Evaluation of hierarchical segmentation for natural vegetation:

a case study of the Tehachapi Mountains, California

by

Yan-Ting Liau

A Thesis Presented in Partial Fulfillment
of the Requirements for the Degree
Master of Arts

Approved October 2013 by the
Graduate Supervisory Committee:

Janet Franklin, Chair
Billie Turner
Soe Myint

ARIZONA STATE UNIVERSITY

December 2013

ABSTRACT

Two critical limitations for hyperspatial imagery are higher imagery variances and large data sizes. Although object-based analyses with a multi-scale framework for diverse object sizes are the solution, more data sources and large amounts of testing at high costs are required. In this study, I used tree density segmentation as the key element of a three-level hierarchical vegetation framework for reducing those costs, and a three-step procedure was used to evaluate its effects. A two-step procedure, which involved environmental stratifications and the random walker algorithm, was used for tree density segmentation. I determined whether variation in tone and texture could be reduced within environmental strata, and whether tree density segmentations could be labeled by species associations. At the final level, two tree density segmentations were partitioned into smaller subsets using eCognition in order to label individual species or tree stands in two test areas of two tree densities, and the Z values of Moran's I were used to evaluate whether imagery objects have different mean values from near segmentations as a measure of segmentation accuracy. The two-step procedure was able to delineating tree density segments and label species types robustly, compared to previous hierarchical frameworks. However, eCognition was not able to produce detailed, reasonable image objects with optimal scale parameters for species labeling. This hierarchical vegetation framework is applicable for fine-scale, time-series vegetation mapping to develop baseline data for evaluating climate change impacts on vegetation at low cost using widely available data and a personal laptop.

For my parents and my younger sister who always support me with love

ACKNOWLEDGMENTS

I thank Dr. Janet Franklin for advising and encouragement to provide me the guideline, comments and edit for completion of this thesis. I also appreciate Dr. Sergio Rey for teaching and discussions on python programming and spatial analyses that formed the main technical basis of this thesis. I am grateful my committee members, Dr. Billie Turner and Dr. Soe Myint to read through the thesis and offer me some suggestions to make this thesis more complete, and in particular, I appreciate Dr. Soe Myint for allowing me access to ENVI and eCognition. I also thank my colleagues in the Vegetation and Landscape Ecology lab, Julie and Jennifer, for providing suggestions, especially for presentations.

The thesis was supported with data provided by Collaborative NSF award EF-1065826 to J. Franklin, ASU (PI: F. W. Davis, UCSB).

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

INTRODUCTION

Vegetation mapping is required for biological conservation and forest inventory; especially time series mapping is commonly used to detect transformations of species or suitable habitats (e.g. Egbert et al., 2002; Loh et al., 2005; Hill et al., 2010) and evaluate impacts of climate change on species (e.g. Pettorelli et al., 2005; Donohue et al., 2009). Species distribution models (SDMs, also called habitat suitability models), which correlate environment variables with species sampling data to map species occurrences (Franklin, 2010), have been used for vegetation mapping, because field-based approaches are cost and labor-consuming, and pure remote sensing imagery interpretations are lacking in ability to detect individual species (Franklin, 1995). Furthermore, variables which are derived from remotely sensed imagery and used as predictors provide more accurate species predictions (Kerr & Ostrovsky, 2003). However, SDMs are viewed as static and equilibrium models capturing species-environment relations at large scales, and ignoring dynamic biological interactions, such as dispersal, migration, facilitation, competition, mutualism and predation at local scales (Pearson & Dawson, 2003). Predictors, which mainly apply climate models, are often in very coarse resolutions and may not capture topoclimatic-controlled species habitats, specifically in rugged mountains (Sekercioglu et al., 2007; Thuiller et al., 2008; Seo et al., 2009; Chazal & Rounsevell, 2009; Franklin et al., 2013; Mateo et al., 2013). One solution is to downscale climate models to finer spatial resolutions (Flint & Flint, 2012), and those studies showed better species predictions at finer scales (Randin et al., 2009; Franklin et al., 2013). The other solution is to map species directly using hyperspatial remotely sensing data (1 to 2 m), and track vegetation transformations over time through repeated mapping.

With advances of sensors, spatial resolutions of remotely sensed data have been improved to centimeter levels and provide more spatial information on species distributions. For example, WorldView-1, which was launched on September 18, 2007, collects Panchromatic imagery at 0.5m, and WorldView-2, which was launched on October 8, 2007, collects Panchromatic imagery at 0.46m and Multispectral imagery at 1.84m. GeoEye-1, which was launched on September 6, 2008, collects Panchromatic imagery at 0.41m and Multispectral imagery at 1.65m. As Nagendra & Rocchini (2008) indicated, hyperspatial imagery provides more accurate locations of tree canopies, than hyperspectral imagery. However, higher spatial resolutions may not have higher classification accuracies, due to higher variances within classes (Woodcock & Strahler, 1987) (also called H-resolution problem, which is defined that land cover elements are larger than pixel sizes (Strahler et al., 1986), so each land cover elements have more pixels with higher variances). In addition, hyperspatial imagery with large data sizes increases loadings of computer hardware requirements (i.e. segmentation procedures have very high memory and CPU requirements), so most studies only test in small areas, because of memory limitations of personal computers and long processing times. Object-based image classifications can be an alternative on account of improving salt and pepper effects and increasing classification accuracies over pixel-based image classifications, which ignore similarity of near pixels (Shandley et al., 1996; Huang et al., 2003; Yan et al., 2006; Yu et al., 2006; Budreski et al., 2007; Varela et al., 2008; Blaschke, 2010). Also, imagery can be stratified into smaller subsets (Strahler, 1981) within the processing capabilities of personal computers.

Object-based image classification includes a two-step procedure, image segmentation and image classification. Image segmentation gathers several similar neighbor pixels together as objects, and image classification categorizes or labels land cover types for each object. In theory, image objects have equal internal variances at a common scale (Woodcock & Harward, 1992), and hyperspatial imagery is helpful to derive detailed objects. However, each class with varying sizes needs different scales to define appropriate objects (Woodcock & Harward, 1992; Hay et al., 2003; Huang et al., 2003), and multispectral bands are helpful to labeling or classification procedures.

The appropriate scale for identifying objects can be found by an iterative workflow (Baatz et al., 2008) using hierarchical semantic models or knowledge (Benz et al., 2004). In other words, there is no single optimal scale parameter, but a spatially-nested (multi-scale) structure (Woodcock & Harward, 1992; Baatz & Schäpe, 2000; Hay et al., 2003; Benz et al., 2004) can be used to identify objects with different sizes and describe the object traits, especially in poor imagery. For example, Yu et al. (2006) pointed out vegetation alliances, which are more general than species types, are also critical to define tree species segmentation, and the similarity of near objects may decrease classification accuracies. Kim et al. (2011) indicated that multiscale image classification involving both spectral and texture traits can increase classification accuracies. Nevertheless, those hierarchical-segmentation applications in hyperspatial imagery are still limited to classify primary land cover categories (Kim et al., 2011) or estimate forest parameters (Chen & Hay et al., 2011; Chen et al., 2012) in small test areas, and there is lacking in a general framework for specific species in large areas.

Previous vegetation mapping frameworks have taken two approaches, the data-based orientation and vegetation-type orientation. In the data-based approach, involving new data resources can increase interpretations of vegetation traits (Xie et al., 2008; Kim et al., 2011; Chen & Hay et al., 2011; Chen et al., 2012). In one example, Xie et al. (2008) used this approach to identify exotic Australian pine with three-level segmentations: NDVI to distinguish vegetation from non-vegetation, tree heights, derived from LIDAR, to distinguish trees from short trees, shrubs and grasses, and shape/color and smooth/compactness weighting parameters for target objects. However, higher data requirements raise costs, and may not be extensively adapted to other regions. In the vegetation-type approach, vegetation nested structures from tree, stands, forest types (e.g. pine, oak and red fir) and vegetation types (e.g. wetland, forest and grassland) are another solution (Woodcock & Harward, 1992). This framework, incorporating object-based image classifications (Woodcock & Harward, 1992) and labeling procedures (Franklin et al., 2000), can be used to identify more general vegetation life form or land-cover types (e.g. conifer forest, hardwood forest, chaparral, soft chaparral) and within them, more specific vegetation types, for example at the level of Associations (e.g. Jeffrey pine, black oak and coast live oak) in the US National Vegetation Classification Systems (http://usnvc.org). However, the labeling procedures used for vegetation types, based on multispectral classification and image interpretation, may not reach very high accuracies for specific species (e.g, accuracies for conifer types ranged from 23% to 100 % in Franklin et al., 2000).

