post-fire cover type) intersecting with areas with different years elapsed since last fire prior to the Las Conchas Fire in 2011.

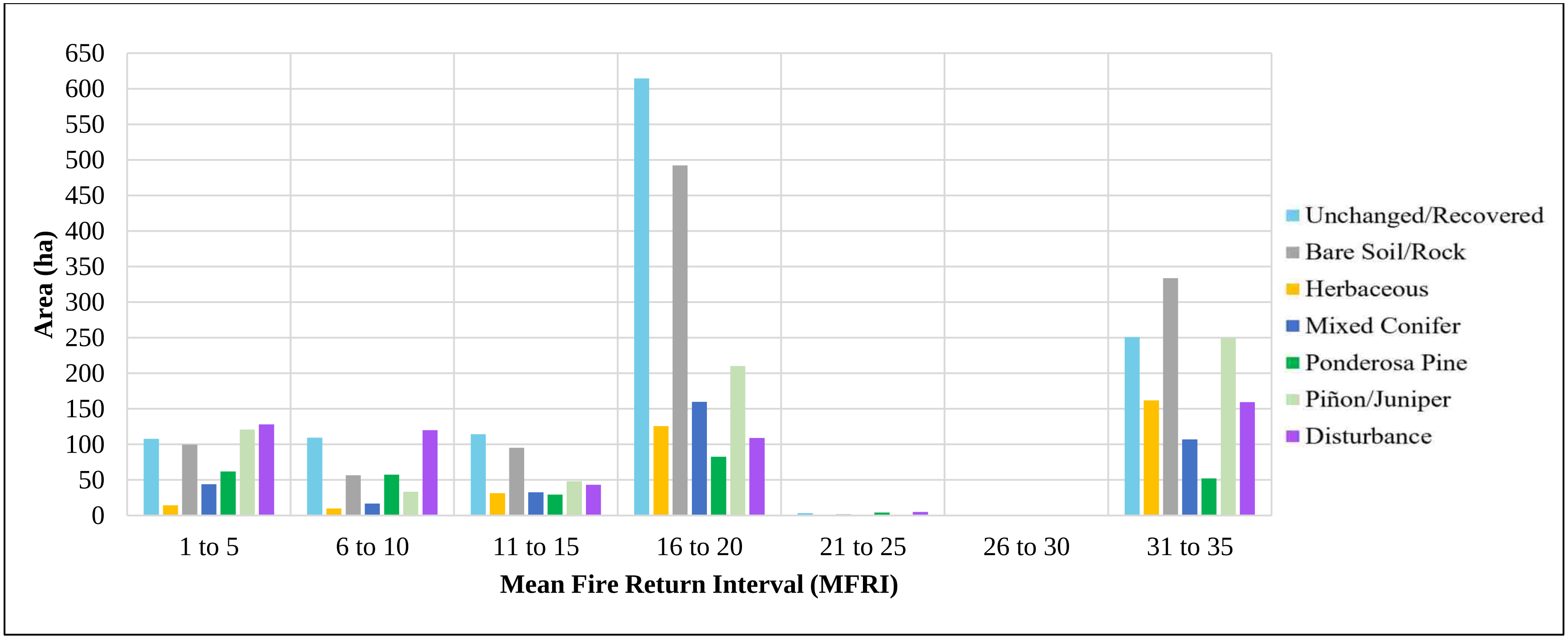


Figure 13: Area per change class (post-fire cover type) intersecting with areas with different mean fire return intervals (MFRI) prior to the Las Conchas Fire in 2011.

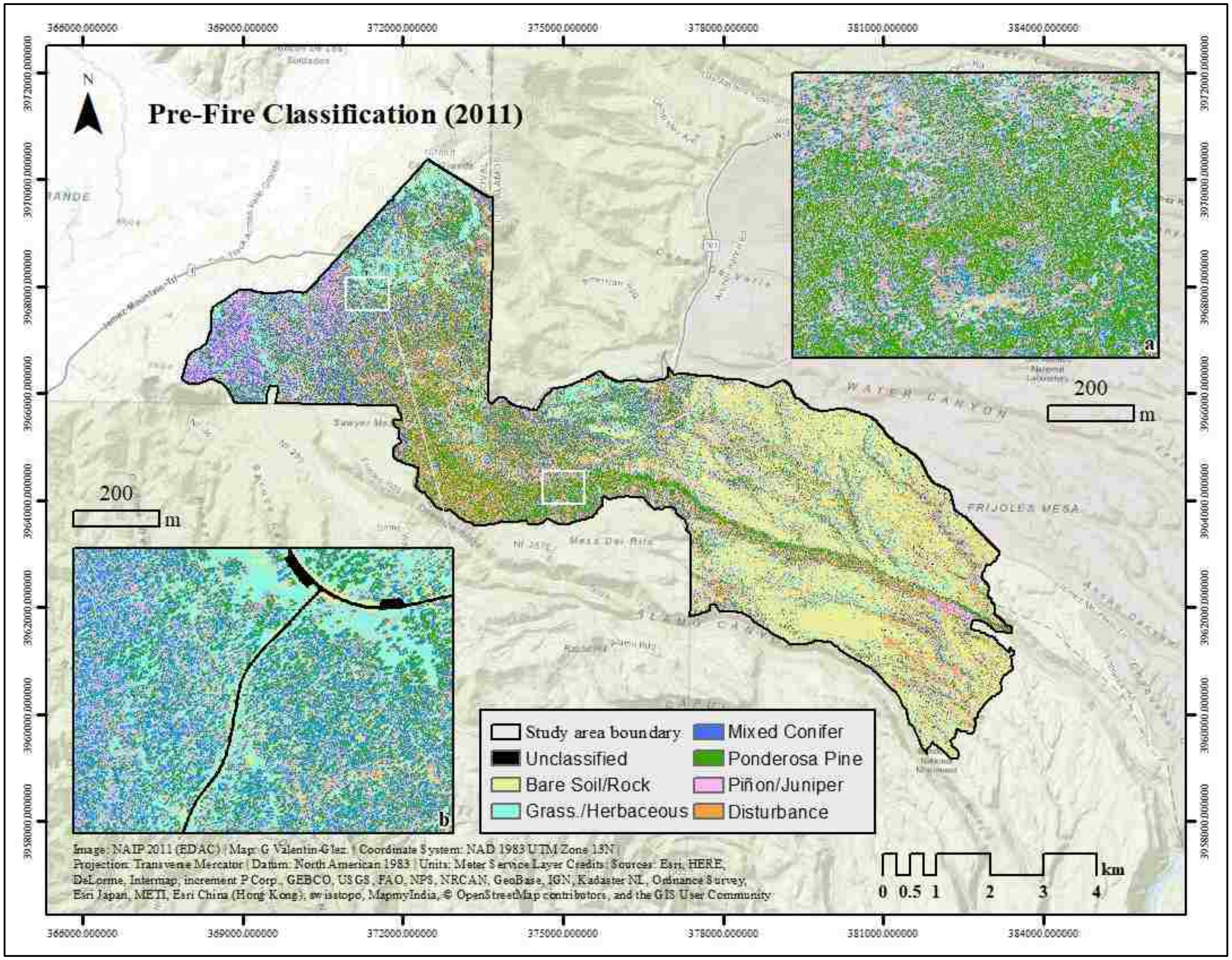


Image: NAIP 2011 (EDAC) | Map: G Valentin-Glez. | Coordinate System: NAD 1983 UTM Zone 13N | Projection: Transverse Mercator | Datum: North American 1983 | Units: Meter Service Layer Credits: Sources: Esri, HERE, DeLorme, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCAN, GeoBase, IGN, Kadaster NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), swisstopo, MapmyIndia, © OpenStreetMap contributors, and the GIS User Community

Figure 14: Pre-fire supervised classifications depicting 6 vegetation/cover classes.

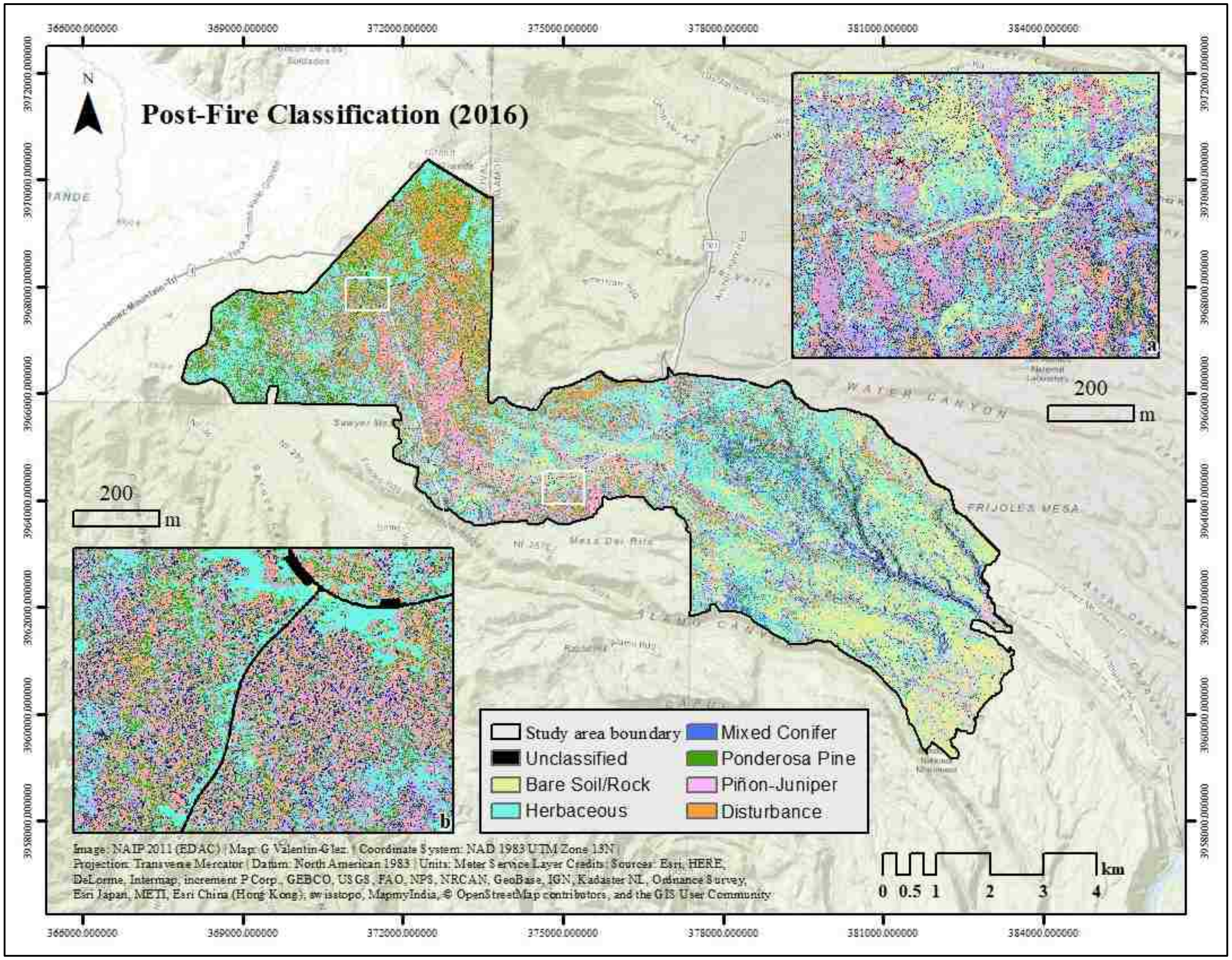


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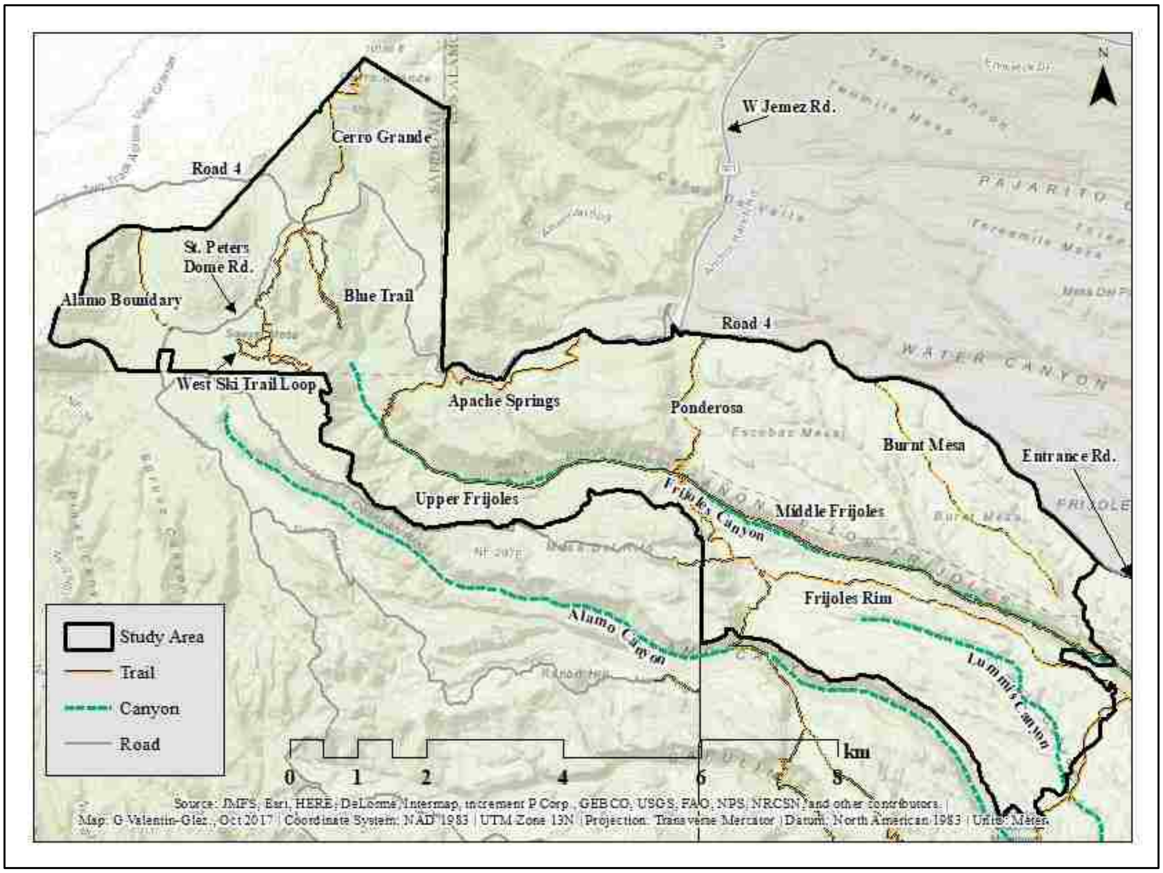
Figure 15: Post-fire supervised classifications depicting 6 vegetation/cover classes.



Source: JMFS, Esri, HERE, DeLorme, Intermap, increment P Corp., GEBCO, USGS, FAO, NPS, NRCSN, and other contributors. |
Map: G Valentin-Glez., Oct 2017 | Coordinate System: NAD 1983 | UTM Zone 13N | Projection: Transverse Mercator | Datum: North American 1983 | Units: Meter

Figure 16: Park trails, roads, and canyons within or adjacent to the study area.

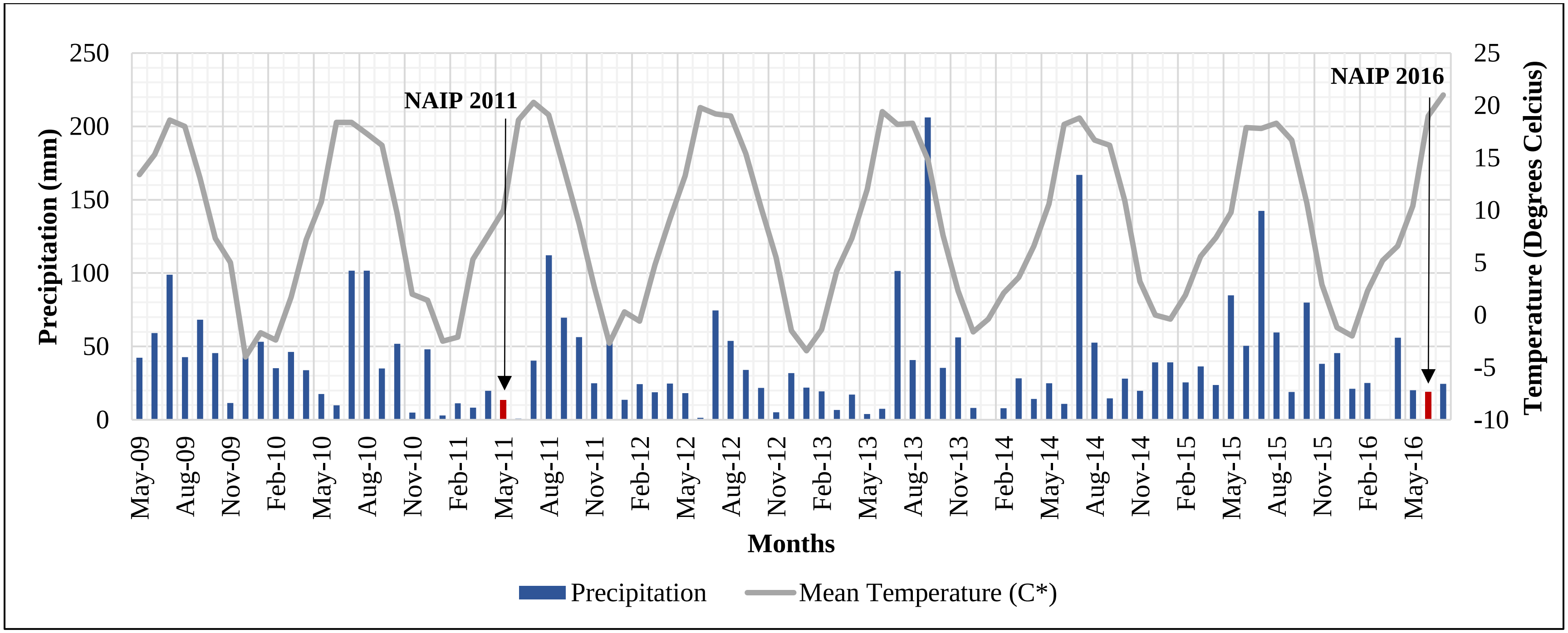
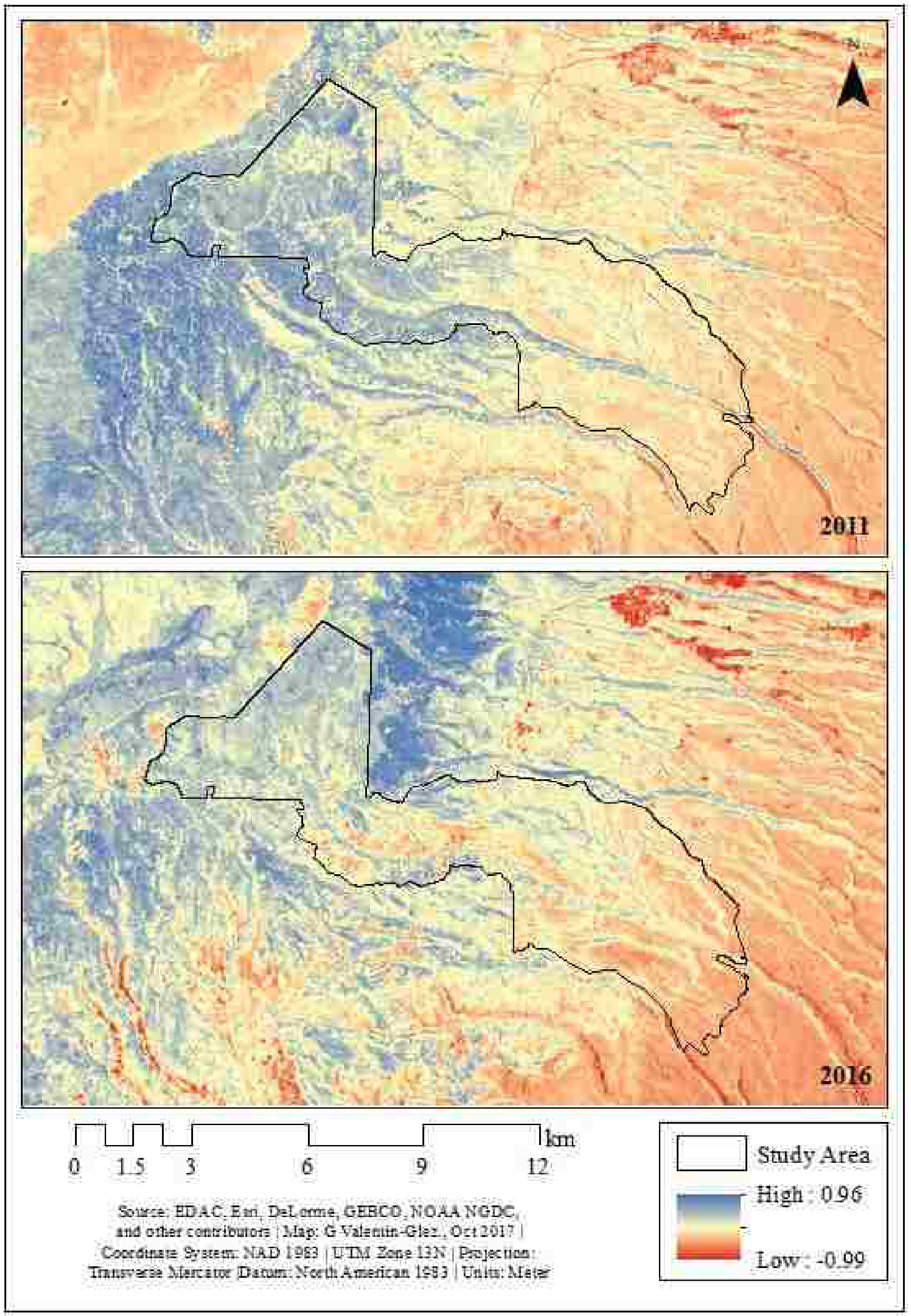


Figure 17: Precipitation (mm) of Los Alamos County from May 2009 to July 2016, showing at least two years of rainfall and precipitation prior to NAIP image collection. Red graph bars represent the precipitation in the month in which each image was collected: May 2011 and June 2016. (Source: PRISM Climate Group, 2011)



Source: EDAC, Esri, DeLorme, GEBCO, NOAA NGDC, and other contributors | Map: G Valentin-Glez., Oct 2017 | Coordinate System: NAD 1983 | UTM Zone 13N | Projection: Transverse Mercator Datum: North American 1983 | Units: Meter

Figure 18: Normalized Difference Vegetation Index (NDVI) of 2011 and 2016 NAIP images.

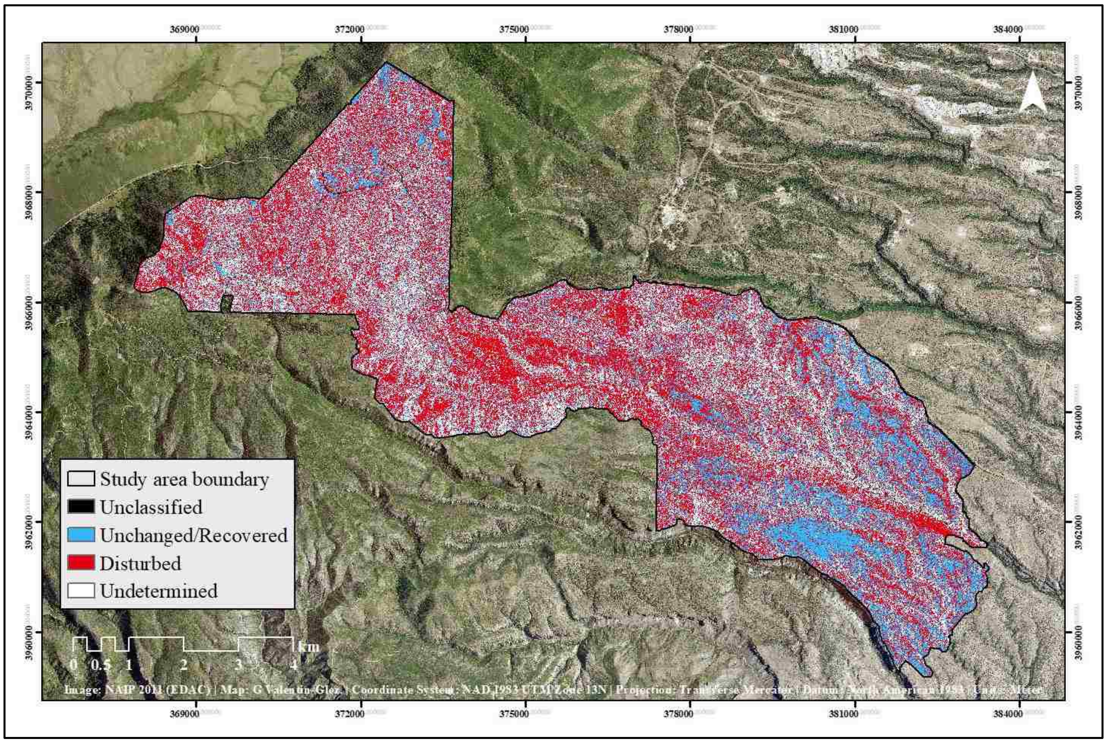


Figure 19: Areas that changed into other vegetation/cover types, and areas that did not change.

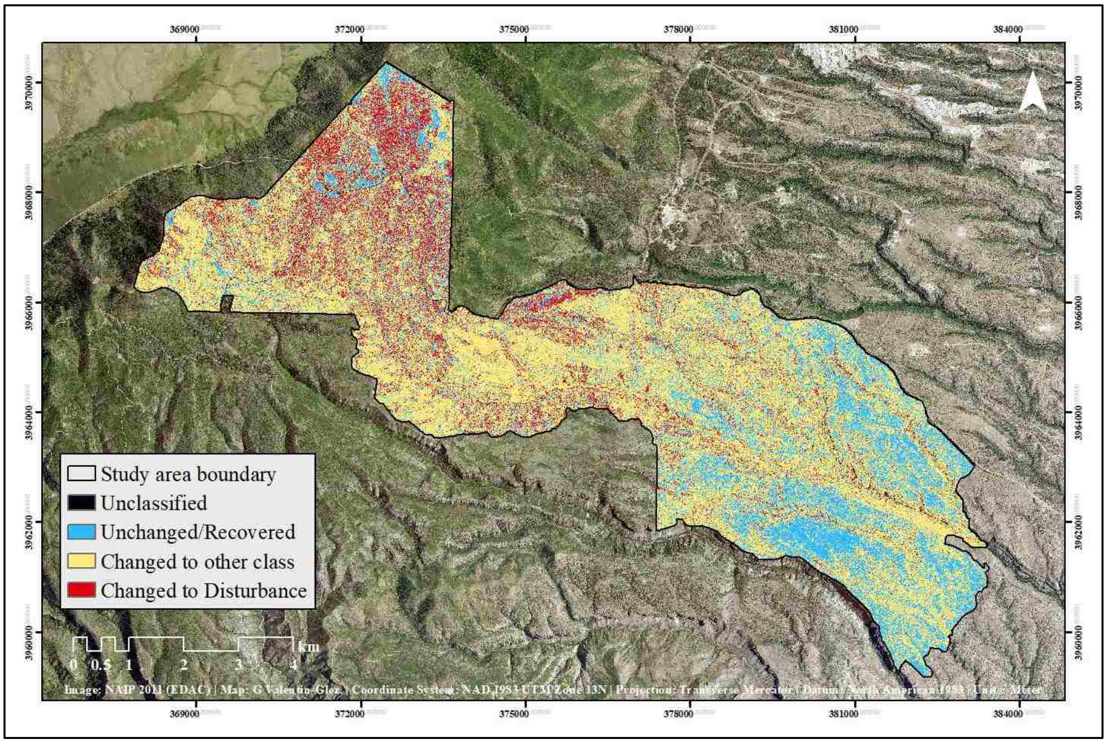
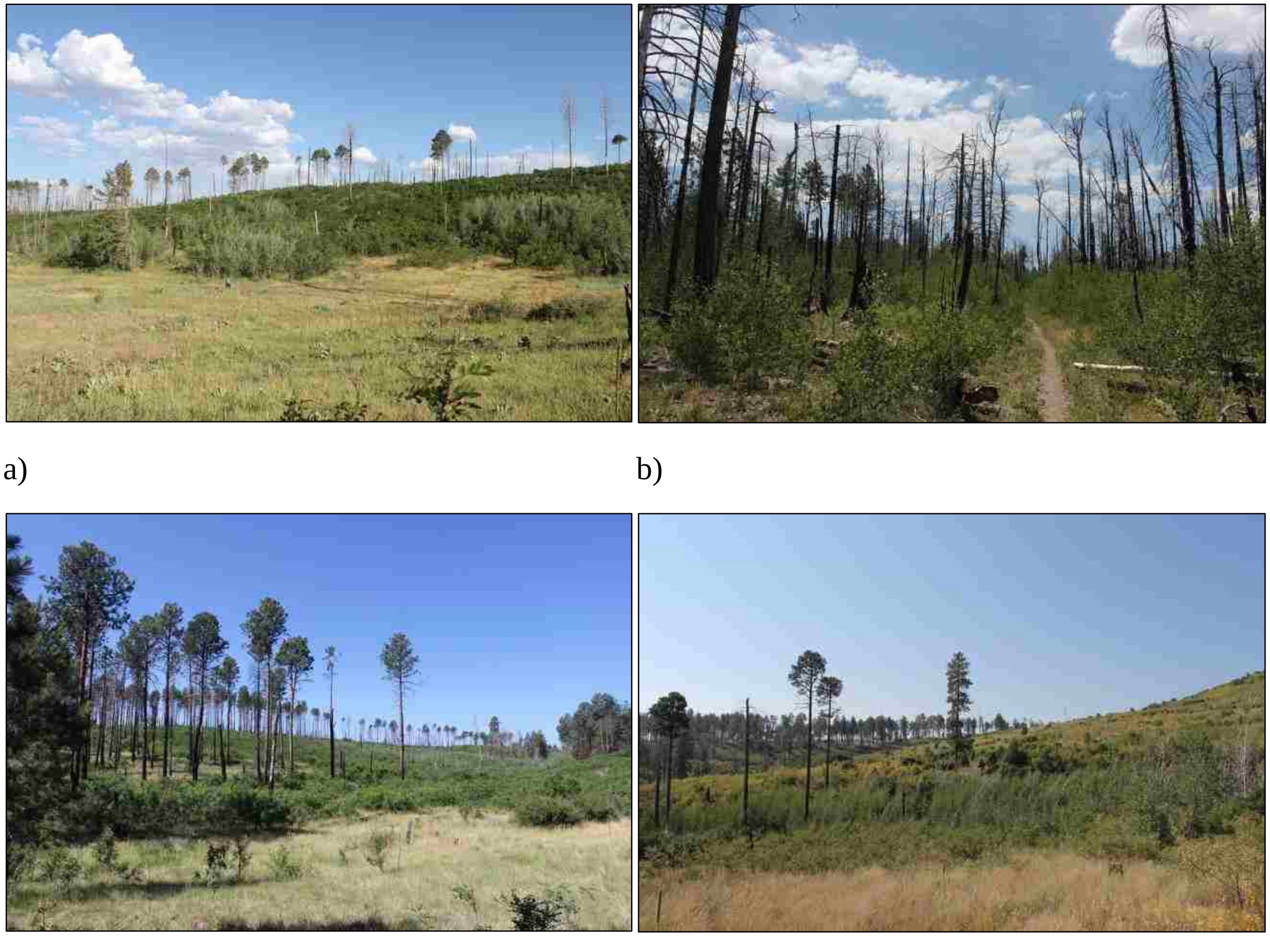


Figure 20: Areas that changed specifically to a disturbance class: Quaking Aspen, Gambel Oak or New Mexico Locust.



a) b)

c) d)

Figure 21: Photos depicting growth of quaking aspen, gambel oak and New Mexico locust together along a) Apache Springs Trail, b) Blue Trail, c) along Road 4, 1.6 km west of W Jemez Rd., and d) an area north of Apache Spring Trail. The photos were taken on July 3 (a,b,c) and September 3 (d) of 2017.

Tables

Year	Fire(s)	Area burned in study area (ha)	Total area burned (ha)
1977	La Mesa	3,298	5,778
1992	Cerro Grande	316	327
1993	Unit 49	101	104
1997	Lummis	653	675
1997	Unit 30	239	245
1998	Unit 29	441	441
1999	Unit 38	561	568
2000	Cerro Grande	529	17,390
2007	Upper Frijoles RX	606	613
2011	Las Conchas	5,459	64,246

Table 1: Fires that have burned the greatest area from 1977 to 2014, as well as the total area burned.

Data	**Spatial resolution**	**Temporal Resolution**	**Source**
NAIP images (CIR)	1 m	May 2011, June 2016	Earth Data Analysis Center (EDAC)
Bandelier NM image (RGB)	15.2 cm	September 2011	USGS Jemez Mountain Field Station (JMFS)
Google Earth images	(Varied)	(Varied)	Google Earth Desktop software
Fire history (perimeters)	(Varied)	1909 to 2014	USGS Jemez Mountain Field Station
Fire severity	30 m MMU	2011	USGS Jemez Mountain Field Station
Vegetation plots	(Unknown)	2004-2008, 2012	Natural Heritage New Mexico (NHNM)
Pre-wildfire vegetative cover classification	Generated from 2m imagery	2010	USGS Science Base
Administrative boundaries	(Varied)	(Varied)	RGIS*; ArcGIS
Photographs	(Varied)	Spring-Fall 2017	G Valentin-Gonzalez

*RGIS: New Mexico Resource Geographic Information System, Earth Data Analysis Center

Table 2: Description of data utilized in this research.

Classes	**Pre-Fire (2011)**		**Post-Fire (2016)**	
	Cal. Pixels	**Val. Pixels**	**Cal. Pixels**	**Val. Pixels**
Bare Soil/Rock	71	70	78	73
Quaking Aspen	68	71	78	87
Ponderosa Pine	92	101	118	119
Mixed Conifer	101	94	100	100
Grassland/Herbaceous	94	96	111	99
Gambel Oak	96	74	77	85
New Mexico Locust	88	74	78	88
Piñon/Juniper	73	90	82	81

Table 3: Number of pixels covered by Regions of Interest (ROIs) for each class, per image, on calibration and validation sets.

		Ground Reference										
	Class	**Bare/ Rock**	**Herb.**	**Mixed Conifer**	**Ponderosa Pine**	**Piñon/ Juniper**	**Quaking Aspen**	**Gambel Oak**	**NM Locust**	**Total**	**User's Acc.**	**Commission Error**
Map	**Bare Soil/Rock**	62	14	0	0	0	0	0	0	76	81.58	18.42
	Herbaceous	8	55	0	0	1	0	4	1	69	79.71	20.29
	Mixed Conifer	0	0	59	21	0	10	14	21	125	47.20	52.80
	Ponderosa Pine	0	0	16	56	4	3	6	6	91	61.54	38.46
	Piñon/Juniper	0	0	4	3	83	0	12	2	104	79.81	20.19
	Quaking Aspen	0	0	11	2	0	44	10	3	70	62.86	37.14
	Gambel Oak	0	0	0	10	0	5	13	6	34	38.24	61.76
	NM Locust	0	2	11	2	8	12	15	51	101	50.50	49.50
	Total	70	71	101	94	96	74	74	90	670		
	Producer's Acc.	88.57	77.46	58.42	59.57	86.46	59.46	17.57	56.67		**63.13**	
	Omission Error	11.43	22.54	41.58	40.43	13.54	40.54	82.43	43.33			

Overall Accuracy: 63.13% **Kappa Coefficient:** 0.58

a)

		Ground Reference								
	Class	**Bare/ Rock**	**Herb.**	**Mixed Conifer**	**Ponderosa Pine**	**Piñon/ Juniper**	**Disturbance**	**Total**	**User's Acc.**	**Commission Error**
Map	**Bare/Rock**	62	14	0	0	0	0	76	81.58	18.42
	Herbaceous	8	55	0	0	1	5	69	79.71	20.29
	Mixed Conifer	0	0	59	21	0	45	125	47.20	52.80
	Ponderosa Pine	0	0	16	56	4	15	91	61.54	38.46
	Piñon /Juniper	0	0	4	3	83	14	104	79.81	20.19
	Disturbance	0	2	22	14	8	159	205	77.56	22.44
	Total	70	71	101	94	96	238	670		
	Producer's Acc.	88.57	77.46	58.42	59.57	86.46	66.81		**70.75**	
	Omission Error	11.43	22.54	41.58	40.43	13.54	33.19			

Overall Accuracy: 70.75% **Kappa Coefficient:** 0.63

b)

Table 4: Confusion matrices showing accuracy of pre-fire (2011) a) 8-class and b) 6-class classifications.

		Ground Reference										
	Class	**Bare/ Rock**	**Herb.**	**Mixed Conifer**	**Ponderosa Pine**	**Piñon/ Juniper**	**Quaking Aspen**	**Gambel Oak**	**NM Locust**	**Total**	**User's Acc.**	**Commission Error**
Map	**Bare/Rock**	73	6	0	0	0	0	0	0	79	92.41	7.59
	Herbaceous	0	80	0	1	4	1	0	3	89	89.89	10.11
	Mixed Conifer	0	0	65	26	4	15	8	3	121	53.72	46.28
	Ponderosa Pine	0	1	21	41	9	11	7	4	94	43.62	56.38
	Piñon/Juniper	0	0	3	7	82	0	0	4	96	85.42	14.58
	Quaking Aspen	0	0	13	2	0	20	10	13	58	34.48	65.52
	Gambel Oak	0	0	11	5	0	8	36	12	72	50.00	50.00
	NM Locust	0	0	6	18	0	30	27	42	123	34.15	65.85
	Total	73	87	119	100	99	85	88	81	732		
	Producer's Acc.	100.00	91.95	54.62	41.00	82.83	23.53	40.91	51.85		**59.97**	
	Omission Error	0.00	8.05	45.38	59.00	17.17	76.47	59.09	48.15			

Overall Accuracy: 59.97% **Kappa Coefficient:** 0.54

a)

		Ground Reference								
	Class	**Bare/ Rock**	**Herb.**	**Mixed Conifer**	**Ponderosa Pine**	**Piñon/ Juniper**	**Disturbance**	**Total**	**User's Acc.**	**Commission Error**
Map	**Bare/Rock**	73	6	0	0	0	0	79	92.41	7.59
	Herbaceous	0	80	0	1	4	4	89	89.89	10.11
	Mixed Conifer	0	0	65	26	4	26	121	53.72	46.28
	Ponderosa Pine	0	1	21	41	9	22	94	43.62	56.38
	Piñon/Juniper	0	0	3	7	82	4	96	85.42	14.58
	Disturbance	0	0	30	25	0	198	253	78.26	21.74
	Total	73	87	119	100	99	254	732		
	Producer's Acc.	100.00	91.95	54.62	41.00	82.83	77.95		**73.63**	
	Omission Error	0.00	8.05	45.38	59.00	17.17	22.05			

Overall Accuracy: 73.63% **Kappa Coefficient:** 0.67

b)

Table 5: Confusion matrices showing accuracy of post-fire (2016) a) 8-class and b) 6-class classifications.

		Ground Reference								
	Class	**Bare Soil-Rock**	**Herb.**	**Mixed Conifer**	**Ponderosa Pine**	**Piñon-Juniper**	**Disturbance**	**Total**	**User's Acc.**	**Commission Error**
Map	**Bare Soil-Rock**	41	6	0	0	0	0	47	87.23	12.77
	Herbaceous	0	30	0	0	0	1	31	96.77	3.23
	Mixed Conifer	0	0	15	14	4	21	54	27.78	72.22
	Ponderosa Pine	0	0	4	8	1	9	22	36.36	63.64
	Piñon-Juniper	0	1	0	3	21	8	33	63.64	36.36
	Disturbance	0	8	2	2	1	50	63	79.37	20.63
	Total	41	45	21	27	27	89	250		
	Producer's Acc.	100.00	66.67	71.43	29.63	77.78	56.18		**66.00**	
	Omission Error	0.00	33.33	28.57	70.37	22.22	43.82			

Overall Accuracy: 60.00% **Kappa Coefficient:** 0.58

a)

		Ground Reference								
	Class	**Bare Soil-Rock**	**Herb.**	**Mixed Conifer**	**Ponderosa Pine**	**Piñon-Juniper**	**Disturbance**	**Total**	**User's Acc.**	**Commission Error**
Map	**Bare Soil-Rock**	37	3	0	0	1	0	41	90.24	9.76
	Herbaceous	0	29	0	0	0	6	35	82.86	17.14
	Mixed Conifer	0	14	15	4	1	31	65	23.08	76.92
	Ponderosa Pine	0	0	5	19	3	7	34	55.88	44.12
	Piñon-Juniper	0	1	1	1	23	1	27	85.19	14.81
	Disturbance	0	0	4	6	1	46	57	80.70	19.30
	Total	37	47	25	30	29	91	259		
	Producer's Acc.	100.00	61.70	60.00	63.33	79.31	50.55		**65.25**	
	Omission Error	0.00	38.30	40.00	36.67	20.69	49.45			

Overall Accuracy: 65.25% **Kappa Coefficient:** 0.58

b)

Table 6: Confusion matrices showing accuracy of 6-class pre-fire (2011) at a) 3-meter and b) 5-meter resolution.

		Ground Reference								
	Class	**Bare Soil-Rock**	**Herb.**	**Mixed Conifer**	**Ponderosa Pine**	**Piñon-Juniper**	**Disturbance**	**Total**	**User's Acc.**	**Commission Error**
Map	**Bare Soil-Rock**	55	0	0	0	0	0	55	100.00	0.00
	Herbaceous	1	35	1	1	2	0	40	87.50	12.50
	Mixed Conifer	0	2	25	7	2	6	42	59.52	40.48
	Ponderosa Pine	0	2	2	15	3	13	35	42.86	57.14
	Piñon-Juniper	1	0	4	0	20	2	27	74.07	25.93
	Disturbance	0	0	0	4	0	77	81	95.06	4.94
	Total	57	39	32	27	27	98	280		
	Producer's Acc.	96.49	89.74	78.13	55.56	74.07	78.57		**81.07**	
	Omission Error	3.51	10.26	21.88	44.44	25.93	21.43			

Overall Accuracy: 81.07% **Kappa Coefficient:** 0.76

a)

		Ground Reference								
	Class	**Bare Soil-Rock**	**Herb.**	**Mixed Conifer**	**Ponderosa Pine**	**Piñon-Juniper**	**Disturbance**	**Total**	**User's Acc.**	**Commission Error**
Map	**Bare Soil-Rock**	40	4	0	0	0	0	44	90.91	9.09
	Herbaceous	0	31	0	0	0	1	32	96.88	3.13
	Mixed Conifer	0	1	16	3	0	9	29	55.17	44.83
	Ponderosa Pine	0	0	2	15	4	13	34	44.12	55.88
	Piñon-Juniper	0	1	0	0	16	0	17	94.12	5.88
	Disturbance	0	1	0	4	0	46	51	90.20	9.80
	Total	40	38	18	22	20	69	207		
	Producer's Acc.	100.00	81.58	88.89	68.18	80.00	66.67		**79.23**	
	Omission Error	0.00	18.42	11.11	31.82	20.00	33.33			

Overall Accuracy: 79.23% **Kappa Coefficient:** 0.74

b)

Table 7: Confusion matrices showing accuracy of 6-class post-fire (2016) at a) 3-meter and b) 5-meter resolution.

		Post-fire Classification (2016)							
	Class	**Unclassified**	**Bare Soil/ Rock**	**Herb.**	**Mixed Conifer**	**Ponderosa Pine**	**Piñon/ Juniper**	**Disturbance**	**Total area (ha)**
Pre-fire Classification (2011)	**Unclassified**	7.09	24.95	11.66	5.94	8.69	8.20	12.90	79.44
	Bare Soil/Rock	5.28	595.56	96.26	45.46	70.60	78.29	106.18	997.63
	Herb.	5.52	445.98	248.91	181.03	211.58	221.60	232.30	1,546.92
	Mixed Conifer	1.48	85.89	75.04	68.20	87.62	70.88	89.96	479.06
	Ponderosa Pine	2.12	36.70	89.96	102.11	101.10	86.00	88.10	506.09
	Piñon/Juniper	3.58	150.24	129.92	128.16	174.74	134.40	185.90	906.94
	Disturbance	4.09	68.04	162.56	163.76	186.08	115.26	193.30	893.09
	Total area (ha)	29.15	1,407.36	814.32	694.66	840.40	714.63	908.64	5,409.18

*Numbers represent area in hectares (ha)

a)

		Post-fire Classification (2016)								
	Class	**Unclassified**	**Bare Soil/ Rock**	**Herb.**	**Mixed Conifer**	**Ponderosa Pine**	**Piñon/ Juniper**	**Disturbance**	**Total**	**Net % change from class (row)**
Pre-fire Classification (2011)	**Unclassified**	0.13	0.46	0.22	0.11	0.16	0.15	0.24	1.47	1.34
	Bare Soil/Rock	0.10	11.01	1.78	0.84	1.31	1.45	1.96	18.44	7.43
	Herb.	0.10	8.24	4.60	3.35	3.91	4.10	4.29	28.60	24.00
	Mixed Conifer	0.03	1.59	1.39	1.26	1.62	1.31	1.66	8.86	7.60
	Ponderosa Pine	0.04	0.68	1.66	1.89	1.87	1.59	1.63	9.36	7.49
	Piñon/Juniper	0.07	2.78	2.40	2.37	3.23	2.48	3.44	16.77	14.28
	Disturbance	0.08	1.26	3.01	3.03	3.44	2.13	3.57	16.51	12.94
	Total	0.54	26.02	15.05	12.84	15.54	13.21	16.80	100.00	
	Net % change to (column) class	0.41	15.01	10.45	11.58	13.67	10.73	13.22		

b)

Table 8: Cross-tabulation of 6-class pre- and post-fire supervised classifications, showing a) area change in hectares and b) percentage of change.

Number of Burns	Unchanged/ Recovered	Bare/ Rock	Herb.	Mixed Conifer	Ponderosa Pine	Piñon/ Juniper	Disturbance	Total area (ha)
1	140.25	53.58	212.72	48.16	115.18	105.50	130.38	805.78
2	452.06	205.36	485.43	162.16	138.00	408.57	326.77	2,178.34
3	683.08	123.29	534.14	173.77	132.30	231.24	215.44	2,093.25
4	65.50	14.46	59.79	25.20	17.30	23.50	22.75	228.51
5	0.57	0.11	0.40	0.10	0.09	0.15	0.36	1.79
Total area (ha)	1,341.47	396.79	1,292.49	409.39	402.88	768.96	695.70	5307.68

a)

Number of Burns	Unchanged/ Recovered	Disturbed	Undetermined	Total area (ha)
1	140.25	396.68	268.84	805.78
2	452.06	1017.55	708.73	2,178.34
3	683.08	872.87	537.30	2,093.25
4	65.50	97.01	66.00	228.51
5	0.57	0.87	0.35	1.79
Total area (ha)	1341.47	2384.98	1581.23	5307.68
% of highest NoB	50.92	36.60	33.98	

b)

Table 9: Cross-tabulation depicting area per a) change class and b) recovery class that intersect with areas that have different number of burns (NoB).

Fire Severity	Unchanged/ Recovered	Bare/ Rock	Herb.	Mixed Conifer	Ponderosa Pine	Piñon/ Juniper	Disturbance	Total area (ha)
Unchanged	378.88	62.25	248.98	84.53	93.92	144.35	133.52	1183.78
Low	687.91	167.32	591.75	216.73	173.44	314.17	301.86	2498.62
Medium	149.19	64.92	224.12	51.40	81.62	147.48	138.04	867.04
High	125.48	102.30	227.64	56.73	53.91	162.95	122.28	859.74
Total area (ha)	1341.47	396.79	1292.49	409.39	402.88	768.96	695.70	5,307.68

a)

Fire Severity	Unchanged/ Recovered	Disturbed	Undetermined	Total area (ha)
Unchanged	378.88	444.75	322.80	1146.43
Low	687.91	1060.92	704.34	2453.17
Medium	149.19	427.08	280.50	856.78
High	125.48	452.22	273.59	851.30
Total area (ha)	1341.47	2384.98	1581.23	5307.68

b)

Table 10: Cross-tabulation depicting area a) change class and b) recovery class that intersect with areas that had different Las Conchas Fire severities.

Years	Unchanged/ Recovered	Bare/ Rock	Herb.	Mixed Conifer	Ponderosa Pine	Piñon/ Juniper	Disturbance	Total area (ha)
3	106.39	14.18	99.78	44.24	62.03	121.11	128.26	583.55
4	6.90	0.23	4.48	2.46	4.40	4.36	9.81	34.57
11	124.38	4.65	81.49	22.27	68.17	37.31	148.64	492.65
12	208.89	46.89	125.40	39.36	22.94	61.38	20.38	542.35
13	160.22	21.75	245.65	94.32	48.95	80.97	57.44	719.55
14	273.21	67.55	149.59	40.17	15.12	77.48	18.48	657.15
15	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
16	20.40	5.61	6.00	1.50	4.03	6.61	8.21	53.10
17	8.22	5.13	16.30	6.00	2.50	9.43	5.95	54.49
18	29.61	12.75	8.74	0.17	0.70	9.40	0.11	63.55
19	2.66	0.32	2.27	0.31	1.27	0.94	1.91	9.79
20	2.44	1.27	1.28	0.17	0.43	1.23	0.64	7.80
21	2.95	0.65	2.73	2.45	0.73	2.33	0.60	12.95
24	3.38	0.02	1.58	0.76	4.09	0.82	5.14	16.26
25	0.05	0.02	0.02	0.00	0.00	0.03	0.00	0.12
26	0.35	0.20	0.55	0.16	0.24	0.54	0.33	2.43
30	0.10	0.01	0.05	0.01	0.01	0.02	0.01	0.21
34	251.07	161.99	333.87	106.90	52.09	249.50	159.42	1,342.10
Total area (ha)	1,341.47	396.79	1,292.49	409.39	402.88	768.96	695.70	4501.90

a)

Years since last fire	Unchanged/ Recovered	Disturbed	Undetermined	Total area (ha)
1 to 5	113.29	256.74	238.60	608.62
6 to 10	0.00	0.00	0.00	0.00
11 to 15	766.70	987.91	608.42	2363.03
16 to 20	63.32	76.47	44.69	184.48
21 to 25	6.38	10.76	11.20	28.35
26 to 30	0.45	1.15	0.98	2.58
31 to 35	251.07	655.28	408.49	1314.84
Total area (ha)	1201.21	1988.30	1312.38	4501.90

b)

Table 11: Area a) change class and b) recovery class intersecting with areas with different years elapsed since last fire prior to the Las Conchas Fire in 2011.

MFRI	Recovered	Bare/Rock	Herb.	Mixed Conifer	Ponderosa Pine	Pinyon/Juniper	Disturbance	Total area (ha)
3	1.9	1.4	2.0	0.1	0.3	4.2	0.6	10.7
4	105.9	12.8	97.5	44.0	61.7	116.5	127.6	573.4
6	6.9	0.4	4.6	2.3	4.2	3.8	9.4	33.3
7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
8	18.2	1.1	11.8	3.1	7.8	5.4	15.2	63.6
9	1.5	0.9	0.8	0.0	0.1	1.0	0.0	4.4
10	82.8	7.6	39.4	11.4	45.5	23.1	95.5	308.7
11	81.3	15.6	78.5	27.8	25.4	29.3	40.1	303.9
12	11.0	3.6	5.9	3.6	1.8	3.1	2.5	33.1
13	0.3	0.3	0.4	0.0	0.1	0.6	0.1	1.8
14	21.7	11.8	10.5	1.1	2.1	15.2	0.4	64.3
16	7.9	1.0	2.4	1.4	3.8	3.8	8.0	28.7
17	580.0	112.8	480.9	158.1	77.4	197.6	100.0	1744.7
18	23.4	10.4	7.2	0.1	0.5	7.6	0.1	51.1
19	1.5	0.2	1.1	0.2	0.6	0.6	1.1	5.3
20	1.8	1.2	0.6	0.0	0.1	0.8	0.0	4.6
24	3.4	0.0	1.6	0.8	4.1	0.8	5.1	16.3
25	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1
26	0.1	0.2	0.4	0.1	0.0	0.4	0.1	1.4
34	250.9	161.9	333.7	106.8	52.1	249.4	159.4	1341.5
Total area (ha)	1341.5	396.8	1292.5	409.4	402.9	769.0	695.7	4500.0

a)

MFRI	Unchanged/Recovered	Disturbed	Undetermined	Total area (ha)
1 to 5	107.8	241.9	226.8	576.5
6 to 10	109.4	186.7	107.8	403.9
11 to 15	114.3	169.7	110.1	394.1
16 to 20	614.6	726.8	452.6	1794.0
21 to 25	3.4	6.8	5.7	15.9
26 to 30	0.1	0.7	0.5	1.4
31 to 35	250.9	655.0	408.3	1314.2
Total area (ha)	1200.6	1987.6	1311.9	4500.0

b)

Table 12: Area a) change class and b) recovery class intersecting with areas with different mean fire return intervals (MFRI) prior to the Las Conchas Fire in 2011.

Month	**2011**	**2016**
January	3.01	21.18
February	11.34	25.15
March	8.24	0
April	19.68	56.01
May	13.38*	20.19
June	0.69	18.99*
Total (mm)	42.27	122.53

* Month when image was collected.

Table 13: Precipitation (mm unit) Los Alamos County in the months preceding NAIP image collections.