AN ANALYSIS OF TREE MORTALITY USING HIGH RESOLUTION REMOTELY-SENSED DATA FOR MIXED-CONIFER FORESTS IN SAN DIEGO COUNTY

A Dissertation submitted in partial satisfaction of the requirements for the degree Doctor of Philosophy in Geography

by

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An Analysis of Tree Mortality Using High Resolution Remotely-Sensed Data for
Mixed-Conifer Forests in San Diego County

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ABSTRACT

An Analysis of Tree Mortality Using High Resolution Remotely-Sensed Data for Mixed-Conifer Forests in San Diego County

by

Mary Pyott Freeman

The montane mixed-conifer forests of San Diego County are currently experiencing extensive tree mortality, which is defined as dieback where whole stands are affected. This mortality is likely the result of the complex interaction of many variables, such as altered fire regimes, climatic conditions such as drought, as well as forest pathogens and past management strategies. Conifer tree mortality and its spatial pattern and change over time were examined in three components. In component 1, two remote sensing approaches were compared for their effectiveness in delineating dead trees, a spatial contextual approach and an OBIA (object based image analysis) approach, utilizing various dates and spatial resolutions of airborne image data. For each approach transforms and masking techniques were explored, which were found to improve classifications, and an object-based assessment approach was tested. In component 2, dead tree maps produced by the most effective techniques derived from component 1 were utilized for point pattern and vector analyses to further understand spatio-temporal changes in tree mortality for the years
1997, 2000, 2002, and 2005 for three study areas: Palomar, Volcan and Laguna mountains. Plot-based fieldwork was conducted to further assess mortality patterns. Results indicate that conifer mortality was significantly clustered, increased substantially between 2002 and 2005, and was non-random with respect to tree species and diameter class sizes. In component 3, multiple environmental variables were used in Generalized Linear Model (GLM - logistic regression) and decision tree classifier model development, revealing the importance of climate and topographic factors such as precipitation and elevation, in being able to predict areas of high risk for tree mortality. The results from this study highlight the importance of multi-scale spatial as well as temporal analyses, in order to understand mixed-conifer forest structure, dynamics, and processes of decline, which can lead to more sustainable management of forests with continued natural and anthropogenic disturbance.
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Chapter 1. Introduction

The primary objective of this doctoral dissertation study is to analyze spatial-temporal patterns of conifer tree mortality for mixed-conifer forests in San Diego, County, California, based on high spatial resolution image data with geospatial and statistical analyses. Monitoring and examining the recent high levels and complex spatial distributions of tree mortality in montane mixed-conifer forests of San Diego County is important, particularly as questions are posed about the effect of climate change on local forests, the risks of wildfires on Palomar, Volcan and Laguna Mountains, and management options that can enhance local forest health. It is also important to identify critical factors that may put forest stands at risk for mortality. Understanding these risk factors should make it possible to predict future areas of concern in order to implement risk mitigation.

Two image classification software packages, one based on a per-pixel artificial neural network (ANN) classifier that exploits spatial contextual signatures (Feature Analyst) and one that uses a true object-based image analysis (OBIA) approach, eCognition (formerly Definiens), were compared for mapping tree mortality, using USGS digital orthophoto quarter quadrangle data for the years 1997, 2000, 2002, and 2005. The Feature Analyst software utilizes spatial contextual information to create a vector product of features that match the spectral and spatial characteristics of target (i.e., training) examples. The OBIA approach uses a segmentation routine to first create objects, which are then classified, creating a raster product of both the target and background classes. Object-based accuracy assessment
techniques were also explored. The image-derived mortality maps were then examined to elucidate the changing temporal and spatial patterns of tree mortality, for each time interval between image data sets. Analytical methods included spatial-temporal analysis to track the spread of morality over time, spatial techniques such as nearest neighbor analysis to quantify spatial relationships for mapped dead and live conifers, and a landscape analysis of conifer mortality to explore relationships between tree mortality and slope, aspect, elevation, and site moisture. An analysis of forest stand characteristics, based on field measurements, was conducted to further understand mortality patterns. The results of this study contribute to a better understanding of the spatio-temporal forms and processes of decline of mixed-conifer forests in San Diego County.

This study seeks to address the following questions:

1. What is the accuracy of spatial contextual ANN and object-based classification approaches to mapping mortality using high spatial resolution data?

2. What are the spatial and temporal changes in mortality patterns from 1997 to 2005, based on image-derived maps?

3. What is the spatial pattern of the conifer dieback, and which species have been most impacted by mortality?

4. Was there a particular time period when mortality was greatest?

5. What are the main ecological and anthropogenic variables that influence tree mortality processes?
6. What are the particular impacts of drought and climatic conditions, physical factors such as slope and aspect, pathogens and disease, fire history, and stand structure on the spatial-temporal distribution of mortality patterns?

7. What variables best model the vulnerability of mixed-conifer forest to mortality processes?

An investigation of the response of vegetation communities to climate change at the landscape scale is an important focus of research for Mediterranean landscapes, such as San Diego County (Hope and Stow 1993). Many climate change studies assert that there is a need to identify ‘indicator’ species of ecosystem condition that can be easily observed (Parmesan 2006; Walther et al. 2002). Remote sensing provides a practical approach to mapping and monitoring tree mortality conditions that is cost-effective, spatially comprehensive, and repeatable (Wulder et al. 2004). Determining which landscape and climate factors correlate most strongly with dieback occurrence from 1997 to 2005 will help forest managers predict areas of future concern in order to implement mitigation. This study utilizes fine spatial resolution image data, because the spatial resolution of the sensor needs to be consistent with the size of the individual tree crowns to effectively map dead trees (Hope and Stow 1993, Wulder et al. 1998). This is particularly important when studying tree health and mortality since damage is associated with individual tree species and differences in stand density, and it is important to identify host tree species reliably (Manion 1991). Classification and analysis of high resolution remotely sensed data can effectively address this issue.
Remote sensing is an important tool for understanding ecosystem functioning. According to Graetz (1990 p.8), remote sensing is the only data source that can be used to assess and monitor vegetation patterns “on time and space scales that are comparable to those of the human transformation of the resource.” In addition to examining the spatial context of ecosystems, imagery is helpful in understanding patterns through time by analyzing remotely sensed data from various dates. Thus, it is feasible to “recreate” the past through historical remote sensing imagery, something that is not possible with traditional ecological field methods. For example, the forests of Cuyamaca State Park were destroyed in the Cedar Fire, however it is still possible to examine imagery previous to that date to assess pre-burn tree mortality conditions.

Murtha (1978) cautions that problems arise in understanding forest decline because one damaging agent can produce several damage syndromes, and one damage syndrome can be produced by widely different and unrelated causes. Remote sensing techniques can elucidate spatial and temporal patterns that can help analysts to infer which damage syndromes are affecting a particular area. In addition, GIS spatial analysis and mathematical modeling techniques can be utilized to further investigate patterns in the tree mortality data derived from the remotely sensed imagery.

In the last few decades, public and scientific concern about widespread forest damage from both natural and anthropogenic causes has increased (Innes 1992). Forest dieback, which has been defined as dieback where whole stands are affected, is now a major environmental issue (Mueller-Dombois 1988, van Mantgem et al. 2009,
Allen et al. 2010). During the 1970s, forest conditions deteriorated in different parts of Europe, largely attributed to air pollution (Bussotti and Ferretti 1998). Many forests worldwide have experienced recent episodes of dieback: ohia forests in Hawaii (Mueller-Dombois 1983), beech forests in New Zealand (Wardle and Allen 1983), Alaska yellow-cedar (Hennon et al 1990), hemlock forests in New England (Royle 2002), and western yellow pine forests in the intermountain west (Logan and Powell 2001, van Mantgem et al. 2009) and in southern California (Savage 1994; Minnich 2007).

This study elucidates further understanding of tree mortality conditions and processes in the local forests of San Diego. In the last century forests in San Diego County have experienced many disturbance events, induced by both human and climate impacts, and will continue to face disturbance. Tree mortality is a natural process. Dead and dying trees are important components of forest ecosystems (Manion 1991, Perry, 1994). Fallen trees provide openings in the forest canopy that allow for the establishment of other shrubs, forbs and eventually trees. Individual snags also provide habitat for many species, including those which are essential in the decomposition processes that convert vegetation into nutrients (Franklin et al. 1987). However, concerns have arisen worldwide about the increase of tree dieback occurring at the stand-level, where whole stands or stand segments are affected, rather than just isolated trees (Mueller-Dombois 1988, Wulder et al. 2006).

There are many factors that can cause stand-level dieback. Dieback can be symptomatic of biotic processes, such as senescence, starvation, consumption or
disease, which have been treated in the literature as pathological problems (Franklin et al 1987). Abiotic factors such as environmental stress, including flooding, drought, heat, wind and climatic change also contribute to dieback. Much of the stand-level dieback in Europe and southern California has been attributed to air pollution, and is considered to be a recent anthropogenically induced abiotic problem (Mueller-Dombois 1988, Savage 1994, Gruelke et al. 2006, Karnosky 2007). However, Innes (1992) and Minnich (2007) state that recent work on pollution-related forest dieback indicates that climatic stresses are considered to have greater impacts than air pollutants. There are also factors that predispose trees to dieback, such as competition, slow growth patterns and nutrient deficiencies (Waring 1987, Bigler 2007). Several authors caution that it is difficult to untangle the complexities of interacting biotic, abiotic and predisposition factors (Allen et al. 2010, Innes 1992, Mueller-Dombois 1988, Franklin et al 1987).

Distinguishing between natural and unnatural dieback is ecologically significant. Mueller-Dombois (1987) asserts that if stand-level dieback in a certain area is due to natural forces, then it probably has occurred there before, and one could expect that biological adaptations in the ecosystem for this dieback would prevent overall negative impacts. However, if anthropogenic or long-term climatic change is affecting the dieback process, than there could be negative long-lasting impacts, which would be of concern (Mueller-Dombois 1987).

A better understanding of the interactions and processes of dead and dying trees is helpful for monitoring forest health conditions. Some pertinent questions for
managers include: Are current dieback conditions indicative of a natural dieback cycle that will eventually “return to normal”? Or, alternatively, have conditions shifted so severely (from either localized anthropogenic or climate-induced changes) that the dieback is indicative of whole ecosystem change, where a return to pre-existing conditions is not possible? How is it possible to differentiate between these two situations (Allen et al. 2010, Mueller-Dombois 1987, 1988, Innes 1992)?

The causes and patterns of tree mortality are complex. As a result of several decades of research on tree dieback, different etiological models describing stand-level dieback have emerged, which address the interactions of these complexities at different levels (Innes 1992). Several studies have focused on single primary causes, such as pollution affecting forests in Europe (European Commission 1997). As a result of studying dieback in New Zealand, Wardle and Allen (1983) developed a three stage etiology to describe the dieback process. In the first stage, the forest stand is in a susceptible stage of development. In the second stage there is a disturbance or stress, and in the third stage pests or pathogens are attracted as a response to the forest’s stressed condition.

The most cited and widely accepted model is the decline-disease theory (Innes 1992, Mueller-Dombois 1987, 1988, Savage 1994). Manion (1991) describes forest decline as an interaction of interchangeable, specifically ordered abiotic and biotic factors which may cause a decline in tree health or outright mortality: (1) disease-initiating long-term factors, called pre-disposing factors, such as climatic change, air pollution, poor soil conditions and old age; (2) short-term inciting factors, such as
mechanical injury, frost damage, and drought; and (3) long-term contributing factors, such as pathogenic fungi, insects, and viruses. Mueller-Dombois (1988) renamed these as (1) predisposing, (2) precipitating, and (3) accelerating factors. By definition, decline diseases are of complex biotic and abiotic origin, and Manion (1991) asserts that they are poorly understood, warranting further work.

Savage (1994) applied this disease-decline theory to investigate the role of anthropogenic disturbance and patterns of mortality in a mixed-conifer forest in the San Jacinto Mountains, California. Based on studies of forest stand structure, she concluded that the proximate causes of mortality in the study area are natural disturbances, and there are also underlying chronic anthropogenic influences, such as the predisposing factors of fire suppression and air pollution. She postulated that these factors, combined with the climate event of drought and the coup de grace by insect attack have resulted in stand level dieback. Savage (1994) asserted that more studies are needed to isolate, by site, the influences of disturbance to better determine the degree to which anthropogenic factors are responsible for tree mortality patterns.

Another indirect anthropogenic disturbance is the impact of air pollution. According to Grulke et al. (2006) exposure of forests to ozone and nitrous oxides increases their susceptibility to drought. As vehicles increase in the backcountry and more pollutants drift from southern California urban sources to the forests, trees are chronically exposed to more ozone and NOx, and tree dieback is more likely. Grulke et al. (2006) found that exposure of trees to these oxidants decreases carbon stored in leaves and roots, results in premature needle and branch loss, decreases root biomass,
increases carbohydrates stored in tree trunks (which may enhance beetle attacks), and increases sensitivity to drought.

The uneven spatial arrangement of tree mortality across the landscape is dependent on many factors, including differing disturbance agents, vegetation patterns and heterogeneity in the physical environment. In order to better understand the ecological implications related to tree mortality, it is helpful to discern the spatial patterns of dead trees, whether dispersed or clustered, at both the site and landscape levels (Franklin et al 1987). Understanding how tree mortality changes over space and time in the southern California region is important, as these aspects have not been explicitly investigated locally.

In addition to understanding current forest conditions and mortality processes, it is important to examine climatic influences on the montane forests of San Diego County. Anticipated climate change trends in California include higher annual average temperatures, night minimum temperatures, and earlier snow melt and increased annual river runoff (California Energy Commission 2005). Predictions include much higher temperatures and a cascading effect on health, water resources, agriculture, forests, and sea levels (Cayon et al. 2008. Projections made from various climate models and scenarios nationally include increased drought and thus, extended fire seasons, more extreme weather, and more frequent large wildfire events (McKenzie et al. 2004).

Climate changes are likely to substantially affect San Diego’s forests in several ways. Extended drought can result in tree dieback and mortality; when the
environmental conditions are too extreme for a species, it is eliminated from that geographic area. When there is insufficient soil moisture and when water stress reduces gas exchange in leaves, tree mortality results when carbohydrate production and reserves cannot sustain them. Hanson and Weltzin (2000) explain how plant species respond differently and that entire species may die off when drought occurs in an area that already has predictable seasonal droughts (such as summers and early autumn in San Diego County and most of southern California).

Extended drought can stress individual trees, increase their susceptibility to insect attack, and result in widespread forest decline. Stressed trees have less resistance to insects, such as bark beetles, that girdle and kill the trees. More indirectly, warmer winter temperatures can increase insect survival and population levels. Logan et al. (2003) explain that drought and abnormally warm years that began in the 1980s have resulted in unprecedented pest outbreaks and tree dieback in western North America. Michaels et al. (1987) assert that the climatic variables of temperature and precipitation explain more than 60% of the variance in the growth of several tree species, and that pest outbreaks can be predicted from temperature and precipitation data.

Another result of extended drought is that it can increase the severity of wildfires when they are ignited. Westerling et al. (2006) showed that large-wildfire frequency and longer wildfire durations increased in the mid-1980s, when there was a marked increase in spring temperatures, decrease in summer precipitation, drier vegetation, and longer fire seasons. In a review commissioned by the National
Assessment on Climate Change, Dale et al. (2001) outline the importance of precipitation and temperature change on forests, and how climate change affects disturbance processes (mostly wildfire in San Diego) and thus, forest composition. Southern California forests had not only experienced several years of severe drought but also chronic exposure to elevated O2 concentration and N deposition, which increased fuel build up on the forest floor (Bytnerowicz et al. 2007). Furthermore, drought and weakened trees promoted insect infestations and massive tree dieback (Minnich 2007). Hot weather and strong Santa Ana winds in the summer of 2003 resulted in the catastrophic Cedar Fire, which was started by one ignition in chaparral then burned into the forest three days later (Keeley et al. 2004). Franklin et al. (2006) surveyed areas in Cuyamaca Rancho State Park during the first two post-fire growing seasons following the Cedar Fire and found that most conifers were killed by the fire and that pine seedlings had not established.

Forest change (dieback, decline, and changes in diversity) is precipitated by two major impacts: climate change (droughts, temperature shifts) and anthropogenic (human influenced) disturbances (e.g., logging, fire suppression, air pollution). The project components for this study are designed to address these two interconnected impacts through: (1) comparison of remote sensing approaches to effectively delineate dead trees from high spatial resolution imagery; (2) analysis of dead tree maps derived from the remote sensing classifications to assess spatial-temporal patterns of tree mortality; and (3) testing of modeling approaches to understand the environmental variables related to tree mortality. Chapter 2 outlines methods to map
dead conifer trees, including enhancement approaches to improve classification accuracies. Chapter 3 provides the details of the spatial-temporal pattern analysis of dead trees, as well as forest stand structure results from plot-based fieldwork conducted on Palomar, Volcan, and Laguna Mountains. Chapter 4 investigates the relationships of environmental and climatic factors, as well as anthropogenic–related fire history, to tree mortality, utilizing modeling techniques to elucidate the significant variables for the several time periods and three study areas.

2.1. Introduction

The montane mixed-conifer forests of San Diego County are currently experiencing extensive tree mortality. Remote sensing provides a labor effective, repeatable and spatially comprehensive approach to assessing and monitoring tree mortality conditions. Currently, high spatial resolution digital aerial orthoimagery provides affordable data that may be available for multiple dates, and is at suitable spatial scales for the study of population level vegetation change (Erikson 2003, Graetz 1990, Gustafson 1998). There is a need for developing more automated approaches, given the extensive areas of mortality, the large-sized remotely sensed data sets available, and the extensive, time-consuming efforts required for manually generating tree mortality maps. To this end, advances in object-based analysis techniques may provide a means for rapidly obtaining spatially explicit information about tree conditions for large areas of forests.

The overall research goal is to better understand the history, current conditions, and climatic influences on the montane forests of San Diego County, with an emphasis on assessing spatial and temporal patterns of tree mortality using advanced remote sensing techniques. The specific objective of this paper is to test the effectiveness of two classification approaches to quickly map tree mortality, utilizing
existing data sets of variable quality. The ultimate goal is to delineate individual trees as objects, classify them as live or dead, and track them through time.

Two commercial off-the-shelf (COTS) software programs were evaluated, an OBIA routine (eCognition), and a per-pixel ANN classifier that exploits spatial contextual information (Feature Analyst). Henceforth the first software approach will be referred to as “OBIA” and the second as the “spatial contextual” approach. Given the usefulness of remote sensing applications, the costs associated with these applications, the many types of software programs available, as well as many types of high resolution data, it is an interesting and useful exercise to examine how effective existing approaches are in handling the task. Interesting questions land managers might ask, for example, would include which approaches might be available and which would be the most cost effective.

The utility of high spatial resolution image data and these two object-based approaches was assessed in the context of mapping tree mortality in 2002, 2005 and 2007, for forested areas of San Diego County that have high variability in landscape structure. The following research questions were addressed:

1. What is the utility of high spatial resolution image data sets and an OBIA routine and a spatial contextual per-pixel classifier to detect and quantify tree dieback over time? How usable are the resultant products? How do products from these methods compare with those from a visual interpretation approach?
2. What is the accuracy of image-derived tree mortality maps as assessed through pixel-based and object-based accuracy assessment approaches? How do the accuracies compare for maps derived by the two approaches?

3. Is one of these classification approaches more reliable than the other, as measured by processing times, ease of application, and computed accuracy?

2.2. Background

Object-based image analysis (OBIA) methods are becoming more prevalent, due to the greater availability of commercial object-based imagery analysis software, high power computing systems, and the increased availability of high spatial resolution remote sensing data (Benz et al. 2004, Blaschke and Strobl 2001). Object-based methods have an advantage over per-pixel approaches in their ability to incorporate spatial/contextual information, and have been shown to provide improved classification accuracies over pixel-based classifications, due in part to their ability to overcome the so called ‘salt and pepper effect’ (Guo et al. 2007, Blaschke 2010).

True OBIA approaches utilize a segmentation algorithm, which incorporates both spectral and spatial information to group homogeneous regions of pixels to create image objects called segments. Image color and shape criteria can play an important role in creating these segments. Segments are then classified using one of a variety of classification approaches, based on sample object, or according to class descriptions with a membership function routine, or using a combination of both approaches (Al-Khudhairy et al. 2005). Finally, in a map generalization phase, the
classified objects can be aggregated, by merging and filtering (Jensen 2005, Blaschke 2009). Another potential advantage of OBIA techniques is their ability to handle differential illumination and view angle effects for image change analysis with multi-date airborne images (Stow et al. 2007).

Object-based approaches have been utilized in forestry applications to detect and possibly delineate stressed and dead trees. Guo et al. 2007 demonstrated the effectiveness of an object-based approach to delineate oak trees affected by sudden oak death syndrome, finding that the segmentation/knowledge-based classifier object-based approach significantly outperformed a pixel-based maximum likelihood classification method. Flanders et al. (2003) found that for several types of forested areas and cut block scars, the classification accuracies were significantly higher using a segmentation object-based approach than a pixel-based method. They also report that a pressing topic of research is a comparison of segmentation routines to neural network algorithms.

Artificial neural networks (ANN) have been successfully used to classify remote sensor data for quite some time, and simulate the nonlinear thinking process of human beings by assigning weights in a network of connecting neurons, based on spectral values or other information such as terrain elevation or slope (Atkinson and Tatnall 1997, Foody and Arora 1997). Neural networks usually consist of an input layer, a hidden layer, and an output layer. In the training phase an analyst selects sites that possess attributes of interest, and then these attributes are passed to the input layer. During the learning phase typically a back-propagation algorithm is used to adjust the
weights in several iterations until the system achieves convergence, and then the classification can be conducted. Neural networks are advantageous in that they are non-parametric and have the ability to adaptively simulate complex and nonlinear patterns (Jensen, 2006). They are also able to incorporate spatial and contextual information into the classification.

Neural networks have also been utilized for mapping tree crowns. Vanderzanden and Morrison (2002) utilized an ANN approach to map cover type, crown closure, and tree structure for a study site in the Tongass National Forest in Alaska, and found the test results to be very promising for future work. It is important to note that although neural networks are not technically an OBIA approach because they do not segment the image before classifying it, they can ultimately produce definitive objects, and therefore can be presented as an object-based approach, in the more general sense of an approach that produces objects for the final classification product.

The segmentation object-based approach (OBIA) software program that was utilized for this study is eCognition version 5, produced by Definiens Imaging, which enables a user to segment objects with a routine that incorporates contextual classifiers based on fuzzy logic and segment-based statistical feature characteristics. A region-growing multi-resolution segmentation is conducted, which is based on several customizable inputs, including scale factor, shape and color, and object compactness. The eCognition routine can incorporate extensive artificial intelligence aspects (Flanders et al. 2003). This object-based approach iterates between processing
and classifying image objects. The scale and shape information for image segments can be optimized and exploited for classification.

The artificial neural network software package that was tested is Feature Analyst, by Visual Learning Systems, Inc., an extension for both ESRI ArcView and ERDAS Imagine software. It implements a suite of machine learning algorithms to extract object-specific geographic features from high resolution imagery using both spectral and spatial characteristics that resemble target examples (i.e. training templates) (Kaiser et al. 2004). The user can select pre-packaged input representations, or search kernel patterns, to optimize object recognition. The software also employs a hierarchical learning process (called “clean up clutter feature”) following initial classifications to improve recognition of the objects that are extracted and thus reduce commission error. A user provides training samples of representative objects, and objects of interest are extracted by matching pixels with spectral and local spatial characteristics that are similar to those of the training pixels (Feature Analyst Extension for ArcView 3.2 User Guide, 2002; Kaiser et al. 2004).

2.3. Study Area

Tree mortality was investigated within the montane mixed-conifer forests of San Diego County, California, USA, which are found on Palomar Mountain, in the greater Julian area, including Harrison Park, Cuyamaca, Laguna Mountain, Descanso and Pine Valley, and in the Lost Valley area near Warner Springs. These coniferous forests occur as “islands” above elevations of 1100 m in areas that receive more than
50 cm of precipitation. The forest areas are remnants from a much more widespread 
forest that was prevalent during the wetter and cooler Pleistocene period. They occur 
within the Peninsular Ranges that extend north-south from the San Jacinto wilderness 
area near Palm Springs to San Pedro Martir in northern Baja California. The 
Peninsular Ranges are comprised of a large westerly-tilted fault block of Cretaceous 
granite (Pryde 1992).

Three specific study sites (as illustrated in Figure 2-1) were utilized. Site 1 
extends from the Fry Creek Campground area to Palomar State Park on Palomar 
mountain, and is comprised of Sierran mixed coniferous forest (white fir, incense 
cedar, Big cone Douglas fir, and Coulter pine), at an elevation of 1500 m and with an 
annual average rainfall of 120 cm. Site 2 is located in the Volcan Mountains just 
north of the town of Julian and consists of a mixture of white fir, incense cedar, Big 
cone Douglas fir, and Coulter pine on the upper slopes of the West side of the 
mountains (elevation 1300 m, rainfall 60 cm). Site 3 is located on Laguna mountain 
(1800 m), and is almost exclusively Jeffrey pine forest, with an average annual 
rainfall of 90 cm.

2.4. Data

The remote sensing analysis was based on several extant orthorectified image 
data sets, with specifications listed in see Table 2-1. These image data sets were 
selected because they were amenable to spatially resolving individual dead trees, 
were readily available for the study areas and for a time period of accelerated tree
mortality (2000 through 2007). The different band combinations – true color (R-G-B), color infrared (G-R-NIR) and multispectral (B-G-R-NIR) -- enabled the efficacy of the two software approaches to be tested on data sets with differing spectral-radiometric qualities. Site differences (for the three study areas, for each date) were also evaluated.

The first date consisted of USGS Digital Orthophoto Quarter Quadrangle (DOQQ) imagery having 1 m spatial resolution for May 2002. This imagery is derived from color infrared (CIR) aerial photographs that are scanned into digital form (green, red, and near infrared (NIR) bands), orthorectified using a digital elevation model (DEM), and georeferenced using surveyed ground control points. A 2005 data set, from the Natural Resource Council, consists of true color (blue, green, red bands) imagery, generated by scanning color aerial photographs, also has 1 m spatial resolution, and corresponds to the coniferous forest areas of the county. These image data sets were subset to conform with the extents of the three study areas. A 2007 data set consists of a four-band (blue, green, red, and NIR) airborne digital UltraCam image, captured for the County of San Diego Office of Emergency Services, November 2, 2007, for the Palomar Mountain study site only. Within each montane area specific study areas were delineated that include topographic variation and forest stands of varying sizes. While these image data sets are readily available, they have varying spectral and spatial characteristics, with differing color qualities, view and solar angles, seasonality, and issues with mosaicking seams, such that dead tree objects can appear dramatically different.
2.5. Methods

Images from the selected dates were subset for the three study areas, and then after collecting calibration and validation data, the imagery was classified using both ANN and OBIA software programs. The resultant tree mortality maps were then compared using an object-based accuracy assessment approach, as well as evaluating processing times, and ease of application, in order to determine the “best map product”. Figure 2-2 shows the general image processing flow.

2.5.1. Image pre-processing

The 2002 and 2005 image data sets had been orthorectified and mosaicked. For the 2007 data, a mosaic was generated from image tiles that had been georeferenced. Additional pre-processing included derivation of multispectral band ratios, which were tested as a means for reducing terrain illumination effects for the OBIA classification process. This was tested for the true OBIA approach as well as for the spatial contextual approach.

2.5.2. Calibration/Validation

Calibration polygons (i.e. training sites) were manually delineated utilizing a systematic aligned approach. A 10 by 10 grid was superimposed over the image, with a point marking the center of each grid cell. From this center point an analyst determined the closest dead tree object, as well as examples of the other classes (forest, non-forest), and manually digitized polygons over the objects. In the event
that there were no dead tree objects (or other classes) in a given grid cell, the analyst
moved on to the next grid cell. In this manner a sufficient sample of dead tree objects
was collected. In imagery from 2002 and dates previous to that, dead tree objects
tended to be scattered and fairly rare; a random point generation approach would have
missed this class. The training data were then randomly sorted using a computerized
pseudorandom function and then partitioned into calibration (30 polygons for each
class) and validation sets (50 polygons for each class). The same calibration and
validation sets were utilized for the analysis of both software approaches. For both
calibration and validation objects the minimum mapping unit was delineated as the
size of a tree canopy, which was approximately equivalent to 9 to 16 contiguous 1 m
pixels. For the calculation of omission error, validation polygons were also collected
for “non-dead tree” objects, which include samples of live trees, roads, fields and
other materials, utilizing the same method.

2.5.3. Image processing: OBIA

Feature inputs and model parameters for OBIA were tested to determine
which were optimal in terms of final product accuracy. Segmentation parameters and
the effectiveness of transforms to improve classification results were tested
interactively.
2.5.3.1. Segmentation parameters

The region-based, local mutual best fitting algorithm utilized for the segmentation process of the OBIA approach relies on several user-specified constraint parameters: scale factor, shape versus color weighting and compactness versus smoothness weighting. These criteria are combined in one parameter defined as within-segments heterogeneity:

\[ f = w \cdot h_{\text{color}} + (1 - w) \cdot h_{\text{shape}} \]

Where \( f \) is the heterogeneity criterion, which is also called the scale factor, and the remaining terms are the user defined weight for color, the color criterion, and the shape criterion, respectively (Frauman and Wolff 2005).

Since these factors, as well as the image feature inputs to the segmentation algorithm influence the success of the segmentation, it is important to optimize them individually for each date of imagery (Baatz and Schape, 2000; Lucieer and Stein, 2002; Neubert and Meinel 2003; Moller et al. 2007). Appropriate parameters were selected using a trial and error procedure, testing each factor in turn and using visual inspection to compare each test segmentation product to training objects to guide the selection of the optimal set of parameters. Ten training objects of dead tree crowns were created by heads-up digitizing of object boundaries for each scene of imagery (after Lippitt et al. 2011). Validation was conducted by visually assessing the segmented objects, qualitatively determining the set of factors, which combined, optimized the representation of dead tree objects. Note that most images included both nadir and oblique tree canopy view angles.
2.5.3.2. Classification with transformation inputs

The objective of this analytical component was to determine if the addition of input data transforms (e.g. vegetation indices, principal components) can improve the reliability of the classification product in representing dead tree objects, since spectral and other transformations have been shown to improve classification results (Lippitt et al. 2011, Kern and Ostovsky 2003, Dymond et al. 2002). Eight different inputs to the classification process were compared to determine which ones improved the classification results, including: spectral bands alone, component 1 from Principal Component Analysis transformation (PCA; Zhao and Maclean 2000), and the Normalized Difference Green Red (NDGR; Gitelson et al. 2002), and a combination of the above feature types (henceforth called the Combination approach). Also included were the Normalized Difference Vegetation Index (NDVI; Rouse et al. 1973), the Soil Adjusted Vegetation Index (SAVI; Huete 1989), and the Simple Ratio (Jordan 1969) which were applied to the 2002 and 2007 images that had a NIR band (2002 imagery). The Visible Atmospherically Resistant Index (VARI; Gitelson et al. 2002) was applied to the 2005 true color image.

PCA is an example of a compression transformation, which can minimize inter-band correlations, reduce data dimensionality and has been shown to yield improvements for segmentation as well as classification results (Almeida-Filho and Shimabukuro 2002). The first principal component was selected as the input because it represents the greatest variance from all wavebands of the original data set, and therefore contains the most information (Small 2001).
The spectral vegetation indices (SVI: NDGR, NDVI, and SAVI) were also tested as they have been shown to improve the discrimination of vegetative landscape features, and have been previously used to enhance the segmentation process of object-based image analysis (Barata and Pina 2002; Gamanya et al. 2008; Conchedda et al. 2008 and Lucas et al. 2007). Table 2-2 shows the SVI formulas. These indices were calculated for each image and then imported into the classification program.

The land cover classification was conducted using a nearest neighbor (Euclidean distance) classifier, for each input data transformation. The spectral bands were tested as one feature input, then transforms were added to the spectral bands one at a time and classified, and then all inputs were combined in a layerstack and classified. Additionally, the transforms were tested individually without the spectral bands. Prior to the classification of the spectral bands plus transforms, the imagery had been segmented based on the spectral bands as the only input features. For testing the individual transforms, the segmentation was conducted first on the transform, and then classified. The nearest neighbor classification in eCognition yielded an OBIA product with the following classes: dead conifer trees, live trees (forest), as well as a non-forest category, which includes grassland, shrubs, roads, buildings, water and shadow. Classification maps portray polygons of dead trees in a matrix of live trees and non-forest objects.
2.5.4. Image processing: per-pixel spatial contextual approach

Three strategies were tested and compared for the spatial contextual approach in order to determine the optimal process of classification. The first strategy involved the creation of a single dead conifer class. For the second strategy a non-forest mask was initially created with the ANN algorithm, using user-defined training samples (n=30 for training samples of bare soil, asphalt, buildings and senescent non-tree vegetation) and then refined using the interactive correction features of the classification program. The mask product was then applied to the image to mask out pixels that tended to be confused with dead conifer pixels (i.e. senescent grass, bare soil, etc.), yielding pixels of potential dead conifers. For the third strategy transformation inputs, the same ones tested with the OBIA approach, were added to the spectral bands and tested alone to see if they improved the classification.

2.5.5. Accuracy and Efficiency Assessment

The OBIA and per-pixel spatial contextual classifiers were compared in terms of their efficiency in producing maps of conifer dieback, as determined by processing times and ease of application, in addition to computed accuracy. The accuracy of the classification products was evaluated using an object-based assessment (Lang et al. 2009, Zhan et al. 2005). The high spatial resolution image data were also manually interpreted to compare mapped objects with plants (tree crowns etc.) from the imagery.
The classification products resulting from the two approaches are slightly different as the OBIA routine yields a raster classification, and the spatial contextual approach produces a single class vector layer (Arc shapefile). In order to standardize the comparison, the dead tree polygons from the OBIA routine were exported from the original classification as vector files.

The object-based accuracy assessment was based on visual interpretation, in order to standardize the comparison between the dead tree products from OBIA and spatial contextual routines. This approach determines the “presence” or “absence” of classified objects utilizing a 50% rule. If a mapped dead tree object and a corresponding validation object overlap by more than 50% then the object is considered in agreement or correct; if the overlap is less than 50% then the object is considered to be erroneous (see Figure 2-3). The resultant accuracy is reported as the total number of classified objects that meet this 50% threshold condition, divided by the total number of validation objects (50).

Omission error, which refers to omitted dead trees, was calculated by subtracting the percentage correct from the total possible correct (Congalton and Mead 1983). Commission error, which refers to objects that have been incorrectly mapped as dead trees, was determined by comparing the dead tree object classification products with a validation set of 50 “non-dead tree objects”, and calculating the percentage overlap.
2.6. Results

2.6.1. OBIA analysis

2.6.1.1. Segmentation

Final parameter selections for the segmentation step of the OBIA approach are found in Table 2-3, which lists the scale, shape/color, and compactness factors selected for the test images. The scale factor had the greatest influence on the segmentation results, and differed according to the imagery characteristics, particularly spatial resolution. The same scale factor was appropriate for all image dates for each study area as the scale factor, or heterogeneity criterion, is tightly linked to the spatial structure of the image (Frauman and Wolff 2005). The same shape/color parameters proved to be applicable to all dates and scenes (study sites) of imagery. The default for the compactness/smoothness parameter, a value of .5, was used throughout the analysis.

2.6.1.2. OBIA classification products

When comparing the results of the object-based classification with varying transformed inputs, four products demonstrated some improvement (Table 2-4). Up to a 5% improvement in accuracy and up to a 13% reduction in commission error was achieved by the transformed products as compared to the spectral bands alone: the combination of all inputs, PCA + spectral bands, NDGR + spectral bands, and NDVI + spectral bands (see Table 2-5 to view the mean accuracy values for all of the transform types in order from highest accuracy to lowest). A paired t-test was
performed to determine whether or not there is a significant difference in accuracies for the dead conifer class between the cumulative inputs (n = 74) of transforms alone, as compared to the inputs of transforms added to the spectral bands. The resultant p value of 1.53377E-07 indicates that there is a significant difference (at the 0.001 level) between results, with the products of the transforms added to the spectral bands having higher accuracies than those of the transforms alone.

2.6.2. Spatial Contextual classification products

The spatial contextual classification products were improved by utilizing a masking technique. An enhanced map product was created using a non-forest mask layer to exclude areas of non-interest prior to classification for the spatial contextual approach. The products from the masking procedure compared to the non-masked products exhibited an increase in mean accuracy of 20.28%, and a decrease in the mean commission error of 4.28% (Table 2-6).

When comparing the classifications conducted with different transformed image inputs, five products showed improvement over the spectral bands alone, based on mean accuracy as well as in most cases mean commission error (Table 2-7). These products include those based on NDGR + spectral bands, VARI + spectral bands, the combination approach, and PCA + spectral bands. The improvement from the NDGR + spectral bands product in comparison to those from spectral bands only is an increase of 13.43% in mean accuracy, and a decrease in mean commission error of 8.29%. When comparing accuracies for the dead conifer class between the cumulative
inputs ($n = 74$) of transforms alone, as compared to the inputs of transforms added to the spectral bands, the student t-test result indicates that there is a significant difference (at the 0.001 level) between results ($p = 1.62771\times10^{-7}$), with again, the products of the transforms added to the spectral bands having higher accuracies than those of the transforms alone.

### 2.6.3. Comparison of final dead-conifer map products

The accuracy assessment results for both the OBIA and spatial contextual products ranged in value from 24% to 92% for the object-based accuracies. A paired student t-test comparing the accuracies of the two approaches indicates that the accuracies for the spatial contextual products were significantly higher than the OBIA products at the 0.01 level ($p = 0.0033$). The commission errors were not significantly different between the two products ($p = 0.6458$). Therefore, the spatial contextual approach generally outperformed the OBIA approach in terms of dead tree class accuracy, but yielded the same amount of commission error.

It is also helpful to examine other quantitative and qualitative aspects of the classifications that relate to the overall reliability of the products. A comparison of the numbers of dead tree objects for each product revealed that there is a significant difference (at the 0.05 level) between products, with the OBIA product having significantly greater numbers of objects than the spatial contextual product.

For the OBIA approach a comparison of results between different dates (types of imagery) revealed that there were no statistically significant differences between
the accuracies for these various classifications. There were, however, statistically
significant differences between the accuracies between all of the study areas. Table 2-
8 lists the probabilities for these comparisons. The classifications from the Volcan
study area had the highest accuracies, followed by Palomar and Laguna.

For the spatial contextual approach, there were no statistically significant
differences between the accuracies for the different dates (e.g. imagery types). When
comparing accuracy values for each study area utilizing a paired student t-test, there
were no significant differences between the Palomar and Laguna, and Palomar and
Volcan study sites. However, there was a difference between the Laguna and Volcan
sites, where accuracies for the Volcan area were significantly higher (at the 0.01
level) than the accuracies for the Laguna site. Table 2-8 lists the probabilities for
these comparisons. Again, the classifications from the Volcan study area had the
highest accuracies, followed by Palomar and Laguna.

2.7. Discussion

2.7.1. Image enhancement types and image processing approaches

The OBIA image enhancement approach of adding transformation inputs to
the classification process, either singly or in combination with the spectral bands,
improved the classification slightly over spectral bands alone (with up to a 5%
average increase in accuracy, and a 13% reduction in commission errors). This
finding is in contrast to an abundance of studies demonstrating more significantly the
effectiveness of adding transformation inputs to improve the OBIA routine (Yu et al.
The inputs alone (without spectral bands) demonstrated no improvement at all. In particular it was noted that without the spectral bands, the segmentation routine did not perform as effectively. Thus this enhancement approach is not very useful in this case, because it does not result in dramatic improvement of the product, and requires extra work and computing power/time to process classifications with added inputs, particularly the combination with all of the inputs together. For example, the larger Laguna scene had to be processed in sections for the 2005 imagery due to its greater data volume, particularly with added inputs.

For the spatial contextual enhancement analysis, there was clearly an important difference between the accuracies from the non-mask and masking methods; the masking approach definitely improved the classification results, over the non-masking approach. This is most likely because the dead conifer class can be routinely confused with other materials such as senescent grass and bracken ferns, bare ground, and roads, so creating a non-forest layer masks out these features, resulting in less confusion and a more accurate classification. Tiede and Hoffmann (2006) also found that masking out the background bare ground dramatically improved their object-based classifications for single tree detection.

For the spatial contextual analysis the enhancement approach of adding transformation inputs to the classification process did improve the classification over spectral bands alone, for several inputs, up to a 13% average improvement with an 8% reduction in commission error. The transforms plus the spectral bands had the
greatest accuracies although notably the PCA transform by itself also outperformed
the spectral bands alone. Including transform inputs increased the efficiency of the
software program in terms of refining the ANN routine, without impacting processing
times significantly.

Based on dead tree class accuracy measures alone, the classification products
from the spatial contextual approach yielded significantly higher accuracies than the
OBIA products. In particular, the addition of transforms to the spectral bands helped
boost the performance of the spatial contextual approach. In addition, the OBIA
products had significantly greater numbers of objects than the spatial contextual
approach, although the commission errors were not significantly different between
products. This is useful to know, if an analyst needs to manually edit a product, as it
would be more efficient to edit a product that has fewer commission objects, as is the
case for the spatial contextual product.

Several qualitative characteristics are evident, when comparing the OBIA and
spatial contextual approaches. The spatial contextual approach is a straightforward
supervised training oriented program which is easy to learn. The OBIA program has a
multitude of options and choices for the analyst to make when classifying an image,
and can take a while to learn. One of the strengths of OBIA routine is the rule-based
approach to classification where the analyst can customize a variety of specific rules
to help refine the classification. This approach was found not to be effective,
however, because of spectral-brightness variation and illumination differences across
the imagery scenes. The “rules” could be satisfactorily developed for one portion of
the image, but did not apply to other portions. One of the greatest advantages of the OBIA program is the versatility of its products. It can produce a raster classification with multiple classes, or if a single class is desired, it can be exported as a vector file.

The segmentation routine is also one strength of the OBIA program, but it requires considerable computing memory, and became problematic with larger image data sets. For example, the Laguna data sets for 1997, 2000 and 2002, which were 102 MB, 102 MB and 233 MB in size respectively, could be processed as complete scenes. However, the 2005 Laguna Mountain imagery data set, which is 967MB in size, had to be segmented in sections, classified, and then the classified sections had to be stitched back together, which generated a whole other set of issues to contend with. The spatial contextual program had no problems handling any of the data sets, although processing times were slightly slower with the larger image extents.

The processing times for both software packages are comparable. The most time-consuming element for the OBIA approach is the segmentation process. The most time-consuming element for the spatial contextual approach is the “clean-up clutter” process, where the analyst identifies correct polygons and incorrect polygons for many sections of the image and then re-runs the classification.

Despite the fairly high accuracies for the dead tree class that were achieved from both of these approaches, the utility of the classification products are limited without further editing of the products. Lang et al. (2009) found that object-based classifications could be improved effectively with the addition of manual approaches, due to the human brain’s enhanced aggregation abilities. An accuracy of around 85%
for a mapped class is an accepted standard in order to consider the product reliable for use in further analysis, While accuracies for many of the map products were in the 60-70+% correct range for the dead tree class, some were in the 30-50% range. However, despite lower accuracies for some of the classification products, using these semi-automated approaches are advantageous over trying to create a dead tree classification from visual interpretation techniques alone. An attempt was made to manually digitize dead tree polygons grid by grid for an entire image, however this proved to be ineffective. For the large areas being mapped, it is much more efficient to edit the errors than to manually generate the map.

2.7.2. Study sites, imagery types and dates

Based on an analysis of the results, both the OBIA and spatial contextual approaches yielded consistent results when applied to multiple types of imagery with different spatial resolutions. However, the resultant products did vary for both approaches by study area, with the classifications for the Volcan study area having consistently the highest accuracies, followed by Palomar, and then Laguna. When comparing accuracy values for each study area for the OBIA method, there were significant differences between all of the study sites. With the spatial contextual approach there was a significant difference between the accuracies for the Volcan and Laguna sites.

The ability to delineate dead trees at the different study sites varied presumably due to potential factors such as background vegetation/cover and study
size area. Furthermore, study design and data availability make it difficult to separate
the effects of these factors. Volcan and Palomar are much smaller in area than
Laguna, and it is possible to achieve higher accuracies when classifying smaller areas
of imagery due to less complexity in background.

Also, the target to background contrast is less defined in the Laguna imagery,
due to the more open nature of the forest, with lots of gaps in between trees, which
leads to confusion of dead trees with such things as bare ground, senescent grass and
decadent shrubs. The forests of Palomar and Volcan consist of closed canopy groves,
so the dead tree to background (live tree) contrast is more distinct. These general
trends are also apparent for the spatial contextual results, although the accuracy
differences are only statistically significant between the Volcan and Laguna sites. In
general, other influential factors explaining differences between study sites could also
be differences in tree types, how mortality is manifested, and the nature of the terrain
at the study sites.

2.8. Summary and conclusions

Accurate and timely tree mortality maps are needed for forest management,
especially in areas prone to drought and frequent fires such as the montane areas of
San Diego County. Digital image processing is a viable method for producing these
maps from freely available high-spatial resolution aerial imagery, however, it is
important to select appropriate image processing techniques to obtain the highest map
accuracy possible. Here I have demonstrated that, although tree mortality is
inherently difficult to map, there are approaches that yield maps of dead trees such
that the majority of dead tree objects are detected with reasonable commission error.
Even though some degree of visual interpretation and editing is required, these
procedures are worth applying.

For each image analysis approach procedures were tested on the imagery in
order to optimize each product, in preparation for comparison. With the OBIA
approach, transformations improved some of the classifications by an average of 5%,
with up to a 13% reduction in commission error. With the spatial contextual
approach, the masking technique improved the accuracy of the classifications by up
to 20%. The addition of transforms improved some of the spatial contextual
classifications by an average of 10%, with up to an 8% reduction in commission
error.

When comparing the classification results from the OBIA and spatial
contextual products, the visual object-based accuracies were significantly different,
with the spatial contextual products yielding higher accuracies. The commission
errors between the two products are not significantly different. The number of dead
tree objects is also significantly different between products, with OBIA products
having a greater number of objects.

There are also several qualitative differences between the two approaches.
There is a much steeper learning curve with the OBIA program: the spatial contextual
routine is much easier and quicker to learn, and implement. The spatial contextual
products have better object quality, with dead trees represented as discrete individual
round objects, while with OBIA products dead tree “objects” tend to occur as larger contiguous blobby areas of dead trees. Both programs demonstrate consistent performances across data types, but also vary in performance based on scene differences.

Other studies have noted that object based approaches have both advantages and limitations. Mallinis et al. (2008) found that their best maps had an accuracy rate of 80%, with added transforms, when using Quickbird imagery and an object-based classification to map forest vegetation, and further use of these maps would need to be considered carefully without additional editing. Chubey et al. (2006) found that object-based classification approaches (eCognition and decision tree classifiers) were very useful for deriving certain forest inventory parameters, such as individual forest species, non-forest land-cover, and percent crown cover, but were not as effective in identifying stand height and age classes. They feel that there is a growing utility of methods such as these to meet operational forest inventory needs.

In conclusion, the methods tested in this chapter also present useful approaches to mapping trees. In comparing the two approaches the dead conifer tree class accuracies were higher overall for the spatial contextual approach than the OBIA approach. Additionally, for the single dead tree class the spatial contextual program is more straightforward and efficient to work with. In general, the accuracies of the resultant products are too low to proceed with additional analysis without manual editing, but it provides a good basis for further improvement. Visual interpretation methods alone cannot accommodate effectively large study areas and
multiple images. With manual clean-up, products can be brought up to a more acceptable level of accuracy, and be made ready for further analysis. In this way the methods discussed in this paper can be effective tools for detecting, mapping, and quantifying tree mortality.
Figures

Figure 2-1. Map of Study Areas, showing the location of Palomar Mountain, Volcan Mountain, and Laguna Mountain.
Figure 2-2. Schematic demonstrating the general workflow for this study.
Figure 2-3. Visual object-based method: if the classified dead tree object covers at least 50% of the validation polygon, then it is considered to be “agreement”.
Tables

Table 2-1. Imagery and Metadata.

<table>
<thead>
<tr>
<th>Date Flown</th>
<th>Spectral bands</th>
<th>Resolution</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>May, 2002</td>
<td>3-band CIR NIR, R, G</td>
<td>1 m</td>
<td>U.S.G.S. Digital Orthophoto Quarter Quadrangle</td>
</tr>
<tr>
<td>September, 2005</td>
<td>3-band RGB</td>
<td>1 ft (0.3 m)</td>
<td>U.S.D.A. Natural Resource Council</td>
</tr>
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<td>November, 2007</td>
<td>4-band NIR, RGB</td>
<td>1 ft (0.3 m)</td>
<td>County of San Diego Office of Emergency Services</td>
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</tbody>
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Table 2-2. Spectral Vegetation Indices.

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<th>Equation</th>
<th>Reference</th>
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</thead>
<tbody>
<tr>
<td>Simple Ratio</td>
<td>red/nir</td>
<td>Jordan, 1969</td>
</tr>
<tr>
<td>Normalized Difference Vegetation Index (NDVI)</td>
<td>nir-red/nir+red</td>
<td>Rouse et al., 1973</td>
</tr>
<tr>
<td>Normalized Difference Green-Red Index (NDGR)</td>
<td>(green-red)/(green+red)</td>
<td>Gitelson et al. 2002</td>
</tr>
<tr>
<td>Soil Adjusted Vegetation Index (SAVI)</td>
<td>(1+L) (nir-red)/(nir+red+L)</td>
<td>Huete, 1989</td>
</tr>
<tr>
<td>Visible Atmospherically Resistant Index (VARI)</td>
<td>(green-red)/(green+red-blue)</td>
<td>Gitelson et al. 2002</td>
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</tbody>
</table>

Table 2-3. OBIA (eCognition) segmentation parameters.

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<th>Shape/Color</th>
<th>Compactness</th>
</tr>
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<td>0.3/0.7</td>
<td>0.5</td>
</tr>
<tr>
<td>2005</td>
<td>50</td>
<td>0.3/0.7</td>
<td>0.5</td>
</tr>
<tr>
<td>2007</td>
<td>150</td>
<td>0.3/0.7</td>
<td>0.5</td>
</tr>
</tbody>
</table>
Table 2-4. OBIA classification accuracy results comparing addition of transforms to spectral bands and transforms alone, for each date of imagery, for each study site.

### A. Palomar

<table>
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<tr>
<th>Classification</th>
<th>Palomar</th>
<th>2002</th>
<th>2005</th>
<th>2007</th>
<th>2009</th>
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<td><strong>O</strong></td>
<td><strong>A</strong></td>
<td><strong>C</strong></td>
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<td>46</td>
<td>52</td>
<td>54</td>
<td>64</td>
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<td>**</td>
<td>**</td>
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<td>**</td>
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<td>44</td>
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<td>62</td>
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<td>*</td>
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<tr>
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* = no NIR band available to construct these particular transforms  
** = no blue band available to construct this particular transforms
## B. Volcan and Laguna

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<th></th>
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<th></th>
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<td>32</td>
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<tr>
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<td>64</td>
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</table>

* = no NIR band available to construct these particular transforms
** = no blue band available to construct this particular transforms
Table 2-5. A list of the mean values for classification product accuracy measures (compiling results for each date of imagery and each study area), comparing overall performance of transforms added to spectral bands, transforms alone, and spectral bands alone, for each software approach. The results are listed in order of highest to lowest mean accuracies, top to bottom respectively.

<table>
<thead>
<tr>
<th>OBIA (eCognition)</th>
<th>mean accuracy</th>
<th>mean commission</th>
<th>mean omission</th>
</tr>
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<tbody>
<tr>
<td>Combination</td>
<td>65.71</td>
<td>47.14</td>
<td>34.29</td>
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<tr>
<td>PCA + spectral bands</td>
<td>64.57</td>
<td>36.00</td>
<td>35.43</td>
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<td>NDGR + spectral bands</td>
<td>63.43</td>
<td>42.86</td>
<td>36.57</td>
</tr>
<tr>
<td>NDVI + spectral bands</td>
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<td>39.50</td>
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<td>Spectral bands only</td>
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<td>39.71</td>
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<td>Simple ratio + spectral bands</td>
<td>59.50</td>
<td>51.50</td>
<td>40.50</td>
</tr>
<tr>
<td>SAVI + spectral bands</td>
<td>58.50</td>
<td>46.50</td>
<td>37.00</td>
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<td>VARI + spectral bands</td>
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<td>39.50</td>
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Table 2-6. Dead conifer tree class accuracies for the spatial contextual (Feature Analyst) classifications, comparing the results for the single class approach and the single class + masking approach.

<table>
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<tr>
<th>Classification product</th>
<th>mean accuracy</th>
<th>mean commission</th>
<th>mean omission</th>
</tr>
</thead>
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<td>79.14</td>
<td>38.57</td>
<td>20.86</td>
</tr>
<tr>
<td>VARI + spectral bands</td>
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<td>45.00</td>
<td>29.00</td>
</tr>
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<td>Combination</td>
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<td>41.43</td>
<td>30.57</td>
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<td>PCA + spectral bands</td>
<td>68.00</td>
<td>44.29</td>
<td>32.00</td>
</tr>
<tr>
<td>PCA transform only</td>
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<td>55.14</td>
<td>32.29</td>
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<td>42.50</td>
</tr>
<tr>
<td>NDGR transform only</td>
<td>49.14</td>
<td>49.14</td>
<td>50.86</td>
</tr>
<tr>
<td>NDVI + spectral bands</td>
<td>38.86</td>
<td>47.50</td>
<td>32.00</td>
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<tr>
<td>SAVI transform only</td>
<td>37.50</td>
<td>47.00</td>
<td>39.00</td>
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<tr>
<td>Simple ratio + spectral bands</td>
<td>37.43</td>
<td>48.00</td>
<td>34.50</td>
</tr>
<tr>
<td>Simple ratio transform only</td>
<td>34.29</td>
<td>53.00</td>
<td>40.00</td>
</tr>
<tr>
<td>NDVI transform only</td>
<td>30.86</td>
<td>52.50</td>
<td>46.00</td>
</tr>
</tbody>
</table>

Table 2-6. Dead conifer tree class accuracies for the spatial contextual (Feature Analyst) classifications, comparing the results for the single class approach and the single class + masking approach.

<table>
<thead>
<tr>
<th>Technique</th>
<th>Imagery</th>
<th>% Correct</th>
<th>% Commission error</th>
<th>% Omission error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single Class</td>
<td>Palomar</td>
<td>2002</td>
<td>50</td>
<td>34</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2005</td>
<td>32</td>
<td>58</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2007</td>
<td>70</td>
<td>28</td>
</tr>
<tr>
<td></td>
<td>Volcan</td>
<td>2002</td>
<td>52</td>
<td>34</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2005</td>
<td>68</td>
<td>66</td>
</tr>
<tr>
<td></td>
<td>Laguna</td>
<td>2002</td>
<td>24</td>
<td>76</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2005</td>
<td>22</td>
<td>62</td>
</tr>
<tr>
<td></td>
<td></td>
<td>mean =</td>
<td>45.43</td>
<td>51.14</td>
</tr>
<tr>
<td>Mask + Class</td>
<td>Palomar</td>
<td>2002</td>
<td>69</td>
<td>34</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2005</td>
<td>60</td>
<td>70</td>
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<td></td>
<td></td>
<td>2007</td>
<td>88</td>
<td>32</td>
</tr>
<tr>
<td></td>
<td>Volcan</td>
<td>2002</td>
<td>64</td>
<td>34</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2005</td>
<td>76</td>
<td>70</td>
</tr>
<tr>
<td></td>
<td>Laguna</td>
<td>2002</td>
<td>46</td>
<td>42</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2005</td>
<td>66</td>
<td>46</td>
</tr>
<tr>
<td></td>
<td></td>
<td>mean =</td>
<td>65.71</td>
<td>46.86</td>
</tr>
</tbody>
</table>
### Table 2-7. Spatial contextual classification accuracy results comparing addition of transforms to spectral bands and transforms alone, for each date of imagery, for each study site.

A. Palomar

<table>
<thead>
<tr>
<th>Classification</th>
<th>2002</th>
<th>2005</th>
<th>2007</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A</td>
<td>C</td>
<td>O</td>
</tr>
<tr>
<td>Spectral bands</td>
<td>60</td>
<td>34</td>
<td>40</td>
</tr>
<tr>
<td>Combination</td>
<td>72</td>
<td>34</td>
<td>28</td>
</tr>
<tr>
<td>PCA + bands</td>
<td>78</td>
<td>40</td>
<td>22</td>
</tr>
<tr>
<td>PCA transform</td>
<td>70</td>
<td>46</td>
<td>30</td>
</tr>
<tr>
<td>NDGR + bands</td>
<td>84</td>
<td>36</td>
<td>16</td>
</tr>
<tr>
<td>NDGR transform</td>
<td>62</td>
<td>38</td>
<td>38</td>
</tr>
<tr>
<td>VARI + bands</td>
<td>**</td>
<td>**</td>
<td>**</td>
</tr>
<tr>
<td>VARI transform</td>
<td>**</td>
<td>**</td>
<td>**</td>
</tr>
<tr>
<td>NDVI + bands</td>
<td>78</td>
<td>56</td>
<td>22</td>
</tr>
<tr>
<td>NDVI transform</td>
<td>66</td>
<td>72</td>
<td>34</td>
</tr>
<tr>
<td>SAVI + bands</td>
<td>66</td>
<td>42</td>
<td>34</td>
</tr>
<tr>
<td>SAVI transform</td>
<td>26</td>
<td>32</td>
<td>74</td>
</tr>
<tr>
<td>SA + bands</td>
<td>60</td>
<td>50</td>
<td>40</td>
</tr>
<tr>
<td>SA transform</td>
<td>66</td>
<td>66</td>
<td>34</td>
</tr>
</tbody>
</table>

* = no NIR band available to construct these particular transforms
** = no blue band available to construct this particular transforms
**B. Volcan and Laguna**

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Spectral bands</td>
<td>64</td>
<td>34</td>
<td>36</td>
<td>76</td>
</tr>
<tr>
<td>Combination</td>
<td>68</td>
<td>44</td>
<td>32</td>
<td>70</td>
</tr>
<tr>
<td>PCA + bands</td>
<td>76</td>
<td>34</td>
<td>24</td>
<td>66</td>
</tr>
<tr>
<td>PCA transform</td>
<td>70</td>
<td>36</td>
<td>30</td>
<td>66</td>
</tr>
<tr>
<td>NDGR + bands</td>
<td>86</td>
<td>38</td>
<td>14</td>
<td>70</td>
</tr>
<tr>
<td>NDGR transform</td>
<td>60</td>
<td>58</td>
<td>40</td>
<td>58</td>
</tr>
<tr>
<td>VARI + bands</td>
<td>**</td>
<td>**</td>
<td>**</td>
<td>78</td>
</tr>
<tr>
<td>VARI transform</td>
<td>**</td>
<td>**</td>
<td>**</td>
<td>74</td>
</tr>
<tr>
<td>NDVI + bands</td>
<td>78</td>
<td>40</td>
<td>22</td>
<td>*</td>
</tr>
<tr>
<td>NDVI transform</td>
<td>66</td>
<td>74</td>
<td>34</td>
<td>*</td>
</tr>
<tr>
<td>SAVI + bands</td>
<td>66</td>
<td>46</td>
<td>34</td>
<td>*</td>
</tr>
<tr>
<td>SAVI transform</td>
<td>46</td>
<td>38</td>
<td>34</td>
<td>*</td>
</tr>
<tr>
<td>SA + bands</td>
<td>68</td>
<td>48</td>
<td>32</td>
<td>*</td>
</tr>
<tr>
<td>SA transform</td>
<td>68</td>
<td>64</td>
<td>32</td>
<td>*</td>
</tr>
</tbody>
</table>

*= no NIR band available to construct these particular transforms
**= no blue band available to construct this particular transforms

**Table 2-8.** Probabilities from t-test analyses comparing accuracy results of classifications by imagery date and imagery scene (study site), for both software approaches.

<table>
<thead>
<tr>
<th>P- values</th>
<th>Comparing Imagery dates</th>
<th>Comparing Imagery scenes</th>
</tr>
</thead>
<tbody>
<tr>
<td>OBIA method</td>
<td>0.6699</td>
<td>0.6361</td>
</tr>
<tr>
<td>Spatial Contextual method</td>
<td>0.0682</td>
<td>0.2602</td>
</tr>
</tbody>
</table>

* significant at the .01 level
** significant at the .001 level
Chapter 3. Patterns of mortality in a montane mixed-conifer forest in San Diego County, California

3.1. Introduction

Montane mixed-conifer forests of San Diego County are currently experiencing extensive tree mortality, which is defined as tree dieback where whole stands are affected. This mortality is likely the result of complex interaction of many variables, such as altered fire regimes, climatic conditions such as drought, as well as forest pathogens and past management strategies. In general, concern over the health of western forests has increased as rates of tree mortality have increased in recent decades (van Mantgem et al. 2009, Millar et al. 2007). Forests are currently experiencing mortality levels outside their historic range of variability (Covington and Moore 1994; Schoennagel et al. 2004, Hessburg et al. 2005, van Mantgem and Stephenson 2007). Several studies demonstrate that the extent and severity of tree mortality increases as a result of increases in stem density, basal area, and reduced tree species diversity – all related to past fire suppression (Savage 1997, Minnich 2007, Brown et al. 2004, North et al. 2007). The principal causes of tree mortality, in addition to fire, are drought, insects and pathogens. However, there is little information on how this mortality affects forest stand structure, composition, and spatial patterns of trees (Smith et al. 2005).

San Diego County’s 97,000 hectares of forests have experienced wildfires, logging, fire suppression, drought, and many more disturbance events over the past
century. Trees within all of the southern California mountains were logged to build houses and produce charcoal in the 1800s. Since then fire suppression and limited forest management have resulted in overcrowded conditions of forest stands, and in the past 10 years, to further stress due to drought (Savage 1997; Minnich 2007).

Increased tree mortality within conifer forests in Southern California was
documented, in conjunction with multi-year droughts lasting from 1975 to 1977, 1988 to 1991, and from 2002 to 2004 (Savage 1994, 1997; Minnich 2007). In some areas, bark beetle populations increased dramatically from their natural low levels in the last
decade, as they attacked and killed drought-stressed trees. Visual forest health surveys by the California Department of Forestry (2004) have estimated that tree
dieback affected 15,000 hectares of San Diego’s forests. In 2003, wildfires burned 29% of woodlands and 33% of all conifer forests in San Diego County. In the aftermath of the 2007 fires it was determined that 37% of San Diego County’s forested areas had been destroyed. This study focuses on unburned remnant forest stands.

Field information about San Diego’s forests is very limited. Stephenson and Calcarone (1999) re-measured plots established in 1934 and showed that mid-elevation mixed conifer forests had more small-diameter trees, fewer large trees (greater than 90 cm dbh), more white fir and incense-cedar, and fewer Jeffrey pine and black oak. Although floristic and stand surveys have been conducted on Palomar Mountain (Lauri 2004; Petit 2006), and mortality conditions have been reported for some areas (White 2005), current data are limited, or not available for all of the study
areas. A better understanding of localized forest structure and composition is essential in order to understand tree mortality patterns at both the local and landscape levels. Furthermore, the theoretical and practical benefits of knowing such patterns include a better understanding of the patterns and drivers of mortality in order to anticipate “tipping points” for large scale die-off, and learning more about the relationship between mortality patterns from fine scale processes (e.g. competition, self-thinning) and from larger spatial scale processes (e.g. drought, and heat stress) (Allen et al. 2010, Dietz and Moorcroft 2011).

An analysis of tree mortality as a spatial phenomenon that changes over time is an important way to further elucidate understanding of dieback in the southern California region. Mortality is not evenly distributed in space, due to differing rates and mechanisms of tree death over the landscape (Franklin et al 1987; Rouvinen 2002). The type of disturbance agent, vegetation patterns and the physical environment all influence the spatial arrangement of tree mortality.

It is helpful to know the spatial patterns of mortality at both the site and landscape level, in order to understand the ecological influences and implications of tree mortality (Franklin et al 1987). Even small changes in mortality rate have been found to have large impacts on tree lifespan, biodiversity, and carbon and nutrient cycling (Franco and Silvertown 1996). There are indications that background mortality rates and episodic die-off events are increasing globally (Allen et al. 2010), and several studies have shown the dramatic effects that these tree mortality events can have on forest dynamics as well as the potential of mortality episodes for driving
the large-scale reorganization of ecosystems (Breshears et al. 2005, Ganey and Vojta 2011).


For this study maps delineating mortality patterns were derived from multiple dates of imagery, for multiple study areas. Then a comprehensive analysis was conducted to further assess the spatio-temporal forms and processes of decline of mixed-conifer forests in San Diego County. Utilizing the most successful, accurate image processing technique determined from a previous study (Freeman et al. submitted), tree dieback maps were manually edited and then analyzed to assess changes in mortality conditions over time and to quantify spatial relationships of dead trees that may be indicative of mortality drivers. Various analytical approaches were used to quantify spatial and temporal changes in tree mortality from 1997 to 2005. The present study is based on the assumption that tree mortality is a spatially diffuse process, initially substantiated by an earlier pilot project that focused on a small area
of Palomar Mountain where the extent of tree mortality spread over time. The following research questions are addressed:

1. How did the tree dieback progress and are there significant shifts over time?
2. What is the spatial pattern of the conifer dieback?
3. Are the dead trees dispersed or clustered, patchy or in complete stands?
4. Is the spatial diffusion of dieback over time homogeneous and omni directional?
5. Which conifer species have been most impacted in terms of mortality?
6. Do observed mortality patterns and field observations indicate particular types of mortality-inducing processes such as pest infestation and diseases, fires, or drought?

3.2. Study Area

Tree mortality was investigated within the montane mixed-conifer forests of San Diego County, California, which occur as ecological “islands” and are found on Palomar Mountain, in the greater Julian area, including Harrison Park, Cuyamaca, Laguna Mountain, Descanso and Pine Valley, and in the Lost Valley area near Warner Springs. These forests occur above elevations of 1100 m in areas that receive more than 50 cm of precipitation. The coniferous forest areas are remnants from a much more widespread forest that was prevalent during the wetter and cooler Pleistocene period (Axelrod 1983). They occur within the Peninsular Ranges, which extend north-south from the San Jacinto wilderness area near Palm Springs to San
Pedro Martir in northern Baja California. The Peninsular Ranges are comprised of a large westerly tilted fault block of Cretaceous granite (Pryde 1992).

This study was conducted for three specific study sites (as illustrated in Figure 2-1, Chapter 2). These three different sites were chosen in order to represent the variety of physical site characteristics and species diversity that are present in the montane areas of the County. Site 1 extends from the Fry Creek Campground area to Palomar State Park on Palomar mountain, and is comprised of Sierran mixed coniferous forest (white fir, incense cedar, Big cone Douglas fir, and Coulter pine), at an elevation of 1500 m and with an annual average rainfall of 120 cm (Lauri 2004).

Site 2 is located in the Volcan Mountains just north of the town of Julian and consists of scattered groves of mostly incense cedar, with smaller amounts of Big cone Douglas fir and Coulter pine on the upper slopes of the West side of the mountains (elevation 1300 m, rainfall 60 cm). Site 3 is located on Laguna mountain, (1800 m) and is almost exclusively Jeffrey pine forest, with an average annual rainfall of 90 cm (Minnich 2007).

3.3. Methods

Imagery from four dates between 1997 and 2005 was subset for the three study areas, and then after collecting calibration and validation data, was classified using a commercial artificial neural network software program (Feature Analyst), to create a single class vector layer of dead conifer trees. In addition, raster classifications were created for each image location and date delineating the extent of
live conifer forest utilizing an object-based image analysis (OBIA) approach (eCognition Version 5). An object-based accuracy assessment was conducted for each product, and manual editing was performed in order to create a product with at least 85% accuracy, in order to facilitate further analysis (Lang 2009). Spatial analysis was then conducted, including cluster analysis and standard deviational ellipses, and then these results were related to forest structure data derived from fieldwork. Figure 3-1 shows the general workflow.

3.3.1. Remote Sensing

3.3.1.1. Image Data

The remote sensing analysis was based on several extant aerial orthorectified and mosaicked image data sets (see Table 3-1). These image data sets were selected because they were readily available for the study areas, and they covered a time period when substantial forest changes appeared to be occurring.

The 1997 and 2002 images are USGS Digital Orthophoto Quarter Quadrangle (DOQQ) data having 1 m spatial resolution for September 1997 and May 2002. They were generated from color infrared (CIR) aerial photographs that were scanned into digital form (green, red, near infrared bands), orthorectified using a digital elevation model (DEM), and georeferenced using surveyed ground control points. The data from 2000 were generated commercially, also by scanning CIR photographs to achieve a 0.6 m spatial resolution, with second generation positioning based on USGS DOQQ data. The 2005 data, from the Natural Resource Council, are true color (blue,
green, red bands) imagery, generated by scanning color aerial photographs, also have 1 m spatial resolution, and correspond to the coniferous forest areas of the county. These image data sets were subset to conform with the spatial extents of the three study areas. Within each montane area, specific study areas were subset to include topographic variation and forest stands of varying sizes.

3.3.1.2. Image processing

Calibration polygons (i.e., training sites) used to establish signature templates for image classification were manually delineated utilizing a systematic aligned approach. A 10 by 10 grid was superimposed over the image, with a point marking the center of each grid cell. From this center point an analyst determined the closest dead tree object, based on color, shape and context, as well as examples of the other classes (oak forest, conifer forest, non-forest), and manually digitized polygons that delineated the objects. In the event that there were no dead tree objects (or other classes) in a given grid cell, the analyst would move on to the next grid cell. In this manner a sufficient sample of dead tree objects was collected. In imagery from 1997, dead tree objects tended to be scattered and fairly rare; a random point generation approach would have missed this class and thus our approach was superior. The training data were then randomly sorted and partitioned into calibration (30 polygons for each class) and validation sets (50 polygons for each class).

The same calibration and validation sets were utilized for analyses of both software approaches. For both calibration and validation objects the minimum
mapping unit was delineated as the size of a tree canopy, which was approximately equivalent to 9 to 16 contiguous 1 m pixels. For the calculation of omission error, validation polygons were also collected for “non-dead tree” objects, utilizing the same method.

3.3.1.3. **Image processing: Dead conifer tree vector maps using spatial contextual approach**

In a previous study (Freeman et al. submitted) it was determined that the most efficient, reliable and accurate way to map dead conifer trees was to utilize a spatial contextual per-pixel artificial neural network software package, Feature Analyst. A masking approach was utilized, where non-forest areas were mapped first and then applied as a mask during the classification of the single dead conifer tree class, in order to reduce error. Transforms were also added to further improve product accuracy. Following image classification with Feature Analyst, the initial vector maps depicting dead tree objects were assessed. Manual editing was then conducted, both to remove false positives, and to add omitted dead tree objects. The resultant products were reassessed using the object-based accuracy assessment. This process, although time consuming, was conducted in order to insure that the derived products were sufficiently accurate for further analysis. The dead tree polygons were then converted into points, to create stem maps for further analysis.
3.3.1.4. Image processing: Live forest/non-forest raster maps using OBIA

After testing several methods it was determined that the most efficient way to map live forest classes was to utilize an OBIA raster classification approach. In order to most effectively and accurately map live conifer trees, the following classes were chosen: live conifers, live non-conifer trees (oaks) and non-forest (vegetation such as grassland, shrubland and bare ground). For the raster maps of live trees, the initial products from the OBIA approach were assessed utilizing a pixel-based accuracy assessment technique, and the accuracies were recorded. Then the live conifer tree portions of the maps were extracted, converted into vector format, manually edited again to remove clutter and add missed live conifer forest objects, and then reassessed, this time with the object-based accuracy assessment method. The live tree polygons were converted into points for further analysis.

3.3.1.5. Accuracy assessment

The object-based accuracy assessment for the dead tree class was conducted using a visually-based comparison method as described in Freeman et al. submitted. This approach determines the “presence” or “absence” of classified objects utilizing a 50% rule. If a mapped dead tree object and a corresponding validation object overlap by more than 50% then the object is considered in agreement or correct; if the overlap is less than 50% then the object is considered to be erroneous. The resultant accuracy is the total number of classified objects meeting this 50% threshold condition, divided by the total number of validation objects (50).
3.3.2. Statistical analysis

3.3.2.1. Density

Tree mortality density (number of dead trees per hectare) was evaluated as the total density at the stand level, for each study area, for each year of imagery, based on the dead tree maps created from the remote sensing classifications. Since the forests in San Diego County typically consist of tightly clustered stands of trees surrounded by expansive areas of grassland or shrubs, density is calculated based on number of dead stems per forested area, instead of total study area. The forested area was calculated based on the remote sensing-derived object-based vector maps of conifer forest. The areas of live tree polygons were calculated in a GIS and added together to determine the total live tree area. Densities were then compared by study area for each date, to analyze change in density of mortality over time. Densities (number of trees per hectare) were also derived for live conifer trees, for each study area. Densities were also calculated for live and dead trees utilizing the plot-based fieldwork data. It is important to note that cumulative density is calculated as the ratio (percentage) of all standing dead trees to live trees, and this ratio is a point estimate including all dead trees, regardless of when they died (Stephens and Gill 2005). In areas where dead trees outnumber live trees, the ratio can exceed 100% (Ganey and Vojta 2011). Median cumulative mortality was also calculated, as the ratio of dead to live trees (Ganey and Vojta 2011). Potential relationships between live and dead tree densities were evaluated using Pearson’s product-moment correlation coefficient (Barber 1988).
3.3.2.2. Mortality rates

The dead and live tree counts that were derived from the object-based maps were utilized to determine mortality rates for the different dates and study sites. These rates were calculated for the time periods 1997 to 2000, 2000 to 2002, and 2002 to 2005 as (Sheil et al. 1995):

\[ m = 1 - \left( \frac{N_1}{N_0} \right)^{1/n}, \]

where \( N_0 \) and \( N_1 \) are counts of trees at the beginning and end of the measurement interval, \( t \).

3.3.2.3. Clustering

Spatial relationships of dead trees were examined for each study area separately using nearest neighbor analysis, which analyzes distances between trees in the point pattern of the image-derived maps. (O’Sullivan and Unwin 2003, Franklin et al. 1985). How this pattern changes over time was also investigated. Additionally, Ripley’s K spatial point pattern analysis was conducted to determine if selected trees were clustered, random or regular in their spatial distribution. Ripley’s K compares distances between all location points in the same plane using the K function to examine spatial associations over a greater range of scales than nearest-neighbor analysis (Ripley 1979, Diggle 1983). This approach summarizes spatial dependence, that is, the clustering and dispersion of features over a range of distances (different scales of analysis) (Michell 2005). Ripley’s edge correction was applied to minimize
edge effects in the analysis. For each study area and date, a 95% confidence interval was calculated using 99 permutations in order to evaluate significant departures from a random distribution (Bailey and Gatrell 1995). The areal extents of this analysis were the areas for each study site. Second order analysis, which includes nearest neighbor analysis and Ripley’s K, is helpful in identifying several important scales of pattern: 1) the distance to nearest neighbor, 2) distance where pattern heterogeneity begins, 3) distance where clustering becomes significant, and 4) distance where maximum clustering is observed (Getis and Franklin 1987).

In addition, determining what the nearest neighbor is also discerns what the spatial lag distance is between tree points, which can illuminate the degree to which variance in the pattern of tree locations depends on distance (Palmer 2002). Variance, by definition, is the square of the standard deviation and is a measure of the spread or variation of data, which is an estimate of spatial correlation (Bivand et al. 2008). Semivariance considers the variance around the mean and also measures how the variance changes as a function of distance. A semivariogram is a plot of semivariance versus the lag distance, and is useful in determining where on the landscape patterns shift between spatially dependent and spatially independent data samples, and thus what the degree and scales are of spatial dependence in the data (Palmer 2002). To this end empirical semivariograms were constructed, and fitted with curves for dead tree density data, for each study area and date, to determine the range of mortality change over distance, and at what spatial scale the correlation may
Semivariograms were also constructed for the 1997 live conifer data for each study area as a comparison.

### 3.3.2.4. Directional change: Standard deviational ellipses

Standard deviational ellipse maps are a visualization tool for examining the spatial spread and directional bias in a point distribution, and how this changes over time. Three components are utilized to define a standard deviational ellipse: the angle of rotation, the deviation along the major axis, and the deviation along the minor axis (Wong 1999). If a set of point locations represents a geographic phenomenon that has a directional bias, then the ellipse can identify the direction with the maximum spread of the points (Lee and Wong 2005). If there is no directional bias, then the resultant figure will be a circle, and if there is homogeneous omni directional change over time, then it would be expected that the circle would spread or contract evenly over time. Conversely, heterogeneous, directional change would result in elongated ellipses, with possible rotation along the long axes (Wong 1999). For example, if a disease impacts a stand of trees, initially infecting a small population, which then spreads from the center outward equally in all directions, the ellipses created from this example could be a small circle, followed by larger circles as time progresses. Or, if an episode of mortality preferentially impacted trees along a dry exposed ridgetop, the axis orientation would reflect the compass orientation of the ridgeline. The length of the axis would reflect the distance the mortality had spread along the ridgetop. Rotation along the ellipse axis will occur if the orientation of the point
spread shifts in a new direction over time. Ellipses were created and compared by study area for each date, to see how the spread and directional bias, if any, changed over time.

3.3.3. Field surveys and forest stand structure analysis

Permits were obtained and field surveys were conducted during the summer of 2008 to determine forest stand structure, mortality conditions and affected conifer species in the following jurisdictional areas: on Palomar Mountain in Palomar State Park and the Fry Creek area of Cleveland National Forest; within the Volcan Mountain Preserve, administered by the San Diego County Parks and Recreation Department; and on Laguna Mountain, which is a part of the U.S. Forest Service Descanso District.

A stratified random sample of 20 meter radius circular plots was surveyed for each study area (Franklin 1998). Logged areas and recent burn areas were excluded from the surveys, to constrain the analysis to mortality agents other than fire or thinning. Data collected in these plots included a census of tree species, health condition of live trees, agents of mortality if possible for dead trees, and the diameter at breast height (dbh) by species. The centers of the plots were recorded using a GPS. An analysis of variance test (Barber 1988) conducted on previously collected forest data indicated that the minimum sample size should be 10 plots per study site: 20 plots were surveyed on both Palomar and Laguna Mountains, and 10 plots were surveyed on Volcan Mountain. The forest stand data were analyzed to determine
stand density, and basal area by species for both live and dead trees, as well as which
tree species and which size-class distributions had the most mortality. The
proportions of live and dead conifers predominant in each study area were compared
using chi-square tests for heterogeneity (Barber 1988).

3.4. Results

3.4.1. Maps of live and dead conifer trees from remote sensing analysis

Image-derived dead and live tree maps were manually edited and re-assessed,
with the results illustrated in Table 3-2. In general, the initial dead tree map
accuracies ranged from 58% to 86%, and after manual editing the resulting improved
map accuracies were 86% to 90%. The live conifer maps had much higher initial
accuracies, from 72% to 96%, with improved maps having accuracies of 86% to 96%.
For maps which already had high accuracies (90% and above), the editing focused on
removing clutter (and not adding missed objects), hence the tree accuracy results did
not change, but the maps were improved. Although it is not known a priori if maps
with 85+% accuracy amounts are the ideal standard for analysis, a reasonable cut-off
was needed, in order to facilitate progress. Further work could determine this more
definitively.

3.4.2. Conifer Density

Image-derived mean cumulative mortality remained fairly static during a five
year period, for the three image dates of 1997, 2000, and 2002, for each study area,
with 4, 2.2, and 4.2 dead conifer trees ha\(^{-1}\) for Palomar, Volcan and Laguna, respectively, as shown in Table 3-3. The 2005 maps show that density of dead conifers increased to 10.3, 7.2 and 5.2 trees ha\(^{-1}\), for the Palomar, Volcan and Laguna study sites respectively. The distinct increase in the density of cumulative mortality for the three year period between 2002 and 2005 occurred across all of the study areas and apparently represents the manifestation of one or more disturbance events that occurred during that time interval, such as the 2002-2003 drought and related pest infestations.

Live conifer densities were derived from the remotely sensed maps as well as from ground-level plot-based estimates from the fieldwork conducted in 2008. The number of live tree objects for the imagery dates 1997, 2000 and 2002 were averaged for each study area and then the mean number of live trees per hectare was calculated by dividing the total number of mean live tree objects by the forested area. Palomar had 113 live conifer trees ha\(^{-1}\) (99 trees ha\(^{-1}\) estimated from field sampling), Laguna had 158 live conifer trees ha\(^{-1}\) (173 trees ha\(^{-1}\) from fieldwork) and Volcan had 107 live conifer trees ha\(^{-1}\), with a field-based estimate of 273 trees ha\(^{-1}\). The disparity in the results for Volcan is likely due to the large closed-crown nature of Incense cedar groves, which host a multitude of younger shade-tolerant trees under the largest mature trees. Many of these younger, understory trees are not captured from the canopy viewing perspective of aerial imagery, but were counted in the field plots.

The ratio of dead to live trees, termed “median cumulative mortality”, was calculated utilizing the numbers of dead and live conifers derived from the remote
sensing classifications for each study area and date. The median cumulative mortality ratios remain consistent for the dates 1997 through 2002, as shown in Table 3-3, and then increase significantly, based on an examination of the standard deviations of the data for 1997-2002, compared with the ratio for 2005. For Palomar, the average was 4% (1997-2002), which increased to 8.6% in 2005; for Volcan the 1997-2002 average was 2.3%, which increased to 15.5% (2005), and for Laguna the initial average of 2.5% rose to 5.4% (2005).

3.4.3. Mortality rates

Conifer tree mortality rates were calculated for each pair of imagery dates, 1997-2000, 2000-2002, and 2002-2005, for each study area. The tree mortality rates for all study sites increase over time, from 1997 to 2005, as shown in Table 3-3. The increase from 2002-2005 is significant for all sites, based on an examination of the standard deviation for the earlier rates. In 2005 Palomar demonstrated a mortality rate of 24.0% year\(^{-1}\), with Volcan at 31.2% year\(^{-1}\), and Laguna at 5.6% year\(^{-1}\).

3.4.4. Spatial distribution of mortality: clustering and spatial scale over distance

The results of the Ripley’s K analysis indicate that the tree mortality exhibits a significantly clustered pattern at multiple scales, for all study areas and all dates. Significant clustering of dead trees occurs at spatial scales of approximately 40 meters and continues until around 4000 m, where the tree pattern becomes
significantly dispersed. The live trees also exhibit a clustered pattern for all of the study areas and dates.

Distance to nearest neighbor (the distance between dead trees) decreased over time for the Palomar and Volcan study sites from 1997 to 2005, from 195 m to 64 m, and 132 m to 55 m respectively. This is presumably due to an increase in the density of the dead trees over time. For Laguna distance to nearest neighbor remained fairly static at around 87 m.

The curves fitted to the empirical semivariograms demonstrate a classic shape, as shown for a generic plot in Figure 3-2a and for the Palomar 2005 data plotted in Figure 3-2b. The nugget is where the curve crosses the y-axis, in this case zero, with nugget values greater than zero generally indicating noise or error in the data (Palmer 2002). The sill is the y-value where the curve tapers off, and a higher value indicates greater variance in the data. The partial sill is the sill minus the nugget, which in the case of all of the results from this study (except for one), is equal to the sill, as can be seen in Table 3-4. The range is the x-value at the point where the curve flattens. For distances less than R spatial dependence exists, while sample points separated by distances greater than R would be considered to be spatially independent, and conventional statistics could be applied with validity (Bivand et al. 2008).

The semivariograms constructed with the dead (and live) tree density data exhibit distinct ranges that vary by date and study area. The ranges for all study areas combined vary from 474 to 2878 meters for the dead trees, and 182 to 2668 meters.
for the live trees. Generally, the ranges for all study areas increase over time from 1997 to 2002, and then become smaller again in 2005.

3.4.5. Directional changes over time

A comparison of standard deviational ellipses for each study area, compiled by date, reveals that there is a directional bias for each of the study areas. The data from Palomar demonstrate a NW trend on the long axis for all dates. The long axis of the ellipses for Volcan are oriented just slightly west off of the N-S axis. The ellipses for Laguna are oriented NNW along their long axes. Overall the rotation of the ellipses did not shift substantially over time. What the ellipses do show is a contraction in the dispersion of points by the 2005 date, indicated by their smaller size, which may be a function of continued intensification of mortality in the centers of the study areas (Figure 3-3). The exception to this is the Laguna study site, which agrees conceptually with the static distance to nearest dead neighbor analysis. There is no evidence of an outward dispersion or spreading (omnidirectional or otherwise) of the point data over time, or the diffusion of points from one location to another over time.

3.4.6. Species distribution of tree mortality

From the 2008 field survey a total of 1743 trees were recorded and measured (1227 live trees and 516 dead trees). Conifer mortality was pervasive, and occurred in 100% of the 50 plots surveyed. Seven tree species in total were found across all the
plots (five conifer and two oak species), although not all species were present in all of the study areas and/or plots. The five conifer species present were: Jeffrey pine (*Pinus jeffryi*), Coulter pine (*Pinus coulteri*), Incense cedar (*Calocedrus decurrens*), White fir (*Abies concolor*), and bigcone Douglas-fir (*Pseudotsuga macrocarpa*). Two oak species were also present in the plots: Canyon live oak (*Quercus chrysolepis*) and Coast live oak (*Quercus agrifolia*). The oak data, however, was not included in this analysis, and will be addressed in follow-on research.

The predominant conifer species in the Palomar study area is White fir. White fir constitutes 55% of the conifer stem population, with 65% of the conifer basal area, 44% of the stem population for all trees, and 44% of the basal area for all tree species present in the plots. In the Volcan study area the dominant conifer species is Incense cedar, constituting 95% of the total conifer stems, 83% of the total stem population for all tree species, 92% of total conifer basal area, and 56% of the total basal area of all trees present in the plots. The predominant conifer species in the Laguna study area is Jeffrey pine, comprising 96% of conifer stems and 86% of total tree stems, with 99% of the conifer basal area and 67% of the total basal area for all tree species.

At the landscape level, for all study sites combined, the greatest proportion of dead trees (in terms of number of stems) were White fir (54% dead) followed by incense cedar (32% dead), and then Jeffrey Pine (23%), Coulter pine (17%) and Big cone Douglas fir (16%), as shown in Table 3-5. When considering basal area (that is the areas of all of the measured trees’ cross sections added together) for all species, the greatest amount and proportion of dead tree basal area for all study sites combined
was White fir (with 41 m², 62%), followed by Jeffrey Pine (27 m², 23%), and then Incense Cedar (11 m², 9%), as shown in Table 3-6.

At the local level, a large variation in both the amounts of dieback and species affected was observed across the three study areas. Specifically, the number of live and dead trees varied for each tree species, for each study area, for both stem count and basal area. In the Palomar study site White fir had the largest proportion of dead tree stems and dead tree basal area (55% and 40 m²). Incense cedar had the greatest proportion of mortality (36% stems and 8 m² basal area) for the Volcan study area. For the Laguna study site, which had neither White fir nor Incense cedar, the greatest proportion of conifer mortality occurred with the Jeffrey pines (23% stems, 27 m² basal area). Several chi-square tests were conducted to compare the proportions of live and dead trees for White fir, Incense cedar and Jeffrey pine, and the results indicate that the proportions are significantly different (at the 0.001 level) for each species.

When total tree stems are combined, 37% of the conifer tree stems were dead (31% of the total trees) for the Palomar study site, with 35% of the conifer trees dead (33% of the total trees) for Volcan and 23% of conifer trees dead (25% of the total trees) within the Laguna site. The totals for percent of dead conifer tree basal area per study area are 50% for Palomar, 35% for Laguna, and 9% for Volcan.
3.4.7. Diameter distribution of dead versus living trees

The diameter distributions of the live and dead tree species from the plot data were compared. In general, each study site exhibited different patterns of mortality, in terms of which species had the greatest mortality, and in which size classes (Table 3-7). It is helpful to investigate these patterns for all trees combined, as well as for the dominant conifer tree species, for each study area.

For the Palomar study area, when all the tree species were combined, the diameter distributions of live trees had a reversed J-shape, demonstrating a greater number of stems in the lower size classes, and subsequently fewer in the larger size classes (Figure 3-4). However, numbers of dead trees are fairly static in their distribution across the size classes. The greatest proportion of dead to live trees is found in the greatest diameter classes (80 cm and higher), indicating that the largest, oldest trees had experienced the highest levels of mortality.

In the Palomar study site White fir had a total mortality proportion of 55%, with the greatest amounts and proportions of mortality were high across the range of diameter classes, as shown in Figure 3-5. Of all of the conifer species at the Palomar study site, White fir had the greatest total amount and proportion of mortality by total number of trees (live and dead) per species.

The diameter distributions of the trees in the Volcan study area, as shown in Figure 3-6, demonstrate that the greatest numbers of live trees are found in the 35 to 49 cm diameter class. The diameter distributions of the dead trees had a reversed J-shape, with the greatest amount of dead stems in the smallest size class, followed by
fewer in the next two larger size classes, with almost no mortality in the last four size classes.

In the Volcan study site Incense cedar has a total mortality proportion of 36% for stems and 7% of basal area. The greatest proportion of Incense tree mortality, as shown in Figure 3-7, occurs in the 10 to 19 cm diameter class, with smaller amounts in the next two size classes and almost none in the largest size classes. This pattern indicates that the youngest trees had experienced the greatest mortality, and the oldest trees the lowest levels.

The diameter distributions of the trees in the Laguna study area, as shown in Figure 3-8, also demonstrate a pattern where the greatest numbers of live trees are found in the 35 to 49 cm diameter class, with all of the other classes having fewer trees. Dead trees are fairly evenly distributed across all of the size classes; however, the greatest proportion of mortality (43%) is found in the largest size class, which represents the oldest trees.

In the Laguna study area Jeffrey pine has a total mortality proportion of 23% for stems and 25% of basal area. The greatest amount of both live and dead Jeffrey pines occur in the 35 to 49 cm diameter class, with the greatest proportion (7 out of 9 trees) of mortality in the largest diameter class, as shown in Figure 3-9. For this study area mortality was fairly evenly proportioned across the diameter classes.
3.4.8. Conifer tree mortality conditions

Based on field observations, many of the dead trees showed no visible signs of external biotic or abiotic causes of mortality. Around 50% of the white firs showed signs of attack from wood boring insects, with holes in the bark and excessive sap on the trunks, and around 20% of the white firs, typically those with the largest diameters, had White fir dwarf mistletoe present. It was difficult to detect any insect damage with the Incense cedars and Big cone Douglas firs, probably due in part to their thick bark. It was also difficult to determine the exact pathway of mortality for most of the dead trees due to the length of time since death. Very few of the trees had died within the year previous to field observations, as would be indicated by dead needle retention. Most trees had experienced complete loss of needles, some loss of bark and occasionally more advanced wood decay, indicating earlier mortality, most likely during the catastrophic dieback period of 2002 to 2004.

3.5. Discussion

3.5.1. Spatial and temporal patterns of conifer mortality at the landscape level

At the landscape level, across all three study areas, the spatial and temporal patterns of conifer mortality were very similar. In all areas a distinct increase in the amount of cumulative mortality occurred during the same time period (2002 to 2005), even though for each study area a different species was dominant in terms of greatest amount of mortality. This is strong evidence supporting a drought-driven mechanism for the mortality. Since tree diseases and insect pests tend to be host specific, a single
causal biological agent cannot be responsible for the ubiquitous mortality in multiple conifer species, during the same time period. Rather, drought stresses trees significantly, making them less resistant to multiple diseases and insect pests (Allen et al. 2010). In addition to ongoing long-term drought conditions in the west since the 1980s, rainfall levels in San Diego county forests dropped dramatically, to the lowest level since instrumental records were started in 1849, during the 2001-2002 growing season (2002 water year) and continuing through 2004. These exceptionally low rainfall totals likely account for the distinct increase in tree mortality we infer from the remotely sensed imagery captured between May 2002 and 2005.

Both live and dead conifer trees had significantly clustered distribution patterns, for all dates. The dead trees form distinct spatial groupings, as opposed to a situation where the deaths of single trees form a spatially random pattern. Conifer mortality occurs where conifers grow, which tend to be in patches spread non-uniformly across the landscape (Minnich 2007), thus resulting in clustering of both live and dead conifer trees.

The results of the semivariogram analysis indicate that there are definite inflections in curves, which most certainly relate to different processes operating at different scales. Palmer (2002) asserts that semivariograms demonstrate pattern in the data, but it is up to the researcher to infer processes underlying those patterns which match the corresponding spatial size of the range value. The range values, which are from 20 to 50 meters in size for this study, are too large to be explained as relating to canopy gap sizes (which would be on the order of 10 m or so), but could
be related to patch sizes of dead trees. The expansion of the range values over time
fits in nicely with this idea: as more trees die over time, due to an increase in
mortality rates over time, the patches of dead tree occurrences increase in size as well.
Note that the range values for the 1997 dead trees also correspond to the 1997 range
values for live trees. Then there is the contraction of the range values between 2002
and 2005, which is puzzling. What can be said is that whatever the underlying process
is, the distance of spatial dependence for dead tree densities expands from 1997 to
2002, and then contracts between 2002 and 2005.

For all study areas the spatial diffusion of mortality over time was fairly
homogeneous, but not omni directional. The spread of mortality occurred
homogeneously within patchy forest clumps, as a function of increasing density of
tree mortality. The distinct long axes of the ellipses, however, indicate directionality.
These axes tend to be oriented in same direction as the longitudinal forested ridges
that occur in each study area. On Palomar the ridges trend in a NW-SE direction,
while in the Volcan study area the ridges trend in a N-S direction. In the Laguna
study area the ridges and meadows separating the forested areas trend in a N-S
direction. That the axes tend not to shift over time is probably a function of the
underlying topographic structure of the overall landscape.

Based on the amount of clustering in the dead tree data set, dieback is more
prevalent in some areas than others. Again, this is partly due to the presence of live
conifer forests in certain areas and not others, and other physical factors that influence
the distribution of tree mortality. Note that the N-S ridge orientations discussed above
result in east and west facing forested slopes, which have implications for solar insolation, precipitation variability and evapotranspiration amounts, typically with west facing slopes being warmer, drier, and having higher evapotranspiration rates. The degree to which variation in such factors as elevation, precipitation, slope, and aspect correlate with tree mortality levels is the topic of the next chapter.

3.5.2. Relating mortality patterns to stand structure and species distributions

At the local stand level, patterns of mortality appear to be closely tied to forest species composition and the natural history traits of individual species. Each of the study areas had slightly different species assemblages, with different predominant species: White fir on Palomar, Incense cedar on Volcan, and Jeffrey pine on Laguna. Each of these species also experienced the greatest amount of mortality at each site respectively, based on tree basal area calculations. Within each study site, and for each species, the distribution of live and dead trees across diameter classes also varied.

For the Palomar study area, the greatest number of live White fir trees was found in the smallest size class (10-19 cm), while the greatest number of dead trees was found in the small (10-19 cm) and mid-size class (35-49 cm), although the distribution of mortality was fairly even across several classes (see Figure 3-4). The “reverse J” pattern of live trees indicates a forest where successful recruitment of young trees results in a large amount of individuals in the smallest size class. Subsequently, fewer trees in the larger size classes as trees grow, compete with one
another for limited resources, and only a few survive to grow into the largest diameter trees. The proportions of mortality were spread across all diameter size classes, indicating that all sizes and ages of White fir were impacted similarly by mortality processes.

White fir is considered to be a shade tolerant and drought intolerant species, usually occurring in the understory of Sierran type mixed-conifer forests (Valladares and Niinemets 2006). If growth conditions are optimal for several seasons, then overstocking can occur, and if resources become scarce again (e.g., due to a drought), then dramatic mortality can ensue. Smith et al. (2005) found that in the Sierra Nevada white fir tended to grow in very dense thickets, and was the dominant species of dead trees in all field plots that they sampled.

In the case of Palomar there has not been a history of modern extensive forest management, such as thinning or controlled burns. Prior to the 2003 and 2007 fires, there were no recorded stand fires in the study area since at least 1910 when records were first kept (Fire Resource Assessment Program database – frap.cdf.ca.gov). Although the forests were logged heavily at the turn of the 20th century, most stands have since returned to robust second growth conditions, and some larger trees are over 200 years old (Everett 2008).

For the Volcan study area, the greatest amount of live Incense cedars was found in the mid-size diameter class (35-49 cm), with the greatest amount and proportion of dead cedars found in the smallest size class (10-19 cm). The distribution pattern of mortality across diameter classes is a reverse J pattern, with the
greatest amount of mortality in the smallest classes and then progressively less with each size class. Thus it has been the youngest trees that have been impacted by mortality. Incense cedar is also considered to be a shade tolerant species, and is again susceptible to overstocking, and then self-thinning when growing conditions are no longer optimal (van Mantgem et al. 2003, Minnich 2007).

In the Laguna study area the greatest amount of live Jeffrey pines was in the mid-size diameter classes (35-64 cm), with the greatest amount and proportion of dead pines found also in the same range. For Jeffrey pine, the mortality tends to be proportional across all of the size classes. These are all indications of a more youthful stand, with solid recruitment of young trees and a large proportion of mid-size trees, but significantly less of the larger diameter old trees. Laguna Mountain has experienced more extensive forest management than the other study areas, including controlled burns and selective cutting and brush mastication programs (USDAFS 2010).

A key contributing factor to mortality conditions and subsequent forest structure can most certainly be tree densification, which has been often cited in other studies as an important factor (van Mantgem et al. 2003, North et al. 2004, Minnich 2007). One would expect that forests, or areas within the forest, with higher tree densities would experience greater levels of mortality, due to increased competition for resources. When plot densities are examined, this pattern appears to hold true for two of the study areas. Figure 3-10 shows the scatter plots, with fitted trend lines, for numbers of live and dead conifer trees for each of the field-based study plots for each
of the three study areas. For both the Palomar and Volcan study areas, the trend lines suggest that for study plots with a greater number of live trees, there were also a greater number of dead trees. The results of the Pearson’s product-moment correlation analysis support this, for Volcan with $r = 0.67$ ($p = .017$), and for Palomar $r = 0.39$ ($p = .044$), both are significant at the $p = .05$ level. For the Laguna study area however, there was no increase or decrease in amount of mortality, with an increase in trees per plot ($r = -0.023$, $p = .461$, not significant). This probably relates to the more even-aged character of the Jeffrey pine stands in Laguna., the assumption here being that densification can be one of the primary drivers of increased tree mortality in the plots, and because of past thinning procedures in Laguna the trees are not only not growing as densely, but there are not a lot of younger trees and very old trees, which in the other sites tend to have the highest mortality rates.

In terms of overall cumulative density at the landscape level, the hypothesis that greater forest density leads to a greater incidence in tree mortality does not appear to be confirmed in the present study. The highest cumulative live tree density for all field plots occurred in the Volcan study area (276 trees ha$^{-1}$ basal area live trees 82 m$^2$ ha$^{-1}$), which also had the lowest amount of tree mortality (8 m$^2$ ha$^{-1}$). The Laguna study area had lower live tree density (173 trees ha$^{-1}$, basal area m$^2$ ha$^{-1}$), and a greater amount of tree mortality (11 m$^2$ ha$^{-1}$). The Palomar Study area had the least density of live trees (99 trees ha$^{-1}$, 20.7 m$^2$ ha$^{-1}$ basal area), but also had the highest amount of mortality for the three study sites (18 m$^2$ ha$^{-1}$). It is important then, to understand the
fine-scale patterns of localized clustering for both live and dead trees, since combining data at the landscape level may obscure spatial patterns. Examining the range values of the semivariograms gives the threshold at which these scale changes occur, and can help define for each time period and study area what “localized” means.

Differences in tree densities and tree mortality levels between the study areas may also be attributable to differences in forest characteristics, including different dominant conifer species. The results of the chi-square tests support this idea, with the proportions of dead and live trees being significantly different (at the 0.001 level) for each of the dominant conifer species. It may well be that the natural history traits of the Incense cedar at the Volcan study site allow for increased density without resulting mortality. With deep tap roots and thick pest-resistant bark, young trees may be better adapted to suppressed growing conditions for decades, waiting in the shade of the dominant trees for a gap to form. The white fir, which predominates on Palomar, has been shown to be more susceptible to mortality, than Incense cedar, and Jeffrey pine (van Mantgem et al. 2003, Minnich 2007).

In terms of conifer mortality levels, the amounts observed from both the field plot data and remote sensing analysis are substantially higher than those reported from other Sierran mixed-conifer forests. The cumulative mortality for the Palomar, Volcan and Laguna study areas combined as measured by standing dead trees was 31%, as compared to cumulative mortality of 8.7%, derived from fieldwork conducted in 2000, in the Teakettle Experimental Forest (Smith et al. 2005),
cumulative mortality of 14.0% for forests in the Lake Tahoe Basin (Barbour et al. 2002) (field dates not given), and 12.7% cumulative mortality for forests in the Sierra San Pedro Martir National Park of Baja, Mexico (field dates not given), with mean annual mortality rates reported as being less than 1% year$^{-1}$ (Maloney and Rizzo 2002). In addition, Ganey and Vojta (2011) reported mortality rates in the range of 0-28.5% year$^{-1}$ (median was 2.0% year$^{-1}$), for mixed conifer forests in Arizona for the time period 1997 to 2007. The range of mortality rates for the San Diego forests is 0.3% to 31.2% year$^{-1}$ (median was 4.65% year$^{-1}$), for 1997 to 2005. The comparatively high amount of cumulative mortality as well as relatively high mortality rates for the forests of San Diego County are indicative of severe forest health problems, as many workers consider that a sign of unhealthy forests are mortality rates outside of the historic range of variability (Smith 2005, Savage 1997, Minnich 2007).

3.6. Summary and Conclusions

At the landscape level, the amount of cumulative tree mortality remained fairly static for all study areas from 1997 to 2002, and then accelerated between 2002 and 2005. The image-derived mean mortality from 1997 to 2002 was 4 trees ha$^{-1}$ for Palomar, 2.2 trees ha$^{-1}$ for Volcan, and 4.2 trees ha$^{-1}$ for Laguna. Between 2002 and 2005 there was a distinct increase in the amount of dead conifer density to 10.3, 7.2 and 5.2 trees ha$^{-1}$, for Palomar, Volcan, and Laguna respectively. Median cumulative mortality ratios also remained steady from 1997 to 2002, with 4%, 2.3%, and 2.5%
for Palomar, Volcan and Laguna, then increased to 8.6%, 15.5% and 5.4% between 2002 and 2005. The mortality rates showed a steady increase through time, with the lowest range from 1997 to 2000 (.3% to .6 % year⁻¹), followed by the range of 2.2% to 8.9% year⁻¹ from 2000 to 2002, and then a distinct increase to a range of 5.6% to 31.2% year⁻¹ between 2002 and 2005. The notable increase in mortality seen in the imagery captured in May 2002 and September 2005, coincided with a severe drought in Southern California.

The spatial pattern of dead trees is significantly clustered at multiple spatial scales (typically significant clustering is observed beginning from 20 m to 40 m extending to 4000 m to 5000 m), for all dates and study areas, for both live and dead trees. This corresponds with the patchy nature of conifer trees in the study forests, as well as specific site factors that certainly influence localized mortality levels. Over time, trees continued to die within clustered groups, intensifying in numbers within forest patches. Again, the most relevant result revealed in this study is the substantial increase in mortality between 2002 and 2005.

The spatial diffusion of mortality over this time period is neither homogeneous, nor omni directional at local and landscape levels. The patchiness and directionality of the mortality is likely influenced by the patchiness and orientation of the forest stands themselves. There did not appear to be a pattern of mortality starting in one area and then spreading outward over time as one might expect in the case of an outbreak of disease. Rather, the forest areas experienced localized densification of
tree mortality within stands, particularly between 2002 and 2005, and this occurred over the entire landscape.

Certain areas are more affected than others in terms of mortality conditions, which may relate to multiple factors, such as physical site conditions like topography, elevation, climate variation (which will be investigated in the next chapter) or also forest density. For Palomar and Volcan, plots with a greater density of live conifer trees demonstrated a greater number of dead trees, so it may be assumed that specific areas in the landscape are more prone to mortality conditions. Further analysis is warranted to consider the particular localized factors influencing these patterns.

In terms of the amount of basal area, White fir was the most impacted species over the entire landscape, most certainly due to its growth habits, as a shade-tolerant species that tends to grow in dense thickets during optimal growth periods and then becomes more prone to dieback in less than optimal conditions. Not only did young trees show distinct levels of mortality, but all class sizes, and therefore ages, of trees were impacted dramatically.

It is clear that the severe multi-year drought of 2002 to 2004 was the primary driver for the increased mortality that was observed between the 2002 and 2005 images. The large-scale mortality patterns observed across all study areas, with multiple tree species affected, are indications of the rapid impacts that this drought had on San Diego County’s forests. The impacts of pathogens and pests were exacerbated by the drought as lowered sap pressure impeded trees’ abilities to defend against predators and disease, in addition to other impacts.
There is a growing realization that healthy forests cannot be maintained by preventing them from changing, rather land managers need to employ methods of active forest management in order to sustain healthy forest ecosystems (Porter 2005). Best management practices are guided by better understanding of the dynamics at both the local and landscape levels (Graetz 1990). As demonstrated by this study, processes can exhibit consistency over large areas, such as extensive tree mortality occurring during the same time frame with the same basic spatial pattern, but the same processes can then exhibit significant differences when examined at a finer scale (Royle 2002). In the present analysis, mortality impacted different species within each study area, in areas with differing forest structures, in differing amounts. Any mitigation would require an understanding of these site differences, underscoring the importance of using high resolution remotely sensed imagery for analysis, as well as fieldwork to complement the spatial data with finer-scale information (Blaschke 2010; Stoltman and Fraser, 2000).

Ultimately, the build-up of fuels in forests in San Diego County contributed to the large-scale wildfires in 2003 and 2007, which further highlighted the potential threats that increases in vegetation mortality can pose when left in situ (Porter 2005). Dramatic fuel-load reduction programs have been undertaken, to try and reduce future catastrophes, but in the absence of regular wildfires or other processes which thin forests, older forests with dense stands of long-lived conifer species will continue to be at risk for extensive mortality conditions (Minnich 2007).
**Figure 3-1.** General workflow for the data preparation and analysis in this chapter. The same set of remotely-sensed imagery was utilized to create dead conifer tree maps with one software application, and another application was utilized to create live conifer maps. The resulting products were utilized to conduct a spatial analysis of their point distribution patterns. Plot-based fieldwork results were utilized to conduct an analysis of stand structure and stem diameter distribution patterns. The results from both of these analyses were combined for a multi-scale analysis of forest dynamics.
Figure 3-2a. Generic semivariogram showing the nugget, sill and range.

Figure 3-2b. An empirical semivariogram fitted with a curve for dead tree density data from Palomar, 2005. The nugget is zero (0,0), the partial sill is 52.32 feet (15.95 m), the range is 2562 feet (781 m), and the lag size is 392 feet (199 m).
Figure 3-3a. Standard Deviational Ellipses for the Palomar study area. Ellipses were created for each imagery-derived dead tree point map data set, 1997 through 2005. Note the contraction of the ellipse from the earliest date, 1997, to the latest date of 2005.

Figure 3-3b. Standard Deviational Ellipses for the Volcan study area, for each imagery-derived dead tree point map data set, 1997 through 2005.
Figure 3-3c. Standard Deviational Ellipses for the Laguna study area, for each imagery-derived dead tree point map data set, 1997 through 2005.

Figure 3-4. Diameter distribution of total live and dead conifer trees for the Palomar Study area. The tree diameters measured at breast height (dbh) are given in centimeters.
**Figure 3-5.** Diameter distribution of live and dead incense cedar and white fir trees for the Palomar study area.

**Figure 3-6.** Diameter distribution of total live and dead conifer trees for the Volcan Study Area.
**Figure 3-7.** Diameter distribution of live and dead incense cedar trees for the Volcan Study Area.

**Figure 3-8.** Diameter distribution of total live and dead trees for the Laguna Study Area.
Figure 3-9. Diameter distribution of live and dead Jeffrey pines for the Laguna Study Area.

Figure 3-10. Tree densities in field plots for both live and dead trees for each study area.
Tables

**Table 3-1.** Remotely sensed imagery data sets, 1997 – 2005, that were utilized to create maps of both live and dead conifer trees, for the three study areas on Palomar Mountain, Volcan Mountain, and Laguna Mountain.

<table>
<thead>
<tr>
<th>Date Flown</th>
<th>Spectral bands</th>
<th>Resolution</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>May, 1997</td>
<td>3-band CIR NIR, R, G</td>
<td>1 m</td>
<td>U.S.G.S. Digital Orthophoto Quarter Quadrangle</td>
</tr>
<tr>
<td>July, 2000</td>
<td>3-band CIR NIR, R, G</td>
<td>0.6 m</td>
<td>Commercial product</td>
</tr>
<tr>
<td>May, 2002</td>
<td>3-band CIR NIR, R, G</td>
<td>1 m</td>
<td>U.S.G.S. Digital Orthophoto Quarter Quadrangle</td>
</tr>
<tr>
<td>September, 2003</td>
<td>3-band RGB</td>
<td>1 foot</td>
<td>U.S.D.A. Natural Resource Council</td>
</tr>
</tbody>
</table>

**Table 3-2.** Accuracy results for dead conifer tree maps and live conifer tree maps. Results are presented for both the original maps, and then the maps after they were manually edited.

<table>
<thead>
<tr>
<th></th>
<th>Dead Conifer Tree Map Accuracies</th>
<th>Live Conifer Tree Map Accuracies</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Palomar</td>
<td>Volcan</td>
</tr>
<tr>
<td>Editing:</td>
<td>Pre</td>
<td>Post</td>
</tr>
<tr>
<td>1997</td>
<td>68%</td>
<td>86%</td>
</tr>
<tr>
<td>2000</td>
<td>70%</td>
<td>86%</td>
</tr>
<tr>
<td>2002</td>
<td>84%</td>
<td>88%</td>
</tr>
<tr>
<td>2005</td>
<td>74%</td>
<td>86%</td>
</tr>
</tbody>
</table>
Table 3-3. Density of dead trees, median cumulative mortality (ratio of dead/live trees), and mortality rates for dead conifers. All measures based on tree counts derived from remotely sensed imagery.

<table>
<thead>
<tr>
<th></th>
<th>Density, dead trees per hectare</th>
<th>Median cumulative mortality</th>
<th>Mortality rates, % per year</th>
</tr>
</thead>
<tbody>
<tr>
<td>Palomar</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1997</td>
<td>3.80</td>
<td>4.00%</td>
<td></td>
</tr>
<tr>
<td>2000</td>
<td>4.50</td>
<td>3.80%</td>
<td>0.30%</td>
</tr>
<tr>
<td>2002</td>
<td>3.80</td>
<td>4.20%</td>
<td>8.90%</td>
</tr>
<tr>
<td>2003</td>
<td>10.30</td>
<td>8.60%</td>
<td>24.00%</td>
</tr>
<tr>
<td>Volcan</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1997</td>
<td>2.18</td>
<td>2.10%</td>
<td></td>
</tr>
<tr>
<td>2000</td>
<td>2.20</td>
<td>2.10%</td>
<td>0.50%</td>
</tr>
<tr>
<td>2002</td>
<td>2.34</td>
<td>2.60%</td>
<td>2.90%</td>
</tr>
<tr>
<td>2003</td>
<td>7.2</td>
<td>15.50%</td>
<td>31.20%</td>
</tr>
<tr>
<td>Laguna</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1997</td>
<td>4.08</td>
<td>3.30%</td>
<td></td>
</tr>
<tr>
<td>2000</td>
<td>4.14</td>
<td>2.20%</td>
<td>0.60%</td>
</tr>
<tr>
<td>2002</td>
<td>4.34</td>
<td>2.00%</td>
<td>2.20%</td>
</tr>
<tr>
<td>2003</td>
<td>5.06</td>
<td>5.40%</td>
<td>5.60%</td>
</tr>
</tbody>
</table>
Table 3-4. Semivariogram parameters for models fit to empirical semivariograms constructed from trees densities for each study area and date. All distances are given in meters.

<table>
<thead>
<tr>
<th></th>
<th>Nugget</th>
<th>Range</th>
<th>Partial Sill</th>
<th>Lag size</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>DEAD CONIFERS</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Palomar</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
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<td>1997</td>
<td>0</td>
<td>185.55</td>
<td>726599.92</td>
<td>21.71</td>
</tr>
<tr>
<td>2000</td>
<td>0</td>
<td>190.42</td>
<td>669724.54</td>
<td>22.97</td>
</tr>
<tr>
<td>2002</td>
<td>0</td>
<td>1011.10</td>
<td>669724.5</td>
<td>142.07</td>
</tr>
<tr>
<td>2005</td>
<td>0</td>
<td>781.12</td>
<td>13.95</td>
<td>119.38</td>
</tr>
<tr>
<td>Volcan</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1997</td>
<td>0</td>
<td>591.37</td>
<td>35.06</td>
<td>73.54</td>
</tr>
<tr>
<td>2000</td>
<td>0</td>
<td>764.07</td>
<td>154.63</td>
<td>102.13</td>
</tr>
<tr>
<td>2002</td>
<td>215460.68</td>
<td>2878.37</td>
<td>646223.55</td>
<td>381.92</td>
</tr>
<tr>
<td>2005</td>
<td>0</td>
<td>659.40</td>
<td>24.63</td>
<td>79.73</td>
</tr>
<tr>
<td>Laguna</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1997</td>
<td>0</td>
<td>1198.66</td>
<td>967478.48</td>
<td>144.94</td>
</tr>
<tr>
<td>2000</td>
<td>0</td>
<td>1079.93</td>
<td>835631.76</td>
<td>132.44</td>
</tr>
<tr>
<td>2002</td>
<td>0</td>
<td>409.99</td>
<td>0.95</td>
<td>45.74</td>
</tr>
<tr>
<td>2005</td>
<td>0</td>
<td>474.06</td>
<td>2.69</td>
<td>52.82</td>
</tr>
<tr>
<td><strong>LIVE CONIFERS</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Palomar</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1997</td>
<td>0</td>
<td>182.69</td>
<td>676378.94</td>
<td>23.45</td>
</tr>
<tr>
<td>Volcan</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1997</td>
<td>0</td>
<td>2668.97</td>
<td>127.53</td>
<td>320.01</td>
</tr>
<tr>
<td>Laguna</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1997</td>
<td>0</td>
<td>1190.99</td>
<td>977368.63</td>
<td>144.94</td>
</tr>
</tbody>
</table>
Table 3-5. A. Numbers of measured live and dead conifer trees (2008), and percent of dead trees, from the field plots, by species, for each study area. The total percent of dead trees per study area is given at the bottom of the table.

An * indicates that the species is not present in the study plots.

<table>
<thead>
<tr>
<th>Tree Species</th>
<th>Palomar</th>
<th></th>
<th></th>
<th>Volcan</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Live</td>
<td>Dead</td>
<td>% Dead</td>
<td>Live</td>
<td>Dead</td>
<td>% Dead</td>
</tr>
<tr>
<td>Western Yellow Pine</td>
<td>4</td>
<td>0</td>
<td>0</td>
<td>*</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>Coulter Pine</td>
<td>7</td>
<td>0</td>
<td>0</td>
<td>17</td>
<td>3</td>
<td>15%</td>
</tr>
<tr>
<td>Incense Cedar</td>
<td>112</td>
<td>20</td>
<td>15%</td>
<td>325</td>
<td>186</td>
<td>36%</td>
</tr>
<tr>
<td>White Fir</td>
<td>98</td>
<td>119</td>
<td>55%</td>
<td>4</td>
<td>1</td>
<td>20%</td>
</tr>
<tr>
<td>Big Cone Douglas Fir</td>
<td>27</td>
<td>5</td>
<td>16%</td>
<td>*</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>Total number of trees</td>
<td>248</td>
<td>144</td>
<td></td>
<td>346</td>
<td>190</td>
<td></td>
</tr>
<tr>
<td>Total % of dead trees per study area</td>
<td></td>
<td></td>
<td>37%</td>
<td></td>
<td></td>
<td>35%</td>
</tr>
</tbody>
</table>
B. Numbers of measured live and dead conifer trees (2008), and percent of dead trees, from the field plots, by species, for all study areas combined, and the total percent of dead trees for all study areas.

<table>
<thead>
<tr>
<th>Tree Species</th>
<th>Live</th>
<th>Dead</th>
<th>% Dead</th>
</tr>
</thead>
<tbody>
<tr>
<td>Western Yellow Pine</td>
<td>421</td>
<td>127</td>
<td>23%</td>
</tr>
<tr>
<td>Coulter Pine</td>
<td>41</td>
<td>7</td>
<td>17%</td>
</tr>
<tr>
<td>Incense Cedar</td>
<td>437</td>
<td>206</td>
<td>32%</td>
</tr>
<tr>
<td>White Fir</td>
<td>102</td>
<td>120</td>
<td>54%</td>
</tr>
<tr>
<td>Big Cone Douglas Fir</td>
<td>27</td>
<td>5</td>
<td>16%</td>
</tr>
<tr>
<td>Total number of trees</td>
<td>1028</td>
<td>465</td>
<td></td>
</tr>
<tr>
<td>Total % of dead trees per study area</td>
<td></td>
<td></td>
<td>31%</td>
</tr>
</tbody>
</table>
Table 3-6. A. Basal area of measured live and dead conifer trees, and percent of dead trees, from the field plots, by species, for each study area. The total percent of dead tree basal area per study area is given at the bottom of the table, along with the total percent of dead tree basal area for all study areas.

<table>
<thead>
<tr>
<th>Tree species</th>
<th>Palomar</th>
<th></th>
<th></th>
<th>Volcan</th>
<th></th>
<th></th>
<th>Laguna</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Live (m²)</td>
<td>Dead (m²)</td>
<td>% Dead</td>
<td>Live (m²)</td>
<td>Dead (m²)</td>
<td>% Dead</td>
<td>Live (m²)</td>
<td>Dead (m²)</td>
</tr>
<tr>
<td>Western Yellow Pine</td>
<td>0.63</td>
<td>0</td>
<td>0</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>83.18</td>
<td>27.05</td>
</tr>
<tr>
<td>Coulter Pine</td>
<td>1.44</td>
<td>0</td>
<td>0</td>
<td>4.64</td>
<td>1.44</td>
<td>23.68</td>
<td>0.93</td>
<td>0.42</td>
</tr>
<tr>
<td>Incense Cedar</td>
<td>19.3</td>
<td>3.05</td>
<td>13.64</td>
<td>96.21</td>
<td>7.67</td>
<td>7.38</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>White Fir</td>
<td>23.03</td>
<td>39.57</td>
<td>63.21</td>
<td>1.77</td>
<td>1.03</td>
<td>36.43</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>Big Cone Douglas Fir</td>
<td>7.53</td>
<td>2.06</td>
<td>21.48</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
<td>*</td>
</tr>
<tr>
<td>Total basal area</td>
<td>51.94</td>
<td>52.68</td>
<td>102.6</td>
<td>10.14</td>
<td>84.1</td>
<td>27.46</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total % of dead tree</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>basal area per study</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>area</td>
<td>50.35%</td>
<td></td>
<td></td>
<td>9.00%</td>
<td></td>
<td>24.61%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

An * indicates that the species is not present in the study plots.
B. Basal area of measured live and dead conifer trees, and percent of dead trees, from the field plots, by species, for all study areas combined, and the total percent of dead tree basal area for all study areas.

<table>
<thead>
<tr>
<th>Tree species</th>
<th>Total by species, for all study areas</th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Live (m²)</td>
<td>Dead (m²)</td>
<td>% Dead</td>
<td></td>
</tr>
<tr>
<td>Western Yellow Pine</td>
<td>83.81</td>
<td>24.54</td>
<td>22.65%</td>
<td></td>
</tr>
<tr>
<td>Counter Pine</td>
<td>7.01</td>
<td>1.86</td>
<td>20.97%</td>
<td></td>
</tr>
<tr>
<td>Incense Cedar</td>
<td>115.51</td>
<td>21.82</td>
<td>15.89%</td>
<td></td>
</tr>
<tr>
<td>White Fir</td>
<td>24.8</td>
<td>40.6</td>
<td>62.08%</td>
<td></td>
</tr>
<tr>
<td>Big Cone Douglas Fir</td>
<td>7.53</td>
<td>2.06</td>
<td>21.48%</td>
<td></td>
</tr>
<tr>
<td>Total basal area</td>
<td>238.66</td>
<td>90.88</td>
<td>27.58%</td>
<td></td>
</tr>
<tr>
<td>Total % of dead tree</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>basal area per study</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 3-7. The diameter distributions of dead and living trees for each conifer tree species for each study site. The size classes of the tree diameter measurements taken at breast height (dbh) are given in centimeters.

A. Palomar

<table>
<thead>
<tr>
<th>Size class cm, dbh</th>
<th>Yellow pine live</th>
<th>Yellow pine dead</th>
<th>Incense cedar live</th>
<th>Incense cedar dead</th>
<th>White fir live</th>
<th>White fir dead</th>
<th>Big cone fir live</th>
<th>Big cone fir dead</th>
<th>All Trees live</th>
<th>All Trees dead</th>
</tr>
</thead>
<tbody>
<tr>
<td>10 to 19</td>
<td>54</td>
<td>10</td>
<td>37</td>
<td>23</td>
<td>11</td>
<td>0</td>
<td>105</td>
<td>32</td>
<td></td>
<td></td>
</tr>
<tr>
<td>20 to 34</td>
<td>8</td>
<td>0</td>
<td>4</td>
<td>11</td>
<td>0</td>
<td>1</td>
<td>13</td>
<td>12</td>
<td></td>
<td></td>
</tr>
<tr>
<td>35 to 49</td>
<td>17</td>
<td>4</td>
<td>17</td>
<td>27</td>
<td>7</td>
<td>1</td>
<td>43</td>
<td>32</td>
<td></td>
<td></td>
</tr>
<tr>
<td>50 to 64</td>
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<td>14</td>
<td>21</td>
<td>2</td>
<td>0</td>
<td>28</td>
<td>21</td>
<td></td>
<td></td>
</tr>
<tr>
<td>65 to 79</td>
<td>2</td>
<td>0</td>
<td>7</td>
<td>5</td>
<td>1</td>
<td>0</td>
<td>16</td>
<td>7</td>
<td></td>
<td></td>
</tr>
<tr>
<td>80 to 94</td>
<td>7</td>
<td>4</td>
<td>13</td>
<td>16</td>
<td>3</td>
<td>3</td>
<td>23</td>
<td>23</td>
<td></td>
<td></td>
</tr>
<tr>
<td>95+</td>
<td>0</td>
<td>7</td>
<td>0</td>
<td>6</td>
<td>16</td>
<td>3</td>
<td>13</td>
<td>17</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>totals</strong></td>
<td>4</td>
<td>0</td>
<td>112</td>
<td>20</td>
<td>98</td>
<td>119</td>
<td>27</td>
<td>5</td>
<td>241</td>
<td>144</td>
</tr>
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</table>

B. Volcan

<table>
<thead>
<tr>
<th>Size class dbh, cm</th>
<th>Coulter pine live</th>
<th>Coulter pine dead</th>
<th>Incense cedar live</th>
<th>Incense cedar dead</th>
<th>White fir live</th>
<th>White fir dead</th>
<th>All Trees live</th>
<th>All Trees dead</th>
</tr>
</thead>
<tbody>
<tr>
<td>10 to 19</td>
<td>2</td>
<td>0</td>
<td>6</td>
<td>119</td>
<td>1</td>
<td>0</td>
<td>9</td>
<td>119</td>
</tr>
<tr>
<td>20-34</td>
<td>4</td>
<td>0</td>
<td>64</td>
<td>48</td>
<td>1</td>
<td>0</td>
<td>69</td>
<td>48</td>
</tr>
<tr>
<td>35-40</td>
<td>1</td>
<td>0</td>
<td>100</td>
<td>15</td>
<td>0</td>
<td>0</td>
<td>101</td>
<td>15</td>
</tr>
<tr>
<td>50-64</td>
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C. Laguna

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Chapter 4. Analyzing relationships of climate and site factors to tree mortality in mixed-conifer forests, San Diego County, California.

4.1. Introduction

A primary objective of this study is to analyze relationships between live and dead conifer tree patterns and landscape structure to identify variables that best capture the presence of coniferous trees and the vulnerability of mixed-conifer tree canopies to dieback processes using a combination of remote sensing and modeling techniques. Landscape factors such as slope, aspect, and elevation play an important role in influencing the presence of conifer trees and their mortality patterns, because they control amounts of solar radiation, temperature, precipitation, soil moisture, and wind exposure at the site level (Garin and Taylor 2005, Kane and Kolb 2011, Stephenson 1990, Woodward 1987). The purpose of this study is to explore spatial relationships between conifer mortality (presence versus absence of dead trees) and landscape factors, using data for specific time periods.

The montane mixed-conifer forests in San Diego County CA have been experiencing high levels of tree mortality, which is defined as dieback where whole forest stands are affected by large-scale mortality conditions (Mueller-Dombois 1988). This mortality, which is a widespread occurrence across the western US, has been triggered by a combination of both endogenous factors, including stand characteristics, and exogenous factors, such as site conditions, climate, insects and pathogens (van Mantgem et al. 2009, Garin and Taylor 2005). In southern California, regional scale drought began in the 1980s and became historically severe
in 2002-2004. These drought conditions have impacted patterns of tree death both directly, with the substantial increase in tree mortality post 2002, as discussed in Chapter 3, and indirectly, in terms of drought-related physiological stress, making conifers more vulnerable to insect attacks and disease (Minnich 2007).

Precipitation and drought history, air pollution, land use history, fire history and forest stand structure are physical factors which have been shown to impact forest health (Grulke 2006, Minnich 2007). The main objective of this study is to explore complex relationships between conifer dieback and these factors, utilizing predictive modeling techniques. The importance of factors related to dead tree locations is examined, as well as factors associated with live tree locations.

Predictive modeling of species’ distributions is based on niche gradient analysis, and represents an important tool in biogeography, ecology, conservation, and species management (Anderson et al. 2003, Guisan and Thuiller 2005, Wiersma et al. 2011). It is based on the premise that species distributions can be predicted from the spatial distribution of environmental variables that control species distributions (Franklin 1995). A variety of methods combine individual occurrence data with biotic and abiotic environmental variables, such as geology, elevation, temperature, precipitation and vegetation type, to create a model of a species’ requirements for those particular variables (Franklin 2010). In general, fine spatial resolution modeling analyses that utilize local predictors such as slope, topographic position, or soil types, provide better predictions for fixed organisms such as trees,
which are represented by the scale of the high spatial resolution (1 meter) remote sensing-derived tree maps used in this study (Guisan and Thuiller 2005).

Species distribution modeling (SDM) efforts are enhanced by the increasing availability of digital maps of environmental variables, many of which influence or are correlated with macro-distributions of species. The model resulting from this study can be used to project a map of a conifer species’ potential geographic distribution within each study region (Guisan and Zimmerman 2000). Alternatively, models and maps can be created delineating factors or areas which may not be favorable for the study species (Franklin 2002).

Primary occurrence or “presence” data are usually in the form of georeferenced coordinates for confirmed localities from vouchered museum specimens, or in the case of the present study, from maps of trees derived from remotely sensed imagery (Ponder et al. 2001, Stockwell and Peterson 2002). Absence data can also be examined, when available (Anderson et al. 2002). In the present study, “absence” data would be represented by mapped dead trees, derived from the remotely sensed imagery. Technically, the trees are not absent, they are dead. However, by modeling them in this way it is possible to determine which environmental factors are different for the locations where live trees occur and those locations prone to tree mortality; then, based on the results, we can predict which areas will continue to be susceptible to tree mortality. Additionally, significant factors may be different for the various study areas and tree species. Several other studies have constructed logistic regression models utilizing the binary response for live and

According to Guisan et al. (2006), an important step in creating a predictive distribution model is to build a conceptual model of the expected species-environment relationships. Environmental predictors fall into the three categories of 1) limiting factors, which control the species’ ecophysiology (e.g. temperature, water), 2) disturbances (e.g. fire), and 3) resources (e.g. water, energy), which are compounds assimilated by organisms (Guisan and Zimmerman 2002). In Mediterranean ecosystems, factors relating to site moisture availability are particularly helpful in modeling plant distributions (Stephenson 1998, Franklin 2002). Understanding how the effects of climate can be mediated by specific site conditions can help to determine areas of increased or decreased moisture conditions (Guarin and Taylor 2005).

In terms of the conceptual species-environment relationships for the present study, sites of enhanced site moisture should be prime locations for live conifer trees, which could include north-facing slope aspects and areas of deep soil, which facilitate root penetration and moisture retention. Sites of reduced site moisture, on the other hand, would be more likely to be correlated with stressed or dead trees, which could include hotter and drier south facing slopes, dry ridge tops, and more permeable, shallow soils. Higher altitudes can have lethal effects, particularly as low temperatures can have a significant impact on setting range limits for plant species (Woodward 1987). These assumptions will be examined in this study, by utilizing
topographic and climatic variables, which are all spatially variable factors in the montane study areas.

The mathematical models commonly utilized to map species distributions include generalized linear models, generalized additive models, and machine learning methods, such as decision trees (Franklin 2010). Generalized Linear Models (GLM) are an extension of linear models that can handle non-normal distributions of response variables, which frequently occur with ecological data. A GLM which utilizes a binomial distribution, called logistic regression, is particularly suited to species distribution modeling because of the binary response (presence/absence observations) of species occurrence data (Franklin 2010). Decision tree classifiers (DTC) are also very useful, as they can treat non-parametric data, and can be used initially to seek patterns in the data, as is the case with the present study.

Maps of live and dead trees were derived from remotely sensed imagery for multiple dates, taking steps to include only those trees which died between image dates for a given time period. Environmental data such as slope, aspect, elevation, precipitation and temperature were included in GIS and statistical analyses. Various spatially explicit statistical and modeling approaches were applied to answer the following questions:

1. When analyzing relationships between mortality patterns and environmental factors, which modeling approach, a DTC or GLM (logistic regression), is the most effective at predicting mortality?
2. Which landscape variables best predict the distribution of dead conifer trees? Which climate variables are most prevalent in predicting the distribution of dead conifer trees?

3. Are data-driven statistical models of conifer mortality stable and stationary over time?

4. Where on the landscapes of the study area have changes in conifer mortality levels occurred most rapidly? What site conditions appear to be more susceptible to dieback?

4.2. Study area

Tree mortality was investigated within the montane mixed-conifer forests of San Diego County, California, USA, which are found in several areas of the North-South oriented Peninsular Range of mountains, including Palomar Mountain, Volcan Mountain and Laguna Mountain. Within each montane area specific study areas (as illustrated in Figure 2-1, Chapter 2) were delineated which include topographic variation and forest stands of varying sizes. Site 1 extends from the Fry Creek Campground area to Palomar State Park on Palomar mountain, and is comprised of Sierran mixed coniferous forest (white fir, incense cedar, Big cone Douglas fir, and Coulter pine), at an elevation of 1500 m and with an annual average rainfall of 120 cm (Laurie 2004). Site 2 is located in the Volcan Mountains just north of the town of Julian and consists of a mixture of white fir, incense cedar, Big cone Douglas fir, and Coulter pine on the upper slopes of the West side of the mountains (elevation 1300 m,
rainfall 60 cm). Site 3 is located on Laguna Mountain, (1800 m) and is almost exclusively Jeffrey pine forest, with an average annual rainfall of 90 cm (Minnich 2007).

4.3. Methods

The general approach of this study was to analyze spatial distributions of live and dead conifer trees portrayed in a time series of maps derived from remotely sensed imagery (Chapters 1 and 2), build a database of environmental factors associated with each tree (live and dead), and then use these factors to create predictive models for mortality conditions, for each time period and study area. The general flow of the study procedures is illustrated in Figure 4-1. Multiple analytical methods were used to validate and compare the various models and test the quality of the maps’ predictive abilities.

4.3.1. Remote sensing data and analysis

Presence and absence data for conifer trees were derived in the form of point distributions from object-based classification of remotely sensed imagery, as discussed in Chapter 2. The remote sensing analysis was based on several extant orthorectified image data sets, including USGS Digital Orthophoto Quarter Quadrangle (DOQQ) color infrared imagery having 1 meter spatial resolution for September 1997 and May 2002, and true color, 1 meter spatial resolution data from the Natural Resource Council, for July 2005. These dates were selected based on the
results of a previous study examining trends in tree mortality from 1997 to 2005, as discussed in Chapter 3. Conifer mortality levels were found to remain fairly stable from 1997 to 2002, and then increase rapidly between 2002 and 2005, providing two different time slices for model comparisons.

As described in Chapter 2, imagery from the selected dates was subset for the three study areas, and then after collecting calibration and validation data, the imagery was classified using a commercial artificial neural network software program (Feature Analyst), to create a single class vector layer of dead conifer trees. In addition, maps of live conifer trees were created for each image location and date utilizing an OBIA approach (eCognition Version 5). Both live and dead tree objects were converted into point data. An object-based accuracy assessment was conducted for each product, and manual editing was performed to create a product with at least 85% accuracy, in order to best facilitate further analysis. The accuracy rates of the map products ranged between 86% and 90% accuracy. Further editing is estimated to have improved accuracies by around 5%.

The dead tree point maps were then updated further to create maps of dead trees unique to each time period between image dates, but limited to trees which were assumed to have died since the last image date, since they were not present as dead trees in earlier map(s). The methods are described in greater detail in a subsequent section.
4.3.2. Predictive distribution modeling

4.3.2.1. Data

The environmental data utilized for developing the predictive models in this study included originally thirteen variables: precipitation, minimum temperature, maximum temperature, elevation, slope, curvature, aspect, flow accumulation, solar radiation, fire frequency, time since last fire, land composition (underlying lithology) and soil properties. An additional three climate variables were added which represented differences between long-term climate averages and averages for specific time periods, for precipitation, minimum temperature, and maximum temperature. These variables were selected because, as mentioned before, they relate directly to site moisture conditions.

Interannual precipitation and minimum and maximum temperature data were interpolated from climate station data for specific time periods relating to the remotely sensed imagery dates, using methods outlined in Franklin (1998) and Franklin et al. (2001). Thirteen weather stations in the region surrounding the study areas that fit these criteria were selected: they had data available for the time periods represented in this study, and those data could be further analyzed to create climate data surfaces for model development. The climate data were obtained from the California Climate Data Archive (www.calclim.dri.edu), which incorporates Southern California RAWS (Remote Automatic Weather Stations) data from the Western Regional Climate Center (www.wrcc.dri.edu).
Two methods were tested in preparing the climate data layers, a simple regression approach and a geostatistical approach. Regression of climate data with topographic variables has been previously utilized to model climate data in mountainous regions (Basist et al. 1994, Daly et al. 1994), as have krigging techniques (Phillips et al. 1992, Hudson et al. 1994). For the regression approach, elevation values were derived for each station location, and these values were regressed separately for each time period’s climate values, to establish regional regression equations. These equations were then utilized to predict the climate data’s spatial distribution based on the elevations for each tree point. For the interpolation approach, the climate stations were used as a spatial framework for krigging techniques, creating interpolated 30 meter gridded raster surfaces based on data values for each time period.

The climate data were compiled for the twelve months prior to the first imagery date of May 1997 (Period 1: May 1996 – May 1997), the period between the 1997 and 2002 image dates (Period 2: June 1997- May 2002), and the period between the 2002 and 2005 image dates (Period 3: June 2002 – September 2005). A modified version of the data from Period 3 was also examined (Period 4: June 2002 – June 2004), to differentiate the “drier” portion of Period 3, before the heavy rains began in October 2004, to see how this shift in precipitation would impact the models. It was during Period 3 that a significant amount of tree mortality took place.

Monthly maximum and minimum air temperatures were averaged (separately) for each time period, with the resultant averages from three weather
stations (those closest to the study plots) shown in Table 4-1. Monthly precipitation was summed for each time period, and then divided by the number of years (or fraction thereof) to determine the average total annual precipitation amount within a period. For the 1997 model analysis, twelve months of climate data were utilized for the “Period 1” period prior to May 1997, since the previous year’s temperature ranges and cumulative rainfall are significant in predicting conifer health and mortality (Royce and Barbour 2001). For the 2002 and 2005 model analyses, climate data were compiled for the total amount of time between imagery dates, since it was not known when during this period that the trees died, so all possible data were incorporated.

For analyses involving the testing of optimal sample sizes for model construction, thirty-year average climate grids were utilized, in order to minimize environmental data variability between time periods. These grids were prepared by Dr. Joel Michaelson at UCSB for San Diego County using methods outlined in Franklin et al. (2001). Climate data specific to each time period were utilized as the primary climate variables for subsequent models.

Three additional climate variables were also added to the models, derived by differencing the climate data for each period with the 30-year average (the time period data minus the 30-year average), to determine what effect deviations from the “average” had on the models. These variables were termed “precipdiff”, “maxtdiff”, and “mintdiff”, for differences between precipitation, maximum temperature, and minimum temperature data respectively, for each time period and for each study area.
Slope, aspect, and elevation variables were derived from a USGS DEM from
the National Elevation data set (NED), at 30 m resolution. Curvature, which is
defined as the first derivative of the slope, was derived from the DEM in ArcGIS.
Flow accumulation, which is a grid-based computation of accumulated water flow
into each cell (based on the number of topologically connected upslope cells) from
the hydrology toolset in ArcGIS, was also derived from the DEM. Solar radiation
(irradiance) data were derived utilizing the model in ArcGIS, which calculated the
cumulative shortwave irradiance over a year for the study sites, accounting for the
local topography and sun angle.

GIS data layers portraying fire frequency and time since last burn were
developed by Dave McKinsey, at the SDSU CESAR (Center for Earth Systems
Analysis Research) lab, utilizing fire data from the CDF Fire and Resource
Assessment Program (FRAP – frap.cdf.ca.gov) database (Chason 2007). With these
layers it is possible to determine within each study area how many times a particular
area has been burned, and how long it has been since the last burn occurred (since
records were kept starting in 1910). A geology GIS data layer was obtained from the
USGS website, and then reclassified based on underlying lithology (igneous,
sedimentary, or metamorphic) to create a land composition data layer.

Soil property data were obtained from the SanGIS database (SanGIS 2012).
The Storie Index data, which is a soil rating system determining suitability of soils for
crop and timber production, were taken from the San Diego Area Soil Survey (USDA
1973) and integrated into the soil database for the study areas. The Storie Index
includes factors related to soil depth and texture, permeability, chemical characteristics, drainage and runoff properties, and limiting factors (salt accumulation, alkali content, unfavorable micro relief), which are all important factors for trees, making this index a useful variable for ecological modeling of conifer distributions (Harradine 1973, Storie 1978, USDA 2011).

4.3.2.2. Data preparation and model building

A GIS database was created for live and dead trees sampled from the remote sensing-derived tree point maps for each study area and date (1997, 2002 and 2005). The sampling procedure involved taking all of the point tree occurrence records, labeling them in the attribute table with the dead trees being modeled as the event, assigning a “1” for dead trees and a “0” for live trees, randomizing the data records, and selecting a portion of the data to work with.

Additionally, other measures were derived for the selected dead tree points, in order to better understand differences that occurred between dates. Unique dead tree data sets were created for each time period, attempting to include only trees which had died during that time period by excluding dead trees which had been previously delineated in an earlier time period. To accomplish this, a GIS selection process was conducted, in which the dead tree shape files were compared to the layers from earlier dates, and duplicate points were removed. Due to inconsistent imagery characteristics and the possibility of differing tree positions and angles, a buffer distance of 20 meters was also utilized. Thus, any dead trees within a 20 meter distance of any
mapped tree from an earlier date were culled. For the 2005 maps this process was done twice, to remove duplicates from both the 1997 and 2002 data sets. A visual scan was also conducted with the resultant dead tree maps, to further remove clutter.

The optimal data set size, in terms of number of records for presence and absence data (live and dead trees), for running both the GLM and DTC models was determined by testing various sample sizes recommended from the literature, and selecting the most effective approach, based on the AUC (Area Under the Curve) accuracy metric. Environmental data, gridded to 30 meter raster cell size, were extracted for each tree point in ArcMap and added to the attribute tables. All of these data were then exported into an Excel data spreadsheet, randomized, divided into calibration and training data, and then formatted to conform to requirements of the R statistical package for model analyses.

4.3.2.3. Predictive modeling approaches: machine learning

A DTC (in R software) was utilized to explore the complex relationships in the multivariate environmental data set, both graphically and quantitatively (De’ath and Fabricius, 2000). Decision trees partition a data set into homogeneous subgroups using recursive binary partitions during the steps of (1) tree building, (2) tree stopping, and (3) tree pruning. The approach utilized in this study was to grow a large tree with liberal stopping criteria, then “prune” the tree to remove the splits that added the least to overall subgroup homogeneity, using cross validation to determine the optimal tree size. The ability of the tree to create robust predictions for new data was
tested by applying the pruned tree rules to a “test” data set, and observing changes to the AUC.

4.3.2.4. Predictive modeling approaches: GLM

Several steps were utilized in developing a generalized linear model (with R software) for predictive distribution models in this study, as outlined by Franklin (2010). The first step was to select a type of GLM based on response of the data, which in this case was logistic regression. Then important candidate predictors were identified and those predictors were evaluated against each other to avoid issues of multicolinearity, utilizing correlation tables. Transforms of predictor variables were then tested to best describe the response function, using, for example, polynomial terms. Next, the set and order of the predictors to be included in the model were chosen, taking care to avoid correlated predictors and selecting those predictors with the strongest relationships to the response. Finally, each model was estimated, its goodness of fit was determined, and then the most appropriate model was selected based on the evaluations of the various models’ performances (based on AUC).

4.3.2.5. Model evaluation and accuracy

Models are simplifications of reality. According to Franklin (2010) there are many types of error and uncertainty associated with species distribution modeling, and it is important to evaluate models in terms of the purpose they were intended for, as well as to understand their appropriateness during development from conceptual
formulation, to statistical formulation, model calibration and model evaluation. Effective models address the problem, and their formulation is consistent with ecological realism. Models also need to have the relevant variables and relationships accounted for, must be capable of producing empirically correct predictions to a certain degree of accuracy, and ultimately need to be acceptable to users. To address these issues several measures were utilized in the development and validation of the present study’s models.

The original data set was partitioned into training and test datasets, as models are most usefully validated with data that were not used to estimate the parameters or fit the model. The training data were used to build the model, and the test data were used to validate the model. Convention holds that the data should be partitioned into 75:25 train: test when the number of predictor variables exceeds 10 (16 total in the present study), and the response is binary (Miller 2005).

Sample size is also another consideration when constructing models. Many authors have found that larger sample sizes of presence and absence data are positively correlated with model performance (Hirzel and Guisan 2002, Reese et al 2005). However, other authors have noted that for feasibility reasons (i.e. practical limitations of available data), successful models have been constructed with smaller data sets (Stockwell and Peterson 2002, Elith et al 2006). One heuristic indicates that an effective sample size should be 20 times the number of predictor variables. If stepwise regression procedures are utilized than the appropriate sample size should be 40 times the amount of predictor variables (Franklin 2010). For this analysis different
sample sizes of live and dead tree data sets were tested, for 13 of the predictor variables, and the accuracies compared, with models created for n=260, n=520, and n=1500.

The Akaike Index Criterion (AIC) metric was utilized to measure the fit of the GLM during the model building process. This information-theoretic statistical approach, is a measure of goodness of fit that includes an accounting of the number of parameters. With each test run of the model a different variable is dropped and the AIC score is observed. In this manner it was determined which variables were significant and most explanatory, depending on how much their presence in the model improved the score. A lower score (lower unexplained deviance) indicates a better model, as there is more deviance explained per number of explanatory variables (Franklin 2010).

For the GLM results the adjusted $D^2$ value, defined as $D^2 = (\text{Null deviance} - \text{residual deviance})/ \text{Null deviance}$, was used as a measure of model fit, and represents the percent deviance explained by the model and thus is an indication of the models’ suitability. Convention holds that a $D^2$ value of 0.2 or above indicates a satisfactory model (Guisan and Zimmerman 2000).

Several measures were utilized to evaluate prediction errors. For the categorical variables of dead and live trees, logistic regression predicts a probability of class membership. In addition, ROC plots (Receiver-operating characteristic plot) and the AUC are threshold-independent measures utilized for binary variables. They
are applicable to both GLM and DTC approaches, and thus can be utilized to compare the results from these two model types (Fielding and Bell 1997).

Misclassification rates were also examined with the DTC, particularly when comparing multiple trees, or in the process of pruning trees (e.g. refining the model to be more parsimonious). The models with the lower misclassification rates were selected. However, it should be noted that sometimes a pruned, parsimonious tree (the desired result) had a slightly higher misclassification rate than a complex tree that was over-fitted to the training data.

4.3.2.6. Testing model prediction effectiveness

After a suitable model of dead tree prediction was developed for the previous date in the time sequence, the model logistic regression (GLM) equations were utilized to construct probability maps of dead conifer tree presence for the subsequent date. The GLM equations were integrated with the digital maps of the predictor variables, in order to predict dead tree presence for unsampled locations. To implement the logistic models for prediction, each predictor variable was multiplied by its model coefficient and then summed to provide the linear predictor (LP) for dead tree presence (Miller and Franklin 2002). A logistic transformation of LP was used to obtain probability values between 0 and 1:

\[
\text{Prob(dead conifer trees)} = \frac{e^{LP}}{1 + e^{LP}}
\]
These probability maps were then compared for each study area, utilizing an overlay analysis to determine how accurately the models from the earlier date predicted subsequent mortality in the later date.

### 4.4. Results

#### 4.4.1. Model development

##### 4.4.1.1. Model preparation

In preparing the climate data for model development, both linear regression and geostatistical methods were utilized. Based on model accuracy results (AUC) derived from resultant models the two approaches are not significantly different (p=.237). The products created with ordinary krigging had results most consistent with the regression approach results. What are different are the data ranges, depending on the krigging type. On the co-krigged products (where the climate variables are krigged along with elevation data) the data ranges tended to be more compressed, particularly with the precipitation values. For example, for the Period 4 precipitation data, the regression surface and ordinary krigged products ranged in value from 421-576 and 370-572 mm, while the co-krigged product ranged in value from 322-332 mm, all based on the same station values. Also the regression and ordinary krigged products preserved the spatial variability of micro topography, while the co-krigged products tended to smooth out this variability.

In constructing the environmental data sets prior to modeling, three different sample sizes were tested for the decision tree classifiers (n= 260, n=520 and n=1500),
and two sample sizes were tested for the GLM models, since stepwise regression procedures were utilized (n=520, n=1500). As shown in Table 4-1, the AUC and D^2 accuracy values were much higher for the smaller data sets. Typically, the accuracy values were higher, in the range of 0.01 to 0.36 for the AUC values, and from .02 to .25 for the D^2 values. For this study then, it is much more efficient and accurate to utilize data sets with smaller sample sizes, possibly due to issues with spatial autocorrelation for the larger data sets.

4.4.1.2. Decision tree classifier

Decision tree models were created for each date and study site. The subsequent trees were pruned iteratively to make them more parsimonious as well as to maximize performance. The criteria for pruning were based on a cross validation analysis to determine the optimal tree size (Franklin 2010). Table 4-3 lists the AUC values for each model. A range of AUC values of 0.5-0.7 indicates a “poorly accurate” rating (model performance is low), 0.7-0.9 is considered to be moderate or “useful”, and >0.9 represents a “highly accurate” performance rating (Swets 1988). The misclassification rates are also recorded, and the lower the rate, the better the model performance.

In general, the AUC results indicate that the DTC models for the 2002 data had predominately moderate to high accuracy (0.74 - 0.92), with the exception of one model that was in the “poorly accurate” range (0.68). The AUC for the best result models for 2005 were in the moderate range (0.73 - 0.83), and the 1997 point data
were in the “poorly accurate” to “useful” range (0.67 - 0.82). The combined models for each date, which were based on pooled data from each study site into a single model, had AUC values in the moderate range for all of the dates, with 0.82, 0.74, 0.75 and 0.88 for the 1997, 2002 and 2005a and b models respectively. The misclassification rates ranged between 0.25 and 0.36 for the 1997 models, between 0.1 to 0.27 for the 2002 models, and 0.1-0.3 for the 2005 models.

4.4.1.3. GLM

For the creation of the GLM, it is important to avoid multicolinearity between candidate predictor variables. Tables were constructed to examine the degree of correlation between environmental variables, with the correlation values ranging from 1 (perfect correlation) to 0 (no correlation), as shown in Table 4-3. The following guidelines were utilized to describe the strength of correlation: 0.90 – 1.00 = very high correlation, 0.70-0.89= high correlation, 0.50-0.69 = moderate correlation, 0.30-0.49=low correlation, 0.00-0.29=little if any correlation (Zady 2000). For all of the models, elevation and the climate variables tended to be correlated. Other variables that tended to be highly correlated included precipitation with both minimum and maximum temperature, and fire frequency and fire age. These correlations were noted for each dataset, and then examined as the model was being developed in order to drop the appropriate terms, usually those with moderate strength of correlation and higher.
Several logistic regression models were created to test which variables were best at modeling the presence of dead conifer trees (dead conifers = the “event”). Note that the models would be the same for modeling either dead or live conifers as the “event”, with just a sign change for the intercept terms. Henceforth the default will be to discuss the models/results for dead conifer trees specifically. Table 4-4 is an example of a GLM output table demonstrating the coefficient values for each of the selected variables, as well as the p-values indicating the significance values for each term. The significance terms were referenced to select most significant variables in order to optimize the models.

The GLM model evaluation results are shown in Table 4-5. The $D^2$ values were all at the satisfactory level (or very nearly so) for the 2002 models and for most of the 1997 models, while the $D^2$ values for the 2005 data were less than satisfactory. The AIC values, although primarily referenced during GLM model building process, are also listed for the final model, and are lower for the satisfactory models than the unsatisfactory ones. In general, the AUC results indicate that the GLM models for all dates had consistently low to moderate performance rates, 0.64-0.77 for 1997, 0.66-0.78 for 2002, and 0.60-0.75 for the 2005 models. Re-running the 2005 models with the Period 4 climate data resulted in a similar range of 0.60-0.76. Additionally, the combined models for each date all were “unsatisfactory” based on the $D^2$ value, in a range from 0.06 to 0.08, and in the poor range for the AUC (0.66-0.70) for the GLM models.
4.4.1.4. Comparison of DTC and GLM model results

The AUC results for both the decision tree classifier (DTC) and logistic regression (GLM) models, as shown in Table 4-5, are somewhat different. A student t-test comparing the AUC values for each model type confirms this, with the results indicating significance at the .01 level (p = 0.007), with the DTC having a higher AUC accuracy, averaging 0.77 as compared to 0.71 for the GLM.

4.4.2. Important predictor variables

Of the sixteen environmental predictor factors, just a few were frequently found in the first position (i.e. were the most significant factor) for both of the model types, as shown in Tables 4-5 and 4-6. Precipitation was the most significant factor for over half of both model types. Maximum temperature was also a significant factor, and elevation was prevalent in the models as well. Factors frequently occupying the second position (i.e., comprising the second tier of significant factors) include: fire frequency (how many times the area has burned), landscape composition, aspect, elevation, and maximum temperature. For five out of eight of the 2005 models, the climate difference variables for precipitation and maximum temperature occupied the first few tiers of importance.

A closer examination of the nodes of the decision trees shows the threshold values of environmental variables that predict the locations of dead trees for each study area, for each date. For example, as is shown in Table 4-6 for the Volcan 2002 location and date, the model predicts dead trees in areas with an average maximum
temperature of less than 34 °C, and that have not burned since 1910 (fire frequency = 0). Comparing threshold values is helpful in understanding the importance of the environmental factors in determining the distributions of the dead conifer trees, as well as possibly elucidating shifts in values over space and time.

4.4.3. Model predictions

The statistical predictions (equations) produced by the logistic regression models were transformed into raster maps in a GIS (see Figure 4-2) and then the probabilities were extracted using the mapped locations of dead trees from later dates, in order to test the effectiveness of the models. The 1997 and 2002 models were tested with the 2005 mapped dead tree locations for each study area. Histograms were created for each analysis, in order to observe the distribution of the y-axis variable (counts of dead trees) as extracted for each mapped x-axis variable (modeled probability), as shown in Figure 4-3. In this way not only was the relative effectiveness of the predictive maps examined, but also sequential models were compared to see how effective the 1997 models results were compared with those from models based on the 2002 climate data.

The models demonstrated variability in their ability to predict locations of higher probabilities for the presence of dead conifer trees. In general the models using the 2002 climate data did a better job of predicting dead tree presence than the models using 1997 weather data. All three histograms demonstrated the distinctive clustering of dead trees located in higher probability areas as designated by all three
predictive maps, with the results from the Palomar map having a distinctive peak at 0.933, and the Volcan map with higher values in the range of 0.89 -0.913. The 2002 Laguna predictive map resulted in a cluster in the higher end of the graph, but the range spanned lower values, so the higher values ranged from 0.65 - 0.68.

The models for the 1997 models had less distinctive peaks in the higher ranges of probabilities. Both the 1997 Laguna and Palomar models had a larger spread of values, with the extent of the range from 0.043 to 0.899 for Laguna and 0.008 to 0.792 for Palomar. The 1997 Volcan predictive map demonstrated the worst performance, with the majority of values below 0.161 probability level.

4.5. Discussion

4.5.1. Modeling approaches

The two types of statistical models that were evaluated for effectiveness at predicting presence of tree mortality: (1) logistic regression, which is a type of generalized linear model compatible with categorical variables and binary response data; and (2) a decision tree classifier. These approaches yielded final model accuracies that were only slightly different. However, the two modeling approaches each had their respective advantages and disadvantages, which are worth discussing.

The primary advantage of the DTC approach is that it can treat non-parametric data, so multicolinearity issues amongst the predictor variables that can be commonplace are not a problem. In this way decision trees can illuminate data relationships that have real ecological meaning. Also, decision trees are very helpful
in visually analyzing patterns in the data. Their main limitation is that it is difficult to convert large trees into predictive maps. Franklin (2002) mentions that in general, decision trees also tend to have lower accuracy rates than GLM models.

The primary advantages of the logistic regression model (GLM) are its ease of use and facile conversion of probability equations to predictive maps. The main disadvantage of the GLM is having to work around multicolinearity issues with the predictor variables. In the present study numerous model adjustments were made in order to remove correlated terms, and these adjustments tended to result in lower AUC values.

In more general terms, the models created in this study can be considered to be useful, despite their moderate accuracy levels. Many of the GLM models are considered to be satisfactory based on their $D^2$ results, and the AUC measures indicated that they were mostly of “useful” accuracy. For some of the GLM models that did not yield “satisfactory” $D^2$ values, the equivalent DTC models did have “useful” accuracy values, such as was the case with the combined study area results. In general, the DTC results were mostly of moderate or “useful” accuracy.

Other studies have reported similar AUC results for modeling the distribution of plant species. For example, Guisan et al. (2007) report AUC accuracy values in the range of 0.58 to 0.75, using a variety of modeling approaches, including DTC and GLM, for modeling vegetation distribution patterns. Miller and Franklin (2002) report AUC accuracy values in the range of 0.61 to 0.95 for their models, for vegetation alliance distributions in the Mojave Desert, CA.
The GLM models for the 2005 data were all considered to be “unsatisfactory”, based on their $D^2$ results. That all of the models based on maps from this date of imagery have the same low level of accuracy may be due to several factors. It could be related to the quality of the maps derived from that particular date of imagery. The true-color, high resolution aspects of the imagery, as well as the study site conditions of trees spaced far apart with often dead underbrush in between, may have contributed to more error in the remote sensing classification, although care was taken to manually edit the semi-automatically derived maps to remove as much error as possible. In addition, the significant increase in tree mortality that had occurred just prior to the date of imagery capture in 2005 may also have influenced model accuracy, as these increased mortality conditions may be the result of non-equilibrium processes. The modeling techniques utilized in this study assume equilibrium between the environment and observed species patterns, and situations with strong disturbance, or non-equilibrium conditions, can only be modeled with difficulty (Guisan and Zimmermann 2000, Guisan et al 1999). This may also explain the lower model accuracies. The GLM models for the combined study areas for each date were also unsatisfactory based on their $D^2$ values, and in this case may indicate that it is difficult to successfully generalize environmental factors over these heterogeneous areas.

An additional modeling run was conducted utilizing “Period 4” climate data reflecting the drier portion (2002-2004) of “Period 3” (2002-2005), in an attempt to see if this would improve the 2005 models. There were no significant differences,
based on AUC results (p=.39). One reason for this lack of improvement may be that the models are more sensitive to spatial variability in climate variables, as opposed to temporal differences in climate data (i.e. amounts of precipitation shifting between time periods). As long as the spatial variability of environmental data remains somewhat constant, the model accuracy results will be similar, although the intercept values (GLM) and node values (DTC) will shift.

Another modeling run was then conducted utilizing three additional climate variables: the differences between precipitation, minimum temperature and maximum temperature amounts for the 30-year average minus those amounts for the same variables from each time period. In this case there was a slight improvement (although not significant, p=.285) in the AUC accuracy rates for five of the 2005 models: two DTC models – combined study area models for 2005a and b, and three GLM models – Laguna 2005b, Volcan 2005a, and the combined study area model for 2005b. Two of the GLM models also had a slight improvement in $D^2$ values as well. In these cases the “precipdiff” variable substituted for the “precip” variable, and the “maxtdiff” substituted for the “maxt” variable. However, with no significant improvement in the models it cannot be definitively stated that changes in climate variables over time are contributing to tree mortality in this instance. Again, the models used in this study are primarily assessing the spatial variability in environmental variables, rather than temporal aspects of these data. Other variables are probably affecting the models’ accuracy to a greater degree than the shifts in climate data, such as expanded locations of dead trees in the 2005 imagery, and in
general the accuracy of the mapped trees (noting that the tree maps in this case were extensively edited).

The predictive models developed in this study are useful in illuminating relationships between environment variables and dead conifer tree presence. Models above 0.5 AUC accuracy have predictive value (Franklin 2010), and can help elucidate where on the landscape continued mortality is likely, via predictive maps or by providing a range of predictive threshold values. More fundamentally, these models illustrate that it is possible to expand the concept of “presence/absence” as originally applied to plant species locations, to “dead/live” locations for particular species, or a collection of similar species, such as the conifer trees in the present study. That some of the models had quite satisfactory results is encouraging, given the subtlety of the relationships one would expect with the environmental factors predicting where a conifer tree once grew (and is now dead), and where it is still growing, as compared to models comparing factors for where an organism is found and where it is not found altogether. This study thus demonstrates that it is useful and feasible to model mortality patterns utilizing the locations of live and dead trees, in place of the more conventional presence/absence data.

Another important result from this study is that adjusting the sample size for the presence/absence location points and manually editing the tree classification products to reduce clutter and improve accuracy, both had direct positive impacts on the accuracy rates. As stated previously, for the DTC models, the greatest accuracy was achieved using a sample size that had 20 times as many observations as predictor
variables (in this case 13, so n=260 or 520 total for both presence and absence points). For the GLM models the n= 520 (or 40 times the number of predictor values) had greater accuracy than the n=1500 sample size. This may stem from spatial autocorrelation for closely spaced data points in the larger data set(s). In addition, extra manual editing, in the form of visual inspection and dropping of points deemed to be unsatisfactory, helped to improve model results slightly. Small improvements such as this can minimize map error inherent in remote sensing classifications. Reduced sample sizes are also more feasible to manually edit, and they are satisfactory for analysis, as the results of this study suggest. One can efficiently create a small, effective, and accurate data set.

4.5.2. Factors controlling dead conifer tree distributions

Based on the modeling efforts from this study a few variables best predict the distribution of dead conifer trees. As was stated previously, over half of the models (55%) had precipitation as their primary, or most significant term. Two of the DTC models (Volcan-1997 and Palomar-1997) had precipitation as the single variable determining the presence of dead trees (or the majority of the cases). Note that the precipitation data are predicted on a grid that approximates the spatial variation of the annual precipitation over the landscape, recalculated for each of the three separate time periods, based on interpolation of weather station data by incorporating topographical effects. With the DTC models, maximum temperature was the second most important variable, often co-occurring with precipitation. The DTC model based
on all study areas combined for 2002 (AUC = 0.74), accounted for all of the dead tree cases with only the precipitation and maximum temperature variables. Precipitation was also a significant term with the GLM models, occurring as the first variable for half of the models, with maximum temperature as the first variable for the other half of the models. Only one model out of the twenty-four did not have precipitation or maximum temperature as key variables.

Other variables commonly utilized in the models were elevation, aspect (between 246 and 365, North to Northwest exposures), flow accumulation, land composition and fire frequency (frequency = 0, which are areas that have not burned since 1910), or time since last fire (70-94 years). Elevation was used as a principal node for the DTC, and was also often listed as a significant factor with the GLM models, but was dropped due to multicolinearity issues. The climate difference variables (the climate data for each time period minus the 30-year average) were important for several of the 2005 models, specifically the difference in precipitation as well as the difference in maximum temperature. It is notable that these variables are present particularly in the 2005 models, indicating that it is the anomalies in precipitation and maximum temperature for this time period that are potentially related (despite a lack of significant improvement to the models) to an increased probability of tree mortality.
4.5.3. Model predictions of dead conifer species distributions

The extent to which the locations of predicted mortality were manifested by actual mortality in later time periods varied by study site. For the predictive map overlay analysis, the models based on the data from the 2002 maps were the most successful, with actual mortality locations clustering in the 0.69 to 0.93 probability range, primarily due to the fairly “satisfactory” strength of the models; $D^2$ values for both the study area specific 2002 models varied from 0.17 to 0.22. Despite extensive manual editing of the semi-automatic image analysis results to improve dead tree mapping accuracy, the models for Volcan 1997 and Palomar 1997 model were not “satisfactory” and thus the resulting analyses were not as successful. The predictive values were not as high as with the Laguna maps. The 2002 models for both Palomar and Volcan were “satisfactory” and the histograms based on this date of models reflected higher probabilities. All of these maps do have predictive and explanatory value, despite variation in probability rates, and thus are potentially useful. They can, for example, direct researchers to potential areas on the landscape more likely to be at continued risk for dieback.

4.5.4. Landscape patterns of dead conifer distributions

4.5.4.1. Areas susceptible to mortality

Based on the model results from this study certain site locations on the landscape appear to have greater tree mortality, and the model results are useful in determining areas susceptible to a higher probability of mortality in the future. These
include areas within certain ranges of spatial variability in precipitation and maximum temperature, areas of higher elevation, north to northwest exposures, areas that have never burned, or have not burned for a long time, and areas of low flow accumulation (i.e. ridge tops).

These findings are consistent with other studies. Precipitation (drought) and maximum temperature are considered to be critical factors regulating and limiting conifer distributions (Daubenmire 1943, Kolb and Robberecht 1996, Breshears et al. 1998). Van Mantgem et al. (2009) assert that the primary contributors to recent increased mortality in forests in the western United States are regional warming and consequent increases in water deficit.

Elevation has commonly been found to be a significant factor associated with tree mortality. Kane and Kolb (2011) found that white fir mortality was negatively correlated with elevation in the Kaibab Plateau in Arizona. Mueller et al. (2005) found that elevation was significantly related to pinyon mortality in Northern Arizona. Wilson et al. (2003) found that in Australia vegetation mortality from the pathogen Phytophthora cinnamomi could be modeled effectively with the variables of altitude and solar radiation. According to Franklin (2010), elevation is a useful variable in models due to its predictive ability, because it can be utilized as a surrogate for both precipitation and temperature, since these variables tend to be highly correlated.

Drought-related forest mortality often occurs along elevation range margins, where climatic factors such as water stress are found to be limiting (Allen and
Breshears 1998, Foden et al. 2007, Jump et al 2009). Tree mortality is often greatest in localized dry positions in the landscape (Dobbertin et al. 2005, Worrall et al 2008), as evidenced in the present study, with models predicting a higher probability of mortality in areas of low flow accumulation and areas of lower precipitation amounts. However, it is also important to realize that there may be confounding effects of ecosite variability and interactions with density-dependent processes, such as competition, which may produce spatially complex patterns of mortality (Fensham and Holman 1999; Lloret et al. 2004). Greater amounts of mortality can occur on more favorable sites for a number of reasons, such as increased tree density leading to increased competition, or if trees do not invest in adequate root systems due to an abundance of moisture, which may later become more limited (Fensham and Fairfax 2007).

An example of this is the prevalence of mortality on north to northwest facing slopes in the study sites. One may have predicted that because south to southwest facing slopes are the more moisture limiting landscape positions, and thus, would have had the greater amount of mortality. However, the greatest density of conifer trees grows on the north to northeast exposure because of greater moisture prevalence, and this is where ultimately the greatest amount of dieback has occurred, both because of a greater likelihood of the presence of conifers to start with (other aspects may tend to be dominated by oaks or shrubs), and because of the greater density of trees which may result in greater competition for resources. Guarin and Taylor (2005) found greater density of mortality occurring on north facing slopes than
south slopes in Yosemite National Park and surmised that dense stand conditions caused by fire suppression, and an outbreak of bark beetles in conjunction with the drought, may have limited any buffering that topographic effects may have had on tree mortality.

The effect of fire suppression has also been much discussed as a contributing factor to increasing forest densification and increasing rates of mortality (Minnich 2007, Stephens et al., 2008; Maloney et al. 2008). In the present study greater mortality likely occurred more frequently in areas with a fire frequency = 0, that is areas that have not burned since records were kept starting in 1910, or in areas where the time since the last fire was in the range of 70 to 94 years. This is presumed to be, at least in part, due to stand densification.

4.5.4.2. Comparison of local and regional scale models

The models developed for each study site outperformed the models with the combined data from the entire study area, for each date. Based on field observations it was determined that each study area had a different dominant conifer species. On Palomar Mountain white fir is dominant, whereas Incense Cedar is dominant at Volcan Mountain, and Jeffrey Pine within the Laguna Mountain site. Essentially, the models created for each study area are accounting for the requirements for a particular conifer species. Conversely, the combined “regional” models represent the requirements for a suite of conifer species, which would be expected to be less straightforward. Also localized ecosite conditions can be more effectively modeled by
study site, than trying to model at the landscape scale considering the differences between study sites. For example, the ridges on Palomar Mountain trend NW to SE, while the ridges on Volcan and Laguna Mountains trend N-S, so the “aspect” variable will be modeled differently, depending on the study area.

In addition, another localized difference between study areas, which may have affected the regional models, is elevation. Laguna Mountain is the highest site, at 1828 m, with Palomar Mountain at 1524 m, and Volcan Mountain at 1316 m. This may lead to differing responses of climate variation during drought conditions. For example, higher elevation sites (Palomar and Laguna) may attain more precipitation from winter snow pack, while the lower elevation site (Volcan) has less snow, warms more quickly and has higher rates of evapotranspiration (ET).

Other studies of conifer mortality in Southern California have noted that the climate variation during drought differed among sites, with respect to elevation. To begin with, there is a large local variation in the zonation of mixed-conifer forest with mean annual precipitation, and forests can occur at lower elevations dependent on seasonal distribution of storms (Minnich 2007). Soil water availability is enhanced at higher elevations by winter snow pack. In the San Jacinto Mountains, just to the north of Palomar Mountain, lower elevation sites experienced greater amounts of mortality than higher elevation sites during the 2002-2004 drought. Mid-elevation conifers, such as White Fir, Incense Cedar, and Jeffrey Pine, died in the lower portions of their respective ranges (Fellows and Goulden 2010). Their work suggests that potential
evapotranspiration declines significantly with elevation and is probably a more critical factor than precipitation in structuring the elevational trend in drought stress.

4.6. Summary and Conclusions

A decision tree classifier (DTC) and a GLM (logistic regression) were similarly effective in predicting relationships between conifer tree mortality and environmental factors with moderate accuracies. The AUC accuracy rates for both approaches were in the range of 0.60-0.92, with the best models created from the 2002 environmental layer maps. Accuracy rates, based on the AUC are significantly different between the two approaches, with the DTC having higher accuracies. Most of the models yielded accuracy rates in the moderate or “useful” range. The GLM approach, while very effective in being able to easily create predictive maps, is parametric, and care must be taken to avoid multicollinearity issues with the predictor variables. The DTC is non-parametric, and is therefore very practical to use, given that many of the predictor variables best able to predict mortality tend to be highly correlated. In addition, it is very helpful in illustrating relationships in the data, due to the visual tree display.

Probability maps created by these modeling approaches can be utilized to understand and predict where conifer mortality is most likely to occur. In addition, the models help to discern which threshold values are important in predicting mortality.
During model development it was determined that the sample size of the presence/absence data had a direct impact on model accuracies. The smaller data sets (\(n=260\) and \(n=520\)) had higher accuracy rates than the models run with the larger data set (\(n=1500\)) for both the GLM and DTC models, which may be due to spatial autocorrelation issues with the higher density of mapped tree data with the larger data set. In addition, manual editing of the dead tree maps also helped improve the models slightly.

A few of the environmental variables were predominant in their importance in predicting the distribution of dead conifer trees. Precipitation was a particularly important variable, and was in the primary position for over half of the models. Maximum temperature was also important, and other variables of moderate importance included land composition, elevation, aspect, flow accumulation, and fire frequency.

Based on an overlay analysis of predictive maps and actual dead tree locations from later dates, the models varied in their ability to accurately predict future mortality. The most successful maps, based on data from the 2002 models, resulted in the majority of the mapped dead trees located in risk areas with a probability range of 0.69 to 0.93. This illustrates how areas of predicted mortality in fact do manifest that mortality in the later time periods.

Modeling dead and live conifer trees as “present/absent” facilitates an understanding of environmental factors related to mortality risk in the landscape. In the present study, the areas on the landscape that are more susceptible to dieback
include areas of mid-range precipitation values, higher ranges of maximum
temperature, higher elevation, north to northwest aspects, areas of low flow
accumulation, and areas with minimal fire frequency. These areas will likely continue
to be at risk for future mortality.

Determining environmental factors associated with conifer tree mortality is
difficult, because tree death is a complex and often gradual and non-linear process,
involving multiple disturbance agents (Franklin et al. 1987; Waring 1987; Allen and
Breshears 1998). The interactions of both biotic and abiotic factors pre-dispose
certain trees to mortality conditions (Manion 1991). Previous analysis (see Chapter
3) revealed that tree mortality levels in San Diego County increased significantly,
based on mapped dead trees, between the imagery dates of 2002 to 2005, which
coincided with an historic drought episode. In Southern California 2002-2004 was a
period of severe, global-climate change type drought, defined as a drought
accompanied by warmer temperatures (Ganey and Vojta 2011, Breshears et al. 2005),
characterized by extreme conifer mortality events which surpassed the combined tree
mortality in this region over the last century (Walker et al. 2006, Minnich 2007).
Thus, the dynamics of this conifer-dominated forest landscape were in part driven by
a severe exogenic disturbance (i.e. the regional drought). However, based on the
results of the models, local-scale autogenic mortality of individual and groups of trees
were clearly also driven by smaller-scale impacts of temperature, spatial variability in
precipitation, and localized topography. The absence of fire in certain areas, and
probable stand densification, has also influenced mortality patterns (Minnich 2007).
In the future, forest managers will need to take into consideration the combined effects of these factors and disturbances, in order to effectively plan for future forest health and mortality conditions, especially in the face of uncertain climate changes.
Figures

**Figure 4-1.** Schematic showing the general workflow. Dead and live conifer tree maps were produced utilizing object-based remote sensing techniques (see Chapter 3 for details), from imagery for 1997, 2002, and 2005. Points were sampled, and edited to produce maps of dead trees that are unique for the time periods between imagery. Environmental data layers were prepared, and data for each tree point was extracted and included in the model as predictor variables.
Figure 4-2. Predictive map of areas likely to experience conifer tree mortality, based on a GLM model derived from the 2002 data for Laguna Mountain. The highest probability areas for conifer mortality are in dark red.
A. Laguna

B. Volcan
Figure 4-3. Histograms derived from overlaying the 2005 mapped dead tree points on the maps predicting tree mortality locations created from the 1997 data and 2002 data for the study areas. The probabilities were extracted for each dead tree location, and then graphed, to demonstrate the relationship between amounts (count) of trees located at the various probability values.
Tables

Table 4-1. Interannual climate summaries for the time periods prior to and between imagery dates, for each study area. Climate data were obtained from the California Climate Data Archive, which incorporates Southern CA RAWS data from the Western Regional Climate Center for the following stations: Mt. Palomar Observatory, Julian (which is adjacent to Volcan), and Mt. Laguna. Long term averages are given for comparison.

<table>
<thead>
<tr>
<th>Area</th>
<th>Time period</th>
<th>Temperature (air), °C</th>
<th>Precipitation (mm)</th>
<th>Average total annual</th>
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<tr>
<td></td>
<td></td>
<td>Maximum</td>
<td>Minimum</td>
<td>Average</td>
</tr>
<tr>
<td>Palomar</td>
<td>long-term average</td>
<td>1901-2012</td>
<td>28.01</td>
<td>-4.00</td>
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<tr>
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<td>May 96-May 97</td>
<td>26.36</td>
<td>2.27</td>
<td>14.54</td>
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<td>June 97-May 2002</td>
<td>24.92</td>
<td>1.75</td>
<td>13.47</td>
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<td>June 02-Sept.2005</td>
<td>26.25</td>
<td>3.29</td>
<td>14.38</td>
</tr>
<tr>
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<td>36.00</td>
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<tr>
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</tr>
<tr>
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<td>-2.00</td>
<td>11.66</td>
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Table 4-2. Model performance based on sample size, comparing the Decision Tree Classifiers (DTC) with the GLM (logistic regression) models. The DTCs were run with all three sample sizes, while the GLM models were run for only n=520 and n=1500, due a minimum sample size requirement for stepwise regression. Note that n=260 actually means 260 presence observations + 260 absence observations, and likewise for the other sample sizes. AUC is the abbreviation for “Area under the Curve”. For all of the validation results, a higher value indicates a better model.

<table>
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<th>n=1500</th>
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</thead>
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</tr>
<tr>
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<td>AUC</td>
<td>D²</td>
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<td>0.2</td>
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<td>Laguna 2005</td>
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<td>0.07</td>
</tr>
<tr>
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<td>0.9</td>
<td>0.22</td>
</tr>
<tr>
<td>Palomar 2005</td>
<td>0.79</td>
<td>0.68</td>
<td>0.05</td>
</tr>
<tr>
<td>Volcan 2002</td>
<td>0.81</td>
<td>0.62</td>
<td>0.28</td>
</tr>
<tr>
<td>Volcan 2005</td>
<td>0.65</td>
<td>0.63</td>
<td>0.06</td>
</tr>
<tr>
<td>All 2002</td>
<td>0.74</td>
<td>0.73</td>
<td>0.07</td>
</tr>
<tr>
<td>All 2005</td>
<td>0.64</td>
<td>0.63</td>
<td>0.04</td>
</tr>
</tbody>
</table>
Table 4-3. Correlation strength between pairs of environmental variables, utilized to help determine which variables are strongly correlated. For example, the correlation coefficient between “age” (time since last fire) and “frq” (fire frequency) is -0.89, which is a very strong negative correlation, while the coefficient between “frq” and aspect is -0.04, which is a very weak negative correlation.

<table>
<thead>
<tr>
<th></th>
<th>elev</th>
<th>aspect</th>
<th>slope</th>
<th>curve</th>
<th>flow</th>
<th>maxt</th>
<th>mint</th>
<th>precip</th>
<th>age</th>
<th>frq</th>
</tr>
</thead>
<tbody>
<tr>
<td>elev</td>
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<td>-0.09</td>
<td>0.01</td>
<td>-0.05</td>
<td>-0.13</td>
<td>-0.47</td>
<td>-0.53</td>
<td>-0.64</td>
<td>0.06</td>
<td>-0.08</td>
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<tr>
<td>aspect</td>
<td>-0.09</td>
<td>1.00</td>
<td>-0.21</td>
<td>0.03</td>
<td>0.08</td>
<td>0.10</td>
<td>0.15</td>
<td>-0.04</td>
<td>0.09</td>
<td>-0.09</td>
</tr>
<tr>
<td>slope</td>
<td>0.01</td>
<td>-0.21</td>
<td>1.00</td>
<td>0.01</td>
<td>-0.14</td>
<td>0.05</td>
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<td>-0.25</td>
<td>-0.27</td>
<td>0.29</td>
</tr>
<tr>
<td>curve</td>
<td>-0.05</td>
<td>0.03</td>
<td>0.01</td>
<td>1.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.05</td>
<td>-0.01</td>
<td>0.04</td>
</tr>
<tr>
<td>flow</td>
<td>-0.13</td>
<td>0.08</td>
<td>-0.14</td>
<td>0.00</td>
<td>1.00</td>
<td>0.04</td>
<td>0.09</td>
<td>0.00</td>
<td>0.05</td>
<td>-0.06</td>
</tr>
<tr>
<td>maxt</td>
<td>-0.47</td>
<td>0.10</td>
<td>0.05</td>
<td>0.00</td>
<td>0.04</td>
<td>1.00</td>
<td>0.35</td>
<td>0.04</td>
<td>-0.25</td>
<td>0.24</td>
</tr>
<tr>
<td>mint</td>
<td>-0.53</td>
<td>0.15</td>
<td>-0.25</td>
<td>-0.05</td>
<td>0.09</td>
<td>0.35</td>
<td>1.00</td>
<td>0.53</td>
<td>0.12</td>
<td>-0.20</td>
</tr>
<tr>
<td>precip</td>
<td>-0.64</td>
<td>-0.04</td>
<td>-0.25</td>
<td>-0.01</td>
<td>0.00</td>
<td>0.04</td>
<td>0.53</td>
<td>1.00</td>
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<tr>
<td>age</td>
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<td>0.09</td>
<td>-0.27</td>
<td>0.04</td>
<td>0.05</td>
<td>-0.25</td>
<td>0.12</td>
<td>0.17</td>
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<td>frq</td>
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<td>-0.09</td>
<td>0.29</td>
<td>-0.02</td>
<td>-0.06</td>
<td>0.24</td>
<td>-0.20</td>
<td>-0.27</td>
<td>-0.90</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Table 4-4. An example of a GLM model output table, showing coefficients and significance values for the selected variables which best model dead tree presence, based in this case on the Volcan 2005 data.

| Coefficients:          | Estimate | Std. Error | z value | Pr(>|z|) |
|------------------------|----------|------------|---------|---------|
| (Intercept)            | -0.721042| 0.339473   | -2.124  | 0.0337  |
| firefrq                | 0.819824 | 0.154515   | 5.306   | 1.12e-07*** |
| precipdiff             | -0.016681| 0.002467   | -6.762  | 1.36e-11*** |
| age                    | 0.06     | 0.09       | -0.27   | 0.12    |
| slope                  | -0.002657| 0.001396   | -1.904  | 0.0569  |

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Table 4-5. Comparison of decision tree classifier (DTC) (pruned parsimonious trees) and generalized linear models (GLM), based on their Area Under Curve (AUC) validation results. Note that the AUC results are for the test data, as opposed to the training data that were utilized to calibrate the model. Additional validation results are also listed for illustrative purposes. 2005a refers to models with climate data compiled for Period 3 and 2005b refers to the models with modified climate data for Period 4.

<table>
<thead>
<tr>
<th>Validation type</th>
<th>Model type</th>
<th>DTC</th>
<th>GLM</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>AUC pruned (test)</td>
<td>Misclassification rate</td>
</tr>
<tr>
<td>Laguna 1997</td>
<td>DTC</td>
<td>0.79</td>
<td>0.26</td>
</tr>
<tr>
<td>Laguna 2002</td>
<td>DTC</td>
<td>0.68</td>
<td>0.27</td>
</tr>
<tr>
<td>Laguna 2005a</td>
<td>DTC</td>
<td>0.74</td>
<td>0.29</td>
</tr>
<tr>
<td>Laguna 2005b</td>
<td>DTC</td>
<td>0.74</td>
<td>0.29</td>
</tr>
<tr>
<td>Palomar 1997</td>
<td>DTC</td>
<td>0.67</td>
<td>0.30</td>
</tr>
<tr>
<td>Palomar 2002</td>
<td>DTC</td>
<td>0.92</td>
<td>0.10</td>
</tr>
<tr>
<td>Palomar 2005a</td>
<td>DTC</td>
<td>0.75</td>
<td>0.30</td>
</tr>
<tr>
<td>Palomar 2005b</td>
<td>DTC</td>
<td>0.66</td>
<td>0.30</td>
</tr>
<tr>
<td>Volcan 1997</td>
<td>GLM</td>
<td>0.68</td>
<td>0.36</td>
</tr>
<tr>
<td>Volcan 2002</td>
<td>GLM</td>
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<td>0.19</td>
</tr>
<tr>
<td>Volcan 2005a</td>
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<td>Volcan 2005b</td>
<td>GLM</td>
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<tr>
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<td>GLM</td>
<td>0.82</td>
<td>0.25</td>
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<tr>
<td>All 2002</td>
<td>GLM</td>
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<td>0.23</td>
</tr>
<tr>
<td>All 2005a</td>
<td>GLM</td>
<td>0.75</td>
<td>0.30</td>
</tr>
<tr>
<td>All 2005b</td>
<td>GLM</td>
<td>0.88</td>
<td>0.18</td>
</tr>
</tbody>
</table>
Table 4-6. Threshold values defining the presence of dead conifer trees, taken from the DTC created for each study area. For those trees with multiple branches defining “presence”, the nodes that had the most observations are listed.

<table>
<thead>
<tr>
<th>Study area</th>
<th>Node 1</th>
<th>Node 2</th>
<th>Node 3</th>
<th>Node 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Laguna 1997</td>
<td>max&lt;28</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Laguna 2002</td>
<td>age&gt;73</td>
<td>aspect&gt;75</td>
<td>mint&gt;-1.8</td>
<td></td>
</tr>
<tr>
<td>Laguna 2005</td>
<td>precip&gt;650</td>
<td>aspect&lt;325</td>
<td>max&gt;29</td>
<td></td>
</tr>
<tr>
<td>Palomar 1997</td>
<td>precip&gt;642</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Palomar 2002</td>
<td>precip&gt;429</td>
<td>elev&lt;1595</td>
<td>aspect&gt;246</td>
<td></td>
</tr>
<tr>
<td>Palomar 2005</td>
<td>precip&gt;641</td>
<td>slope&gt;13</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Volcan 1997</td>
<td>precip&gt;609</td>
<td>precip&lt;623</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Volcan 2002</td>
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<td>firefrq = 0</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Volcan 2005</td>
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<td>flow&gt;1</td>
<td>firefrq = 0</td>
<td>precip&lt;623</td>
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<tr>
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<td>max&lt;31</td>
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<td>precip-diff&gt;6</td>
<td>mint&lt;1.5</td>
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</table>
Chapter 5. Conclusions

5.1. Purpose of this study

The rapid transformation of forested ecosystems due to anthropogenic pressures, as well as impacts of climate change and droughts, is an important issue worldwide (Allen et al. 2010; Thuiller 2007). In forests of western north America, background rates of mortality have rapidly increased in recent decades (van Mantgem et al. 2009), with the implicated causal factors of elevated temperatures and water stress. The ecological effects of increased forest mortality are not fully understood, and further work is needed to assess mortality processes and provide spatially explicit documentation of physical conditions in areas of forest mortality, in order to link tree death to causal climate and environmental drivers (Allen et al. 2010).

The purpose of this study was to conduct an assessment of dieback patterns and drivers in montane mixed-conifer forests of San Diego County. In addition to utilizing object-based remote sensing methods applied to time series of high spatial resolution image data to map dieback patterns over time, temporal and spatial patterns of tree mortality were examined, and predictive models were developed for determining areas of concern for future conifer mortality. The present study worked to link biogeographic patterns with process across dynamic and spatially heterogeneous landscapes, integrating the geospatial technologies of GIS, remote sensing, GPS, spatial analysis, modeling and landscape metric analysis. While the study area is local, accelerated tree mortality is continuing to become an issue at a global scale, and thus the results of this research are widely applicable.
This research adds to the burgeoning field of ecological research and literature examining the increasing global trends of tree and forest mortality. The present work explores both temporal and spatial aspects of mortality processes in a portion of the Peninsular Ranges, the most southern montane forested sky-islands in the Western U.S. Rates of mortality were calculated, which were then compared with rates from other studies, as were spatial patterns of the spread of mortality. Several studies, including Breshears et al. 2005, Van Mantgem et al. 2009, and Meddens et al. (in press), have examined large-scale trends impacting the entire Western U.S. region. This study focuses in on a smaller region, which illuminates the impacts of more localized landscape processes, as well as pervasive larger-scale climatic influences. In this manner, this work contributes another piece of the puzzle to the larger regional and global context of forest dieback.

Furthermore, as sky-islands, the unique aspects of Palomar, Volcan and Laguna Mountains have helped this study in several ways. The forest communities exist in relative isolation at higher altitudes, with cooler and moister conditions than the surrounding “sea” of hotter, drier chaparral and desert ecosystems. These montane habitats are an excellent place to study ecological change, as they are very susceptible to climate shifts, particularly in the lower limits of conifer species’ ranges, which are found in the lower altitude mountains of San Diego County. In areas such as these there is no further potential for an upward altitudinal shift in plant migration as a possible response to warming climate (Minnich 2007). In addition the critical factors impacting these small contained remnant forests can be more readily discerned and
observed than would be possible in a larger more contiguous forest. Sky-islands provide natural strata of ecosystems in miniature, mirroring biomes at the global scale which stretch from the mid-latitudes to the sub-arctic. Lessons learned from studies conducted locally can be further applied and tested in other, broader regions, such as more extensive forests further north.

5.2. Key Findings

The remote sensing approaches tested in this study, a spatial contextual (ANN) and an OBIA image-based mapping approach, yielded useful maps of dead tree locations, with the majority of dead tree objects mapped with reasonable commission error. Procedures utilized to optimize each product, such as masking techniques, and the addition of transforms prior to classification, improved the classification products by 5% to 10%, with an 8% to 13% reduction in commission error. When comparing the two approaches, the dead conifer tree class accuracies are higher overall for the spatial contextual approach than the OBIA approach. The accuracies for both methods ranged from 30% to 90% correct for the dead tree class, and the commission error was similar for both products, but overall, the accuracies were significantly higher for the spatial-contextual approach. From a qualitative perspective, the spatial-contextual approach produced better object quality, and was a much easier program to learn. Manual editing of map products helped to bring the classifications up to more acceptable levels of accuracy, and ready to be utilized for further analysis.
An examination of the spatial pattern and change over time in conifer tree mortality based on the maps of dead conifer trees created with the remote sensing techniques, showed that the dead trees were significantly clustered for all dates, at certain scales of analysis (40 meters to 5000 meters), based on spatial cluster analysis. Other tests indicated no directional shift or spread of mortality over time, but rather an intensification of localized mortality density. Based on cumulative mortality density from image analysis, there was not much change in mortality between the years 1997-2002, and then there was a distinctive increase from 2002 to 2005, presumably attributable to the 2002-2003 drought. Mortality rates also increased from 1997 to 2005. Results from plot-based fieldwork demonstrate that different tree species were impacted at each study site: white fir at Palomar Mountain, incense cedar at Volcan Mountain, and on Laguna Mountain, Jeffrey Pine.

A comparison of a decision tree classifier (DTC) and a GLM (logistic regression) to predict relationships between conifer tree mortality and environmental factors revealed that both modeling approaches were similarly effective, and were in the moderate or “useful” range, of 0.60 - 0.95. AUC accuracy rates for the two approaches were significantly different, with the DTC having higher accuracies overall. The models varied in their ability to accurately predict future mortality, based on an overlay analysis of predictive maps and actual dead tree locations from later dates. The most important predictor variables were elevation and precipitation. Based on the model results, areas on the landscape most susceptible to dieback include areas
of: higher elevation, mid-range precipitation, north to northeast aspects, low flow accumulation, and locations with limited fire frequency.

5.3. Limitations and uncertainties

The remote sensing portion of this project presented multiple challenges. There were inherent limitations with the image data sets utilized to create the classifications, such as differing dates, spectral and spatial characteristics, radiometric quality, view and solar angles, and seasonality, as well as issues with seams associated with the generation of mosaics. Because of this, dead tree objects can have dramatically different spectral-radiometric signatures. Precipitation differences between imagery dates may have also resulted in scene differences, as well watered vegetation and dry vegetation will have differing spectral signatures. These imagery issues then translate to lower classification accuracies, with a lack of consistency in the contextual information to help the computer routines differentiate features, segments, and classes, depending on the approach. Low classification accuracies are also related to a difficulty in separating dead conifer tree pixels from background pixels representing materials such as dead non-tree vegetation (mostly senescent grasses and bracken ferns), pavement, and occasionally bare ground. High commission errors or overmapping of dead tree pixels or objects can result from this. These factors ultimately require manipulation to rectify, such as masking out areas of non-dead trees before classification, or significant manual editing after classification, to clean up the map. These approaches, as utilized in this study, were successfully
able to deal with between date/data set differences and were reasonably successful in improving accuracies.

Another limitation is not having an automated object-based accuracy assessment approach. The visual, expert-based approach is very effective in that the human eye can quickly differentiate a successful object from a non-successful object, but the drawback is that the process is not time-efficient, and can be subjective. One could attempt to reduce interpreter bias by having several people review a validation map, object by object, and then average the results of the group, but again this would not be time efficient. Also, the validation maps, which are created by a person manually digitizing dead objects, are also biased, based on subjective interpretation and contain an unknown degree of error.

One of the limitations with the forest stand structure analysis as it relates to the levels of tree mortality is that the fieldwork was conducted in 2008, while the imagery analysis was conducted for the years 1997 through 2005, so there is some time lag between conditions captured in the imagery and actual field conditions. It would have been ideal to have collected field data for each year of imagery. Also in the intervening years forest fires impacted the study areas, although this was accounted for by masking out burned areas in order to constrain the analysis to mortality caused by factors other than recent fires. There had also been forest thinning projects, so in those areas the fieldwork was constrained to stands that had not been yet thinned.
A fundamental limitation with the GLM modeling efforts is the prevalence of multicolinearity between the environmental variables, which violates the assumption of independence between variables. Because of this restraint, certain variables which could be important ecological predictors were dropped. With the decision tree classifier approach the limitation is that mapping the predictive values with complex decision trees is not straightforward.

Another limitation for the tree mortality analysis was the scale of the study sites and sample sizes. As evidenced with the tests of optimal tree sample sizes, larger, tightly packed samples of tree locations did not result in accuracy rates that were as high as those from smaller, less tightly packed samples of tree locations. The semivariograms calculated in Chapter 3 indicated for some study areas and dates, the ideal sampling distance is over 1000 - 2000 meters. In the smaller study areas this would limit the data points available for analysis. An expansion of the study to include larger areas of forest to the north (San Jacinto) and south (San Pedro Martir) might help in overcoming these sampling issues.

5.4. Future research

There are many aspects of the remote sensing methods that could be further explored. For example, the calculation and addition of texture layers to classification, which has been shown in other studies to be effective in improving accuracies, has not been tested with the present data set. Also, after segmentation, other classification routines could be tested, in addition to the nearest neighbor classifier. Further
development and testing of object-based accuracy assessment techniques would also be warranted. It would also be beneficial to test the spatial-contextual and OBIA routines on additional types of imagery, such as panchromatic, very high spatial resolution image data, which would enable analysis of extant panchromatic imagery from much earlier time periods.

It would be illuminating to expand this study at a broader scale, in terms of extent of study area. The present study was constrained to mountain tops within San Diego County, but the broader geographic region, the Peninsular Range, extends from the San Jacinto Mountains down into Baja, Mexico to the Sierra San Pedro Martir. It would be interesting to expand the study to this larger region and investigate the latitudinal and altitudinal effects on mortality over a broader scale and time. In addition, while this dissertation work focuses on conifers, the oak tree species in the local forests have also been mapped and field data were collected for a stand structure analysis of these oak species. It would be useful to subsequently analyze these data, particularly in light of the spread and resultant dieback from the Gold spotted oak borer, *Agrilus auroguttatus*, in southern San Diego County.

In general, it would be useful to apply the methods and techniques utilized for this dissertation to other areas experiencing tree (or shrub) dieback, or really any patchy phenomena, including further terrain and environmental factors interaction analysis, application of remote sensing techniques (object-based image analysis, land-use change, or analysis of phenological change), time series analysis, and climate change scenario analysis. From a methodological perspective, it would be productive
to continue to refine and explore high resolution imagery analysis techniques, as well as other remote sensing, GIS, and modeling techniques that elucidate useful landscape analysis and understanding.
REFERENCES


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