PROBLEM STATEMENT AND LITERATURE REVIEW

The goal of this study was to implement a hierarchical framework for mapping specific tree species using RGB (red, green blue; visible) bands (widely available as historical aerial photos) derived from 1 m digital orthophoto quadrangles (DOQ) and an evaluative framework to assess the results. A further goal was to evaluate methods that can be implemented on personal computers (with conventional amounts of memory). Although lots of algorithms and classifiers, especially machine learning methods, were extensively used in identifying individual species (e.g. Foody et al., 2005), the hyperspectral and/or hyperspatial imagery (less than 0.5 m) that these methods relied on is not always available. Thus, the hierarchical framework, which was built on widely available data and computing capabilities, and incorporated ecological knowledge of the study area, provided the ability to label segements within specific species types, even if imagery data were not able to support species identifications.

Partitioning the image based on tree density was a key part of the natural vegetation framework used in this study (Figure 1), but previous segmentation studies (reviewed by Fu & Mui, 1981; Pal & Pal, 1993; Jain et al., 1999; Pham et al., 2000; Sonka et al., 2008; Ma et al., 2010) have not been extensively applied to natural vegetation using a robust approach. Among those segmentation methods, which were classified by Fu & Mui (1981), edge-based algorithms were the most vulnerable to noise (i.e. heterogeneous pixels with higher variances, especially in sparse tree stands) (Fu & Mui, 1981), and threshold-based algorithms cannot deal with imagery complexities, even using local threshold approaches (Trier & Taxt, 1995; Sezgin & Sankur, 2004). In contrast, region-based algorithms were widely incorporated with other algorithms, including the Woodcock & Harward (1992) region growing algorithm, eCognition's imagery merging and fractal net evolution approach (Baatz et al., 2000; Hay et al., 2003; Benz et al., 2004), and multiscale object-specific segmentation (MOSS) using size constrained region merging (Hay et al., 2003; Hay et al., 2005). Those algorithms could better deal with noise and avoid over-segmentation, compared to other algorithms, such as the watershed algorithm and the region growing algorithm (Wang, 1997; Sonka et al., 2008; Ma et al., 2010). However, two-step labeling procedures (Franklin et al., 2000) or repetitive testing on parameters (e.g. scale, compact and shape in eCognition) to construct hierarchical frameworks (Baatz et al., 2000; Hay et al., 2003; Benz et al., 2004; Baatz et al., 2008) were still time-consuming and data-intensive. Therefore, a robust alternative using tree density segmentation was necessary.

Furthermore, tree density was the main trait of the hierarchical vegetation framework for two reasons (Figure 1). Tree density reflected different species types (e.g. shade-intolerant species and shade-tolerant species) (King et al., 1996; van Gelder et al., 2006; Poorter et al., 2012; Lines et al., 2012). Additionally, different tree densities also mean different image objects, which required two processing procedures at species levels and landscape levels, according to previous studies. One type of study focused on delineating individual tree crowns and labeling species by multispectral bands using classifiers, whereas the other type of study concentrated on decomposing landscapes into smaller objects (vegetation stands, a group of trees) and label species by the majority classified pixels within segmentations (Shandley et al., 1996), vegetation gradient model adding spectral mixture analysis (Franklin et al., 2000) or non-parametric classifiers (e.g. Benz et al., 2004; Yu et al., 2006).

The first approach, tree crown delineation, was effective at interpreting species counts and types, which can almost substitute for field-based surveys (Haara & Haarala, 2002; Leckie et al., 2003; Leckie et al., 2005; Gougeon & Leckie, 2006; Katoh et al., 2009). This approach mainly applied a series of algorithms to tree crown delineation, such as valley-following, region growing and watershed segmentation (Culvenor, 2003; Li et al., 2008; Ke & Quackenbush, 2011a; Ke & Quackenbush, 2011b; Larsen et al., 2011). Nevertheless, the fundamental assumptions were that tree crowns should be clearly separated in space (not overlap) and should be in regular shapes and similar sizes, according to algorithm functions (Ke & Quackenbush, 2011a; Ke & Quackenbush, 2011b). Practically, this approach was less effective in heterogeneous and denser hardwood stands than conifer landscapes. The other type of studies were more effective at segmenting dense or heterogeneous tree stands at landscape scales into smaller and more homogeneous segmentations (e.g. Yu et al., 2006; Laliberte et al., 2007; Myint et al., 2008; Mallinis et al., 2008; Heumann, 2011), but segmentations in sparse tree stands may not be partitioned well, due to effects of non-vegetation areas or shadows. As a result, two tree densities represent different ecological conditions and image processing challenges, and require different segmentation parameters (or algorithms).

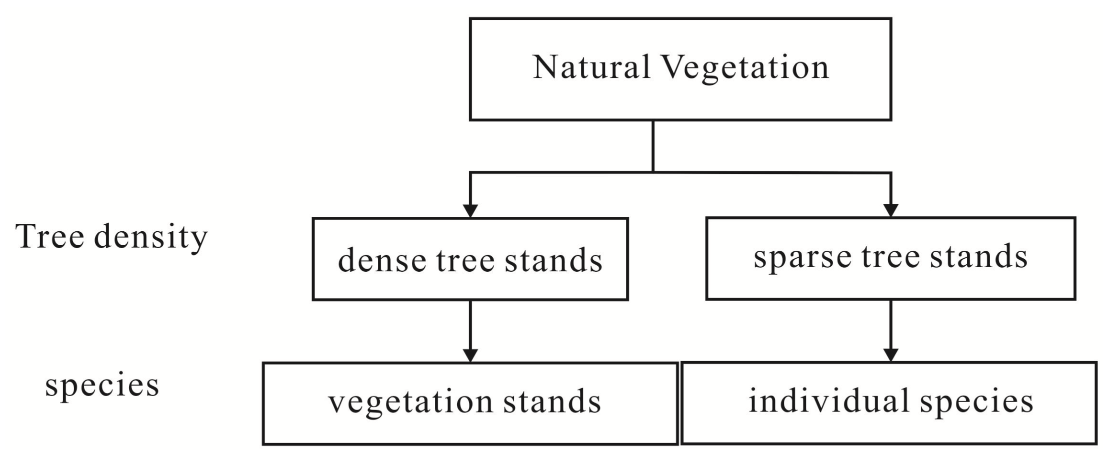


Figure 1. Vegetation hierarchical framework. The text on the left indicates the vegetation attribute discriminated at each stage of stratification and segmentation. Tree density patterns were use as the intermediary between nature vegetation and species as a three-level framework.

Specifically, the hypotheses tested in this study were:

1. Environmental stratification could reduce the variation in tone and texture among strata. I assumed that reducing variance in image tone and texture indices simplified species composition based on studies showing that texture indices (local variances and second order textures) have high correlations with forest structural parameters (e.g. standard deviation of diameters and basal area) (Ozdemir & Karnieli, 2011; Klobučar et al., 2011) clearly distinguish different forest parameters (e.g. stand ages) (Franklin et al., 2001).
2. Identifying tree-density patterns could be used to simplify species types in a given area where there was no recent disturbance. This hypothesis was based on assumptions that shade tolerance was related to variations in tree architectural parameters, such as stem and crown dimensions (King et al., 1996; van Gelder et al., 2006; Poorter et al., 2012; Lines et al., 2012), and species life history traits (e.g. different seedling time between oaks and pines) and environmental conditions (e.g. topographic and climatic conditions), which constrained species regenerations, resulting in different species dominances (pine

dominance and oak-pine codominance) in stands with different tree densities (Gracia et al., 2002; Zavala & Zea, 2004).

3. Different tree density distributions had different optimal scale parameters for image segmentation where the optimal scale parameter was that with the lowest segmentation variances and spatial autocorrelations (Kim et al., 2008; Kim et al., 2009; Johnson & Xie, 2011). The hypothesis was based on studies indicating that different image structures, such as sizes of tree crowns or clumps are a function of different spatial scales (Woodcock & Strahler, 1987).

MATERIALS AND METHODS

A two-step procedure, which involved environmental stratification using the global Otsu's method and image segmentation using the random walker algorithm, was used to identify two tree densities, and in the third step, object-based classification using eCognition was used to extract species objects (Figure 2). Environmental stratification, based on elevation, slope or aspect, was used to partition the whole image into smaller subsets. Large images needed to be subset in order to reduce processing time and variation partitioning can help to statistically characterize certain components by increased stationarity or homogeneity within strata (Osborne & Suárez-Seoane, 2002; Peres-Neto et al., 2006). A non-parametric test applied to local means and variances in image tone was used to see which terrain variable was most effective at reducing variation in local tone and texture measures within strata. The reasons for basing stratification on one environmental variable, rather than all three, were that one of goals in this study was to build a parsimonious procedure for reducing computations, and stratification based on a single variable was simple to implement. Then, the random walker algorithm was applied within the environmental strata to partition imagery into smaller subsets based on tree density patterns. The segmentation was evaluated using species types based on independent vegetation maps (the Timber survey and CALVEG) and evaluating whether the segmentation distinguishes image regions associated with particular species or species associates (Figure 2). Finally, the segmentation of tree densities was further partitioned using eCognition with different scale parameters and evaluated whether the detailed species segmentation related to specific guidelines of scale parameters on identifying species objects (Figure 2). So as to minimize costs, this study mainly used open source python libraries, scikit-image and other free software, and free DOQ imagery, to achieve the above goals.

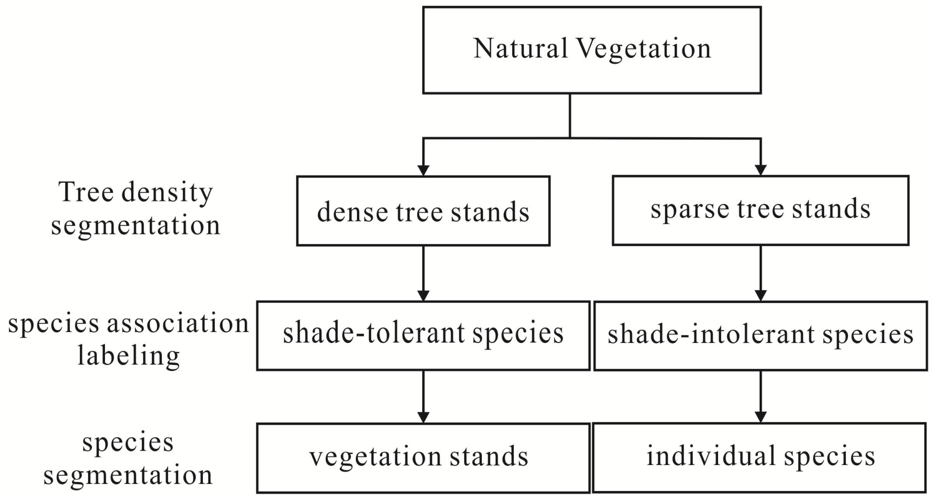


Figure 2. Procedures for Vegetation hierarchical framework. The text on the left indicates the vegetation attribute discriminated at each stage of stratification and segmentation. At the first level, the global Otsu's method and the random walker algorithm were used to partition nature vegetation into two tree density segmentations, dense tree stands and sparse tree stands. At the second level, the two tree density segmentations were tested by species association labeling. In theory, shade-tolerant species tend to occur in dense tree stands, while shade-intolerant species tend to occur in sparse tree stands. At the final level, eCognition was used to partition the two tree density segmentations into smaller subsets for vegetation stands or individual species.

Study Targets And Data Sources

Tejon Ranch, which belongs to Tejon Ranch Company, is located in the convergence of four eco-regions: the Mojave Desert, the Central Valley, the Sierra Nevada, and the Transverse Ranges (Bailey, 1995). The research area is located in the Tehachapi Mountains, elevation ranging from 368 to 2,360 meters (Jarvis et al., 2008) (Figure 3). Based on the only climate station within Tejon Ranch, 434.3 meters elevation, the average yearly temperature is 59.61℉ (1895-2011) and yearly rainfall is 11.29 inches (1899-2011) (Menne et al., 2013). This area has a typical Mediterranean climate. The main rainfall season concentrates in the winter from October to March of the next year, while the dry season is in the summer from July to September. The main vegetation type is oak woodlands, including canyon live oak, interior live oak, blue oak, California black oak, scrub oak, and others along with ponderosa pine and gray pine (United States Department of Agriculture Forest Service: CALVEG, 2010).

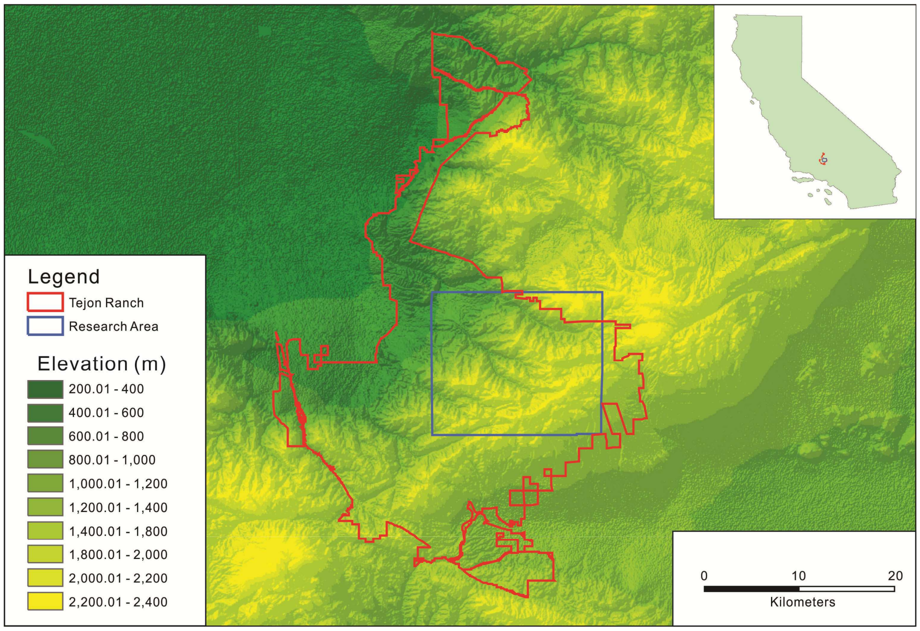


Figure 3. Elevation model of the study area showing the boundary of the Tejon Ranch in red and the Research Area (used in this study) as a blue rectangle

This study focused on two hardwood species, blue oak and California black oak, and two conifer species, ponderosa pine and grey pine. The four species are shade-intolerant (Burns & Honkala, 1990), which tended to occur in sparse tree stands. Nevertheless, the shade tolerance of California black oak varies with age (higher shade-tolerance in sapling and growing taller to the top as less shade-tolerance), so it can sustain in denser tree stands (Burns & Honkala, 1990). More importantly, owing to the long-term fire disturbance history, tree density does not always achieve its maximum possible value, and local adaptations to microenvironments and regeneration played more important roles in determining tree density. For example, ponderosa pines in Southwestern United States were often found in dense stands changing from a range of 49-124 trees ha^{-1} at the time of Euro-American settlement to a range of 1235-2470 trees ha^{-1} now (Habeck, 1992; Fitzgerald, 2005; DeGomez, 2008), due to high density of seedlings and saplings and fast growth near burned areas (Zavala & Zea, 2004). To sum up, species successions were not clearly identified in previous literatures and records and any rules about determinants of tree densities were not extensively applied to regions (Burns & Honkala, 1990), so I only assumed that species have similar tree density patterns within a given area.

Data sources included a one-meter DOQ, SRTM 30m Digital Elevation Data v.4 and two archived vegetation type maps, referred to in this study as Timber survey and the CALVEG. The DOQ was imagery with three 8-bit bands, which was rectified by digital terrain models and ground position points to remove terrain relief and camera tilt (United States Geological Survey, 2001), so every land element was in corrected ground position. This imagery is freely available from United States Department of Agriculture: Natural Resources Conservation Service Geospatial Data Gateway (http://datagateway.nrcs.usda.gov/GDGOrder.aspx) or United States Geological Survey: The National Map Viewer and Download Platform (http://viewer.nationalmap.gov/viewer/). The SRTM 30m Digital Elevation Data, which were produced by National Aeronautics and Space Administration (NASA), were created by collecting elevation points from SRTM3 and a series of auxiliary digital terrain models for the purpose of interpolating voids to create seamless topography (Jarvis et al., 2008). The data provided not only elevation information in 30 m spatial resolution but also slope and aspect gradients by calculating the rates of maximum change and their directions (ESRI ArcGIS 10.0 help, 2011). The Timber survey was a field-surveyed map generated in 1980 for distributions of oak woodlands on Tejon Ranch (Hoagland et al., 2011), and the CALVEG was produced by the USDA Forest Service using Landsat Thematic Mapper to construct a vegetation database across California (Franklin et al., 2000).

Environmental Stratification

To create environmental stratifications, a global Otsu's method was used to separate elevation, slope and aspect images into smaller areas using scikit-image. The goal of this approach was to find an optimal global threshold in image histogram (one-dimension intensity measurements) to partition imagery into two groups by maximizing the intra-group variances and minimizing within-group variances (Otsu, 1979) in order to categorize objects from backgrounds, such as tree crowns from barren lands. Preliminary analyses determined optimal thresholds; the three stratifications were partitioned by thresholds of 1169 m for elevation, 41˚ for slope and 149˚ for aspect (Figure 4).

The global Otsu's method has been shown to be more effective than other binarization methods (Pal & Pal, 1993; Trier & Taxt, 1995) with low computational time. Although those binarization methods produced image subsets that were not spatially separated (Fu & Mui, 1981; Pal & Pal, 1993), and needed to be delineated by hand, spatial distributions of strata showed diverse patterns to reflect tree covers.

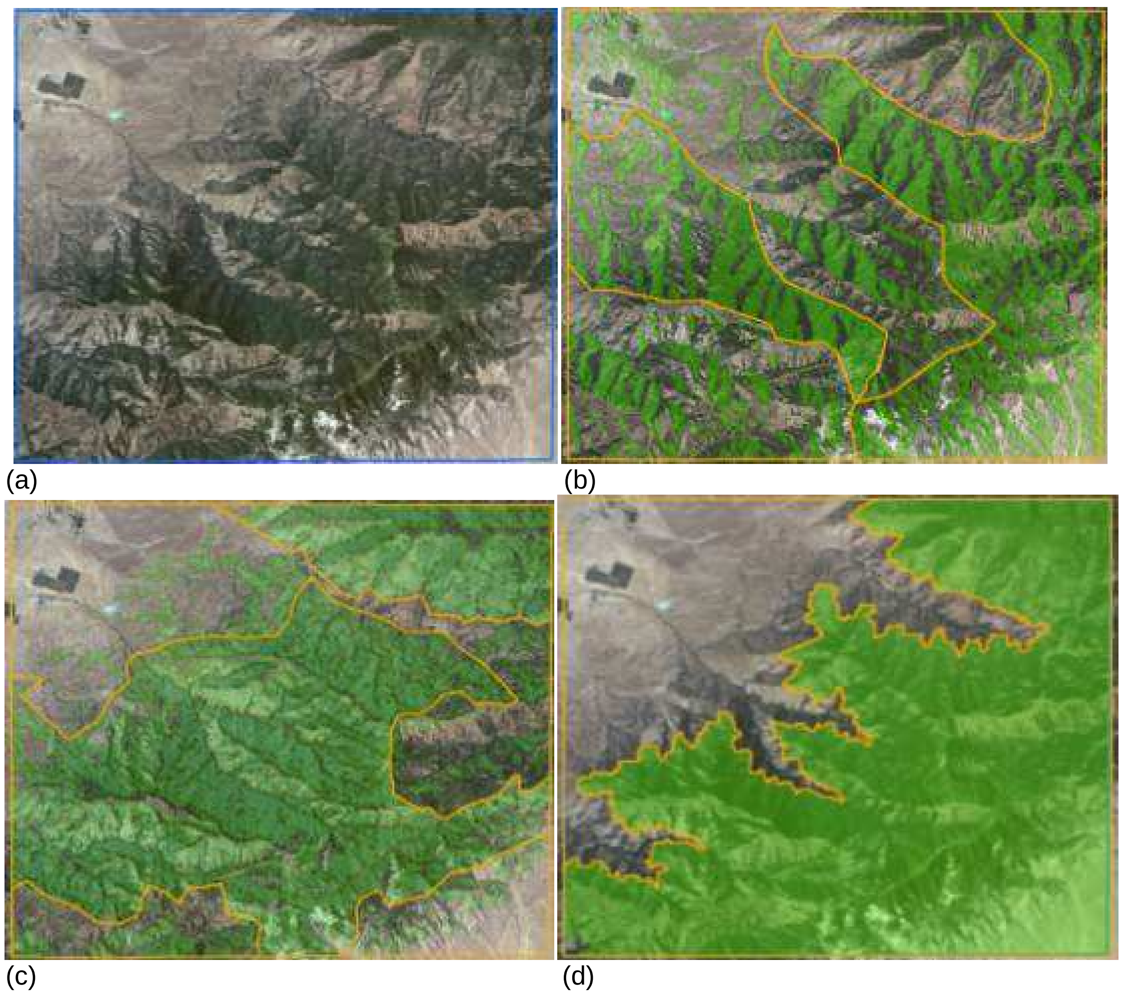


Figure 4. Spatial distributions of two-group separations by global Otsu's method: the green regions represented the environmental layers were above the optimal thresholds. (To visualize clearly and eliminate some salt and pepper effects, the maps applied a majority filter using focal statistics in ArcGIS 10.0) The orange lines showed manual strata of three environmental variables, and blue lines showed boundaries of the study area. Maps showed (a) Original imagery (b) Aspect stratification (c) Slope stratification (d) Elevation stratification

Image Segmentation On Tree Density

In this study, the random walker algorithm was used for image segmentation. Segmentation was based on single red band. The random walker algorithm, which was proposed by Grady (2006), was used to partition imagery into smaller subsets more robustly using scikit-image. The random walker algorithm originated from the graph theory to view the whole imagery as the combinations of vertexes (nodes) and edges (arcs), and the random walkers, which represented each individual pixel, were trying to formulate a path to their neighbors randomly as the probabilities. Therefore, the algorithm started from defining the markers, a group of seeds as the sampling of desired imagery objects. Then, this algorithm would assign each unseeded pixel a probability, which those unseeded pixels reach the nearest seeds based on absolutely distances and assign a piecewise weight by the image intensity. Finally, the algorithm would assign a seed class to those unseeded pixels for cuts, mainly according to the probability, and the cuts might be adjusted by the weights to avoid crossing sharp image intensities. For example, if three out of four neighbors belong to one class, then the focal pixel is assigned to this class. Thus, the random walker algorithm can keep locally consistent boundaries, regardless of spatial extents and attribute ranges.

However, how to define the markers was not described in details in the original paper, and few studies have used the random walker algorithm to identify vegetation types, because the random walker algorithm was under the assumptions (also called supervised segmentation algorithms) that a series of pixels for desired objects and backgrounds were known and nearby pixels between desired objects and backgrounds can evolve to desired boundaries. To handle this issue, the grey-level image tones, which were assumed to be a function of tree densities, were used in the marker designs. The higher image tones were, the lower tree densities were. The map classification using natural break optimizing, which was to reduce within-group variances, in three classes was utilized to derive the thresholds for desired objects and backgrounds. As a result, barren lands or individual trees over the highest threshold were viewed as the desired objects, and denser tree stands below the lowest threshold were treated as the background (Figure 5; Figure 6). Then, the random walker algorithm could produce the correct boundaries between desires objects and backgrounds. In the second segmentation, the same procedures were applied to separate lower tree density stands from higher tree density stands (Figure 5; Figure 6). Finally, barren lands or individual trees and lower tree density stands were combined as lower tree density stands for species association labeling (Figure 5; Figure 6).

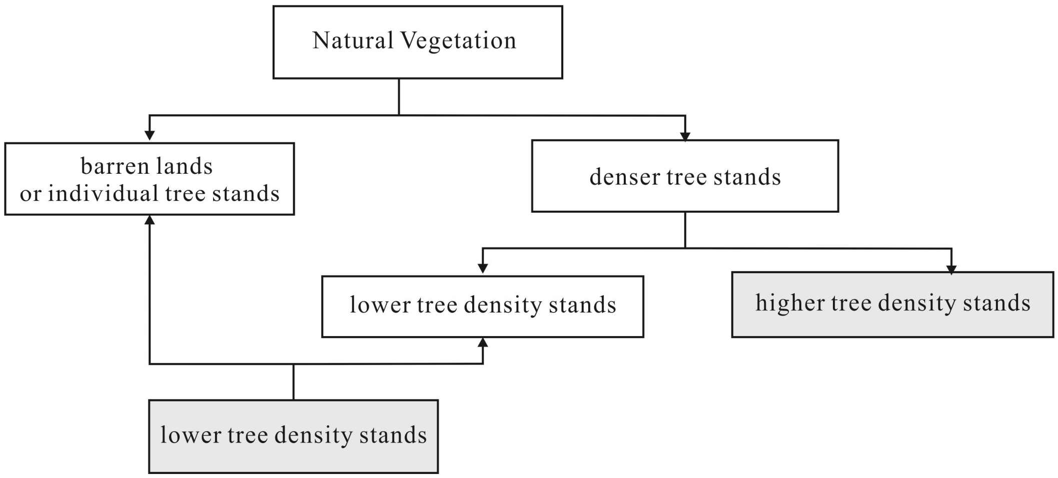
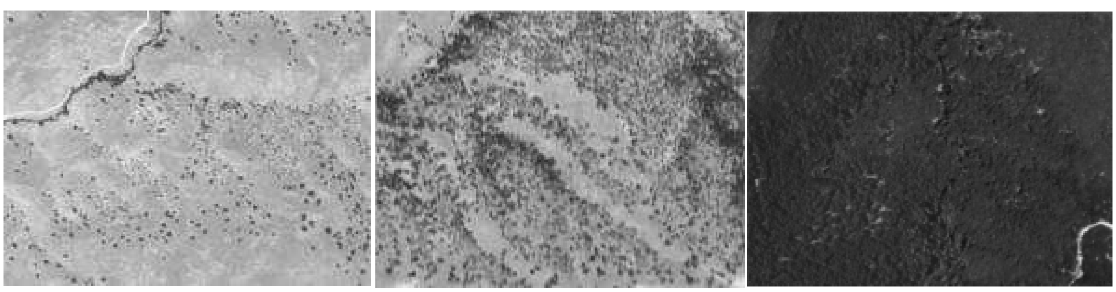


Figure 5. Tree density segmentation framework using the random walker algorithm and combined results: grey squares represent combined results for species association labeling



(a) (b) (c)

Figure 6. Tree density distributed patterns: (a) Barren lands and individual tree stands (b) Lower tree density stands (c) Higher tree density stands

Species Segmentation

Detailed vegetation objects were further partitioned following the tree density segmentation using eCognition, which has been extensively used in studies of object-base image classification for vegetation inventories (e.g. Yu et al., 2006; Laliberte et al., 2007; Mallinis et al., 2008). Segmentation was based on 17 attributes or features: RGB; first-order textures: mean, standard deviation, kurtosis, mean Euclidean distance, skewness, variance; second-order textures: mean, variance, homogeneity, contrast, dissimilar, entropy, second moment, and correlation (Haralick, 1973; Haralick, 1979). Nevertheless, the segmentation using eCognition was neural (without meanings), and the meanings counted on classifiers to label after segmentation procedures. Therefore, as a prior framework, the eCognition segmentation cannot be implemented with appropriate parameters beforehand, but optimal scale parameters needed to be identified.

Segmentation Evaluations

To test the hierarchical vegetation framework and the three hypotheses, a series of evaluations were used. First, image local tone and texture, mean and standard deviation in digital number (DN) of the red band, were used to see which terrain variable could be used to stratify the image most effectively, because image tone and texture correlates with forest structure parameters. A non-parametric test, Kruskal-Wallis test was applied using SPSS Statistics 20.0 to test whether variances were equal among groups.

Second, four focal species were chose to examine the effectiveness of the random walker algorithm by determining whether the two tree density patterns (Figure 5), which were combined from three tree density types (Figure 6), reflected different species type distributions as determined by the archival vegetation maps (reference data). Indices of map agreement, including the kappa value, overall accuracies, user’s accuracies and producer’s accuracies, are based on the values in a confusion matrix (Lillesand et al., 2004; Franklin, 2010) (Table 1). Sampling the maps in order to calculate those indices were based on a stratified random approach accomplished using a “plug-in” sampling design tool in ArcGIS 10.0 to allocate 100 points proportionally by class areas. The strata were based on the three tree density segmentations (Figure 6), where larger segmentation areas had more sampling points.

Table 1

Confusion Matrix And Evaluative Indices

<table>
<tr><th>Reference data / Segmentation results</th><th>Ponderosa pine &California black oak</th><th>Blue oak & Grey pine</th><th>Row total</th><th>User's accuracy</th></tr>
<tr><td>Higher tree density stands</td><td>a</td><td>b</td><td>e</td><td>a/e</td></tr>
<tr><td>Barren land and very few tree stands & lower tree density stands</td><td>c</td><td>d</td><td>f</td><td>d/f</td></tr>
<tr><td>Column total</td><td>g</td><td>h</td><td>i</td><td></td></tr>
<tr><td>Producer's accuracy</td><td>a/g</td><td>d/h</td><td></td><td></td></tr>
<tr><td colspan="2">Overall accuracy = (a+d) / i</td><td colspan="3">kappa value = $\frac{[(a+d)-(((a+c)*(a+b)+(b+d)*(c+d))/n]}{[n-(((a+c)*(a+b)+(b+d)*(c+d))/n]}$</td></tr>
</table>

In order to evaluate the scale parameters used in the eCognition segmentation, this study applied an objective (unsupervised) evaluation approach by using Moran's *I* (Kim et al., 2008; Kim et al., 2009) as a measure of spatial autocorrelation to measure the similarity of segment-averaged attributes as a function of the distance between segments. Supervised evaluations cannot be used as it was in most previous studies because the two reference maps were created at different scales (Hoagland et al., 2011), so it would not be possible to distinguish inaccuracies of vegetation segmentations from boundary errors in maps made at other scales. Another reason was that pixels within segmentations were not spectral homogeneous (Ryherd & Woodcock, 1996).The basic idea of unsupervised evaluation was that attributes of optimal segmentations with clear boundaries (such as average spectral or texture values) should have low between-segment spatial autocorrelation, whereas over-segmentation (many small polygons), and under-segmentation (where the polygons are larger than the optimal segmentations), yielded segments whose attributes had higher between-segment spatial autocorrelation (Figure 7). Kim et al. (2009) pointed out that the optimal scale parameters can contribute to better classification accuracies. Therefore, the segmentations based on different scale parameters were evaluated based on Moran's *I* in two test areas, lower tree density stands and higher tree density stands (Figure 8).

The goal was to see whether there were different optimal scale parameters for segmentation of two tree density patterns, because each has different sizes of individual trees and tree stands. Moran's *I* was calculated using the open software, GeoDa (Anselin et al., 2006)

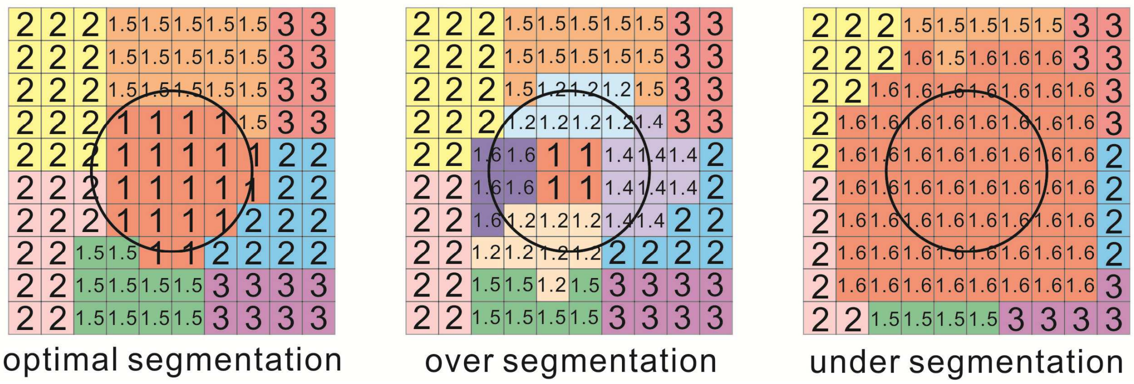


Figure 7. Examples for evaluations of segmentation results: the black circle represents the tree crown object, and the color regions represent the segmentation results

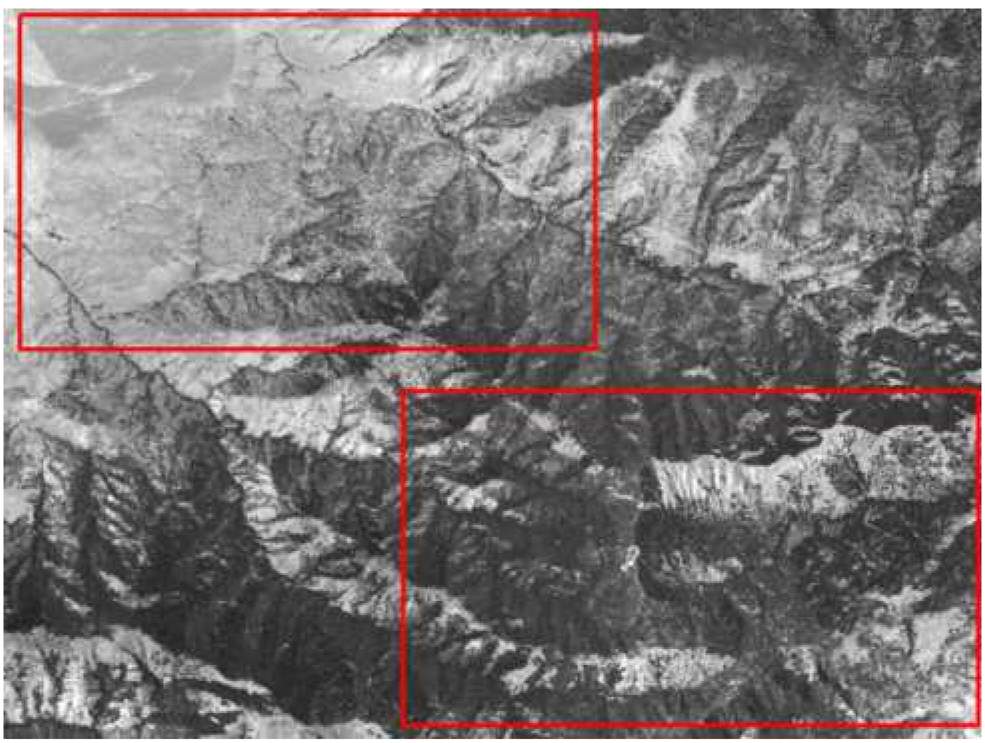
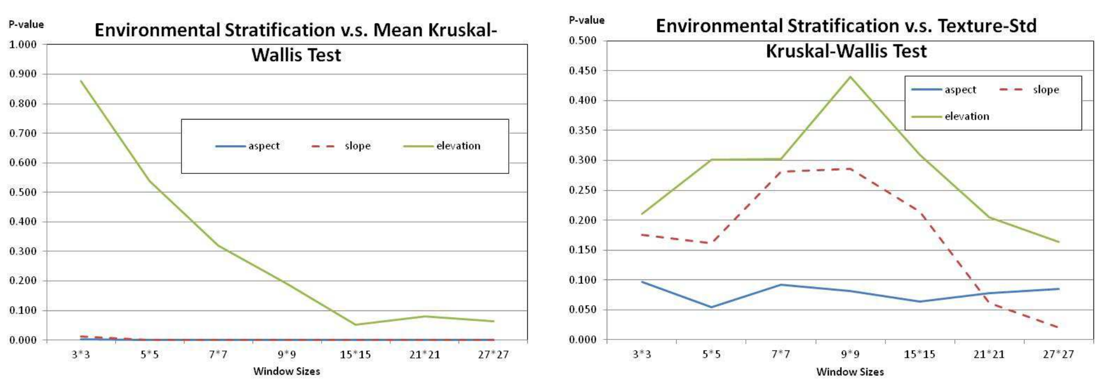


Figure 8. Test areas with two tree densities for detailed vegetation segmentation

RESULTS

Environmental Stratification

The aspect stratification had the best performance in terms of increasing stationarity within strata. Both tone and texture, mean and standard deviation of red-band digital number (DN) for different window sizes, showed significantly reduced variance within strata based on aspect, and the slope strata had the second best performance (Figure 9). Visually, the aspect stratification was most effective in separating tree crowns from barren lands, and the slope stratification again had the second performance (Figure 4). The slope stratification could be used to identify parts of barren lands, which had less steep slopes, but the elevation stratification was not useful for distinguishing woodland cover strata in this study area. Therefore, the aspect and slope variables produced strata that reduced variance in local measures of tone and texture, supporting the first hypothesis.



(a) *(b)*

Figure 9. Local tone and texture evaluations for environmental stratifications showing the p-values of the K-W test as a function of window size. (a) mean image tone (digital number; DN), and (b) standard deviation in DN, for each window size.

Image Segmentation On Tree Density

The two tree density segmentations based on the random walker algorithm effectively separated the two species types. Ponderosa pines and California black oaks tended to occur in dense tree stands, while grey pines and blue oaks tended to occur in sparse tree stands within the study area. Agreement of species types with tree density segmentations reached about 80% overall accuracies and 0.6 kappa values. There was no significant difference between two maps, the Timber survey and CALVEG, but using the aspect stratification for the thresholds of desired objects (firstly, for barren lands or individual tree stands and secondly for lower tree density stands) by natural break optimizing did perform the best to produce tree density segmentations using the random walker algorithm (Table 2). Visually, the two-step procedure was effective to separate tree density patterns into three tree density categories, barren lands or individual trees, lower tree density stands and higher tree density stands, and the two selected regions of two tree densities had similar performances on separations of tree densities (Figure 10).

Table 2
Agreements Between Species Types And Tree Density Segmentations, measured by comparing two existing vegetation maps (Timber Survey, CALVEG) with the segmentations using Kappa, overall accuracy (percent correct classification), user's accuracy (1-commission error), and producer's accuracy (1-omission error).

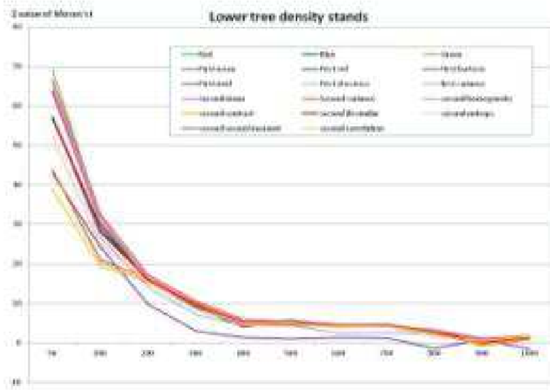
<table>
<tr><th colspan="2">Kappa value</th><th>Elevation Stratification</th><th>Slope Stratification</th><th>Aspect Stratification</th></tr>
<tr><td colspan="2">Timber Survey</td><td>0.52</td><td>0.56</td><td>0.65</td></tr>
<tr><td colspan="2">CALVEG</td><td>0.61</td><td>0.64</td><td>0.65</td></tr>
<tr><th colspan="2">Overall accuracies</th><th>Elevation Stratification</th><th>Slope Stratification</th><th>Aspect Stratification</th></tr>
<tr><td colspan="2">Timber Survey</td><td>0.76</td><td>0.78</td><td>0.83</td></tr>
<tr><td colspan="2">CALVEG</td><td>0.80</td><td>0.82</td><td>0.82</td></tr>
<tr><th colspan="2">Users' accuracies</th><th>Elevation Stratification</th><th>Slope Stratification</th><th>Aspect Stratification</th></tr>
<tr><td rowspan="2">Timber Survey</td><td>Barren land</td><td>0.72</td><td>0.8</td><td>0.88</td></tr>
<tr><td>High density</td><td>0.81</td><td>0.76</td><td>0.76</td></tr>
<tr><td rowspan="2">CALVEG</td><td>Barren land</td><td>0.64</td><td>0.76</td><td>0.72</td></tr>
<tr><td>High density</td><td>0.96</td><td>0.88</td><td>0.92</td></tr>
<tr><th colspan="2">Producers' accuracies</th><th>Elevation Stratification</th><th>Slope Stratification</th><th>Aspect Stratification</th></tr>
<tr><td rowspan="2">Timber Survey</td><td>Blue-oak & grey pine</td><td>0.82</td><td>0.8</td><td>0.81</td></tr>
<tr><td>Black oak & ponderosa pine</td><td>0.71</td><td>0.76</td><td>0.84</td></tr>
<tr><td rowspan="2">CALVEG</td><td>Blue-oak & grey pine</td><td>0.94</td><td>0.86</td><td>0.9</td></tr>
<tr><td>Black oak & ponderosa pine</td><td>0.74</td><td>0.79</td><td>0.77</td></tr>
</table>

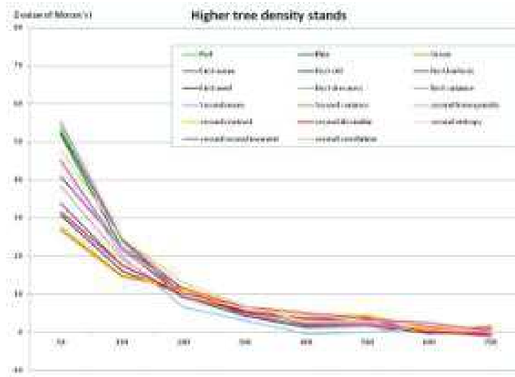
(a) (b)

Figure 10. Results of the random walker algorithm for subimages of two tree densities: Pink regions represented segmentations of barren lands or individual tree stands, and green regions represented segmentation of lower tree density. Other segmentations without colors showed higher tree density stands (appearing dark green as dense tree canopy appears in RGB imagery). (a) lower tree density area (b) higher tree density area

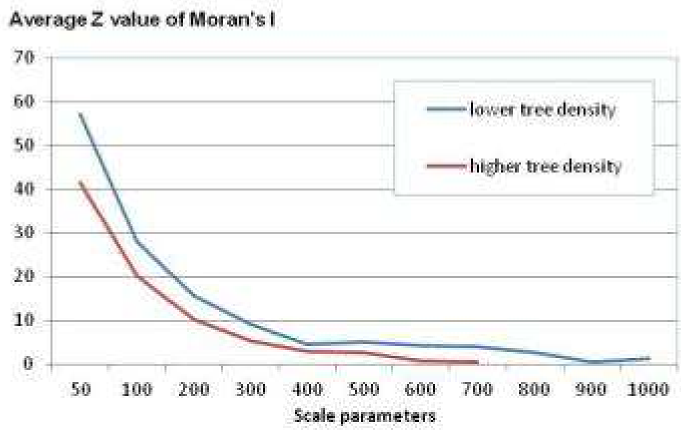
Species Segmentation

The evaluation of scale parameters suggested that eCognition may not be appropriate for detailed vegetation segmentation based on this imagery. Neither lower tree density stands nor higher tree density stands had an optimal scale parameter, which would be indicated by a minimum spatial autocorrelation measure. The Z values of Moran's *I* continuously declined as the scale parameters increase, showing no local minimum (Figure 11). The difference between results for lower tree density stands and higher tree density stands was the magnitude of Z values of Moran's I. The lower tree density stands had higher values, while the higher tree density stands had lower values (Figure 11). High variances of sparse tree stands, especially in large areas of barren lands, dominated the patterns of segmentations, while mixed species and overlapping tree crowns in dense tree stands resulted in similarity among segmentations.





(a) (b)



(c)

Figure 11. Unsupervised evaluation of object-based segmentations from eCognition using the Z values of Moran's I for each of the 17 features: (a) lower tree density stands (b) higher tree density stands (c) average Z values of Moran's I on two test areas

Visually, the larger scale parameters (400-700) did not work well to produce homogeneous segmentations for the final-level segmentations, nor did the smaller scale parameters (50-300) perform well, either in denser tree stands or sparse tree stands (Figure 12). Segmentations with smaller scale parameters showed more homogeneous segmentation results, but even scale parameter 50 was still not adequate to identify vegetation stands or tree crowns. For example, segmentations of barren lands were often mixed with near denser tree density stands, and tree crowns were often mixed with near barren lands (Figure 12).

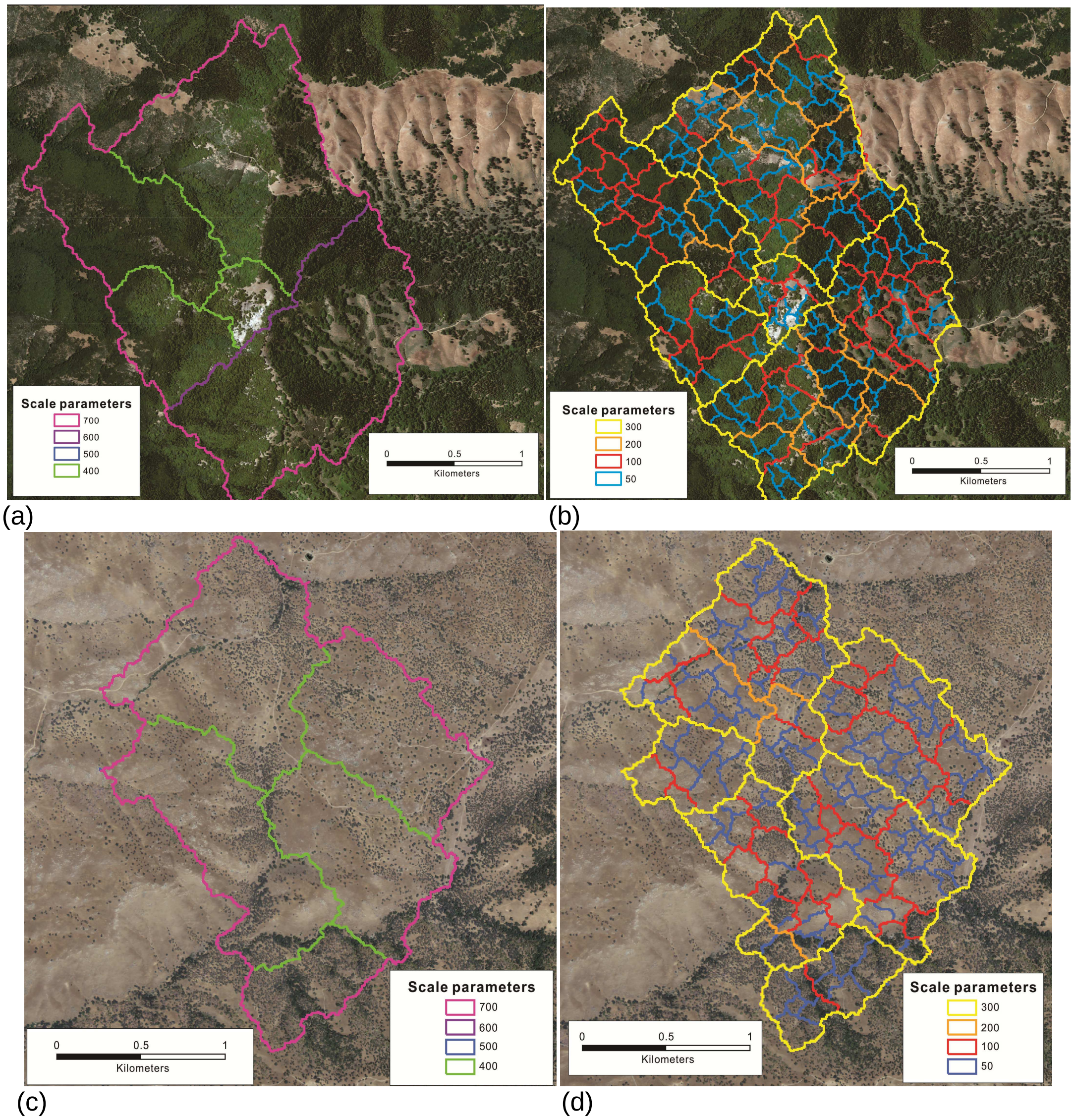


Figure 12. Segmentation examples from eCognition: segmentations with smaller scale parameters were nested or overlapped under segmentations with larger scale parameters (a) larger scale parameters in dense tree stands (b) smaller scale parameter in dense tree stands (c) larger scale parameters in sparse tree stands (d) smaller scale parameter in sparse tree stands.

DISCUSSION

Implications Of Tree Density Segmentations

Under the limitations of long-term available data and computation abilities of personal computers, tree density segmentations demonstrated in this study provided an alternative framework for vegetation mapping, instead of data intensive analyses. The approach involved both the environmental stratification and the random walker algorithm using terrain variables and 1 m hyperspatial imagery with only RGB bands as limited inputs, and those procedures can be carried out in Window 7 64-bit operating system using Intel(R) Core(TM) i7-2860QM CPU with 12 GB memory. The concrete goals were to add environmental variables, which were correlated with by tree cover, and reduce variances within environmental strata and image segmentations. Specifically, those segmentation results reflected the applications of ecological understandings. For one thing, water availability, which west-side slopes, confronting the ocean, had more precipitations than east-side slopes, might be the reason for the best performances of the aspect stratification, although no high-density climate stations can be used to validate. For another thing, because species associations are correlated with forest density in the study area, tree density segmentations could be labeled by specific species associations, even though the third-step procedure of detailed species segmentations did not work well at identifying or labeling individual species, due to inappropriate algorithm selections or coarse spatial resolutions.

In this study area, although four target species are shade-intolerant, they do not all occur in early-successional or low density stands expected for shade-intolerant species, because of their varying shade tolerance at different ages (i.e. California black oak) and the human management history (i.e. ponderosa pine). Ponderosa pines occur in dense tree stands as do California black oaks, while blue oaks and grey pines occur in sparse tree stands. The agreements between tree density segmentations and species types reached about 80%. Further testing of alternative species labeling strategies in different ecosystems is needed.

Indices summarizing the confusion matrix were used to examine the hypothesis 2, species labeling. However, those common indices, especially the kappa value, have confronted harsh challenges in recent decades. The main criticism was that the kappa value was constructed by comparisons between the reference map and classification map, but the two maps may not be meaningfully comparable. Overall, the kappa value requires that both maps followed some assumptions, such as fitting normality and not being affected by other covariates, so adjustments on each map were the key, such as the weighted kappa coefficient (Banerjee et al., 1999). In remote sensing cases, the kappa value was only a summary statistics through randomness sampling as a baseline, not a meaningful index to indicate quantity disagreement and location disagreement (Pontius & Millones, 2011). This study applied the kappa values and the overall accuracy as indices, because the stratified random approach using environmental variables, instead of wholly random sampling was effective to emphasize species locations (e.g. Franklin et al., 1999), and tree density focused on whether species type (multi-species) labels were in specific tree density segmentations, rather than improving detailed land use mapping or species mapping. Thus, simple indices were adequate for comparing the effects of environmental stratifications and assess the correctness of species type locations.

As image structures can be understood by the correlations between spatial resolution and the sizes of the objects in the scene (Woodcock & Strahler, 1987), selection of appropriate scale parameters for image objects, which combine similar neighbor pixels together, is required to match image segments with the objects in the scene more exactly. In particular, natural vegetation composes complex scene models, which consist of more than one land cover class (Woodcock & Strahler, 1987), including shrubs, grasses, oaks woodlands, conifers, barren lands and so forth, and do not have one optimal scale parameter. My study applied tree density segmentations to partition lower density tree stands from denser tree stands for objects of individual tree crowns and vegetation stands separately in two test areas.

Evaluations Of Species Segmentations

Accuracy assessments in object-based image classifications are challenging, compared to accuracy assessments in pixel-based image classifications, which apply sampling points to evaluate agreements (Morgan et al., 2010; Liu & Xia, 2010; Heumann, 2011), because both heterogeneous segmentations and geometric errors are not easy to be assessed by simple indices. Also, some of segmentation tools are proprietary software, such as Berkeley Image Segmentation (BIS) (http://www.berkenviro.com/berkeleyimgseg/) and eCognition (http://www.ecognition.com/), although they have been described in the literature (e.g. Baatz & Schäpe, 2000; Benz et al., 2004; Baatz et al., 2008; Clinton et al., 2010). Therefore, instead of supervised evaluations, goodness of fit measures (unsupervised evaluations) are an alternative for evaluating over-segmentation and under-segmentation errors, and scale parameters play a central role in defining object sizes and segmentation accuracies (Liu & Xia, 2010). One goodness of fit measure is to compare training objects to objects at different hierarchical levels (e.g. Clinton et al., 2010), while another approach is to evaluate whether object extractions are appropriate (e.g. Kim et al., 2008; Kim et al., 2009; Johnson & Xie, 2011). Both approaches require evaluating under a hierarchical framework, since imagery objects with different sizes have different optimal scale parameters. In other words, a semantic framework for delineating objects is more important than selected goodness measures.

My study applied an unsupervised evaluation (the Z values of Moran's ***I*** under 999 permutations) to this vegetation hierarchical framework for designing detailed species segmentations at the level of species associations and assessing the applicability of eCognition. Although this approach only assessed one band at a time, evaluations of individual bands for the segmentations, which were created based on multiple bands, including RGB and texture indices, did not make very significant differences, all showing decreases of the Z values of Moran's ***I*** with increases of the scale parameters (Figure 11). In other words, every band reflected consistence on evaluations, so the Z values of Moran's ***I*** can be used to evaluate segmentation quality for multi-band segmentations. However, the results suggested that image objects in two test areas both violated the object assumption with equal internal variances (Woodcock & Harward, 1992), and imagery objects could not be successfully identified using eCognition in this study.

The poor performance of eCognition resulted from two aspects of object definitions. In higher tree density stands, individual tree crowns could not be delineated, since the 1 m spatial resolution imagery was still too coarse. The result was similar to the outcomes of Woodcock & Strahler (1987), which the coarse spatial resolutions did not have an optimal peak to reflect tree crown sizes (30 m imagery presented an asymptote, which local variances decreased as spatial resolutions increased, while 0.75 m imagery showed a local peak). The Z values of Moran's ***I*** also showed an asymptote, which the Z values of Moran's ***I*** decreased as scale parameters increased. Moreover, the segmentations using eCognition in the lower tree density stands could not derive correct tree crown objects, due to inappropriate algorithm selections, although individual tree crowns were clearly separated visually. As a result, in sparse tree stands, other algorithms of tree crown delineations, as the example in Baatz et al. (2008), may improve segmentation, whereas in the dense tree stands, higher spatial resolution data, especially for oak woodlands, which often have lower classification accuracies (e.g. Katoh, 2004), may be a better alternative.

Although the results showed that eCognition was not effective for detailed species segmentations based on the study imagery and region, the third calibration still provided guidelines to select appropriate algorithms or data sources for specific levels. As Fu & Mui (1981) pointed out, region-based algorithms may differ in segmentation results, according to the order of region-merging, even if region-based algorithms were widely used and had higher classification accuracies than pixel-based imagery classifications. As a result, applying global information as nested models within certain classes is necessary. In other words, a single algorithm may not apply to whole hierarchical frameworks, even with the multi-scale concept. As previous literature indicated, in higher tree density stands, it is adequate to apply landscape-level procedures using region-based segmentations, while in lower tree density stands, species-level tree crown delineations are required.

Applications Of Hierarchical Vegetation Framework

The hierarchical vegetation framework, developed in this study, is more time- and cost-saving for species association labeling and hierarchical imagery segmentations than object-based imagery classification. For one thing, data can be collected and automatically processed at lower costs. Hyperspatial imagery in the form of digital photography is widely available, and environmental variables help to improve imagery processing for broad-area investigations. For another thing, the approach can incorporate current imagery processing methods, and does not require repetitive testing, like procedures in eCognition.

Concretely, aerial photos with single imagery tones are more available data sources for vegetation mapping, and sometimes, aerial photos with hyperspatial resolutions are in archives, either national-level imagery datasets (e.g. USDA: Natural Resources Conservation Service Geospatial Data Gateway or ASO Taiwan Image supplier and services System) or international-level imagery datasets (e.g. EarthExplorer). For example, Corona Lanyard (1963) and Corona KH-4B (from 1967 to 1972) both provided 1.8 m imagery worldwide, and Corona imagery can be bought through EarthExplorer website (http://earthexplorer.usgs.gov/) with very small costs. Meanwhile, SRTM, a digital terrain dataset has worldwide coverage in 90 m spatial resolution, and can be used to assist image processing.

In contrast, Landsat imagery with coarser spatial resolutions has been widely used in long-term land use/ land cover mapping and monitoring (Cohen & Goward, 2004), because of its long-term consistent platforms, since 1972 and multiple bands, which reflect vegetation distributions (near-infrared) and temperature (thermal-infrared). Nevertheless, except in the United States, Landsat satellites may not offer enough imagery with continuous or regular time intervals and good imagery qualities, such as low cloud covers in wetter tropical areas. Furthermore, other detailed ancillary data, which were helpful to assist imagery interpretations, may be available at national-level datasets, such as U.S. National Elevation Dataset 10 Meter (http://datagateway.nrcs.usda.gov/GDGOrder.aspx), U.S. General Soil Map (STATSGO) (http://websoilsurvey.nrcs.usda.gov/app/WebSoilSurvey.aspx), or LiDAR Topography Data (http://opentopo.sdsc.edu/gridsphere/gridsphere?cid=datasets). However, those datasets cannot reflect temporal changes of species distributions and are limited in survey areas.

Future studies should focus on two aspects. One is method for species labeling in different ecosystems. Although the separation of species types on different tree density patterns was successful in this study, species associations do not correlate so strongly with tree density in many forest and woodland ecosystems. Disturbance frequencies and intensities may violate the second hypothesis, especially confronting large, infrequent disturbances, which may result in more heterogeneous species distributions (Turner & Dale, 1998). Thus, ecological knowledge should be applied in vegetation mapping. The other focus of future research should be the techniques themselves. Algorithms of tree crown delineations can be tested at lower tree density stands and appropriate object definitions should be established for higher tree density stands. In particular, individual tree density patterns reflect different biological interactions over times. For example, at the species spreading front, reduced intra-specific competition in dense populations may increase population growth rates and migrations, but sparse populations may suffer decreased migrations (Thuiller et al., 2008). However, highly overlap tree crowns make it difficult to detect changes in density of individual species (e.g. Tyler et al., 2006), and tree crowns in sparse tree stands cannot be identified using eCognition. Therefore, more precise and meaningful object definitions can be helpful not only for individual species information but also for species life history estimations.

CONCLUSION

The three-level hierarchical segmentations and the three-level evaluative approach, based on the available data, SRTM and RGB hyperspatial imagery, partly supported the three hypotheses:

1. The aspect stratification was the most effective to reduce variation in local tone and texture and gather similar components of tree covers within strata.
2. The four target species, when grouped into two species associations, showed about 80% overall agreement between segmentations based on the random walker algorithm and existing vegetation maps.
3. The two tree density distributions did not have an optimal scale parameter using eCognition for detailed species segmentations, but results provided improving guidelines.

Those results showed that identifying tree density segmentations for constructing a hierarchical vegetation framework provided the potential to produce vegetation mapping at finer scales by labeling species associations and evaluating algorithm fits for species segmentations.

REFERENCES

Anselin, L., Syabri, I., & Kho, Y. (2006). GeoDa: An Introduction to Spatial Data Analysis. Geographical Analysis, 38(1), 5-22

Baatz, M., & Schäpe, A. (2000). Multiresolution segmentation—An optimization approach for high quality multi-scale image segmentation. In J. Strobl, T. Blaschke & G. Griesebner (Eds.), Angewandte Geographische Informationsverarbeitung XII (pp. 12-23). Heidelberg: Wichmann-Verlag

Baatz, M., Hoffmann, C., & Willhauck, G. (2008). Progressing from object-based to object-oriented image analysis. In T. Blaschke, S. Lang & G.J. Hay (Eds.), Object-Based Image Analysis: Spatial Concepts for Knowledge-Driven Remote Sensing Applications (pp. 29-42). Berlin Heidelberg: Springer-Verlag

Banerjee, M., Capozzoli, M., McSweeney, L., & Sinha, D. (1999). Beyond Kappa: A Review of Interrater Agreement Measures. The Canadian Journal of Statistics, 27(1), 3-23

Benz, U.C., Hofmann, P., Willhauck, G., Lingenfelder, I., & Heynen, M. (2004). Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. ISPRS Journal of Photogrammetry & Remote Sensing, 58, 239-258

Blaschke, T. (2010). Object based image analysis for remote sensing. ISPRS Journal of Photogrammetry and Remote Sensing, 65, 2-16

Budreski, K.A., Wynne, R.H., Browder, J.O., & Campbell, J.B. (2007). Non-parametric Land Cover Classification in the Brazilian Amazon Using Multitemporal Landsat TM/ETMImagery. Photogrammetric Engineering & Remote Sensing, 73(7), 813-827

Burns, R.M., & Honkala, B.H. (1990). Silvics of North America: 1. Conifers; 2. Hardwoods. Washington, DC: United States Department of Agriculture Forest Service

Chazal, J.d., & Rounsevell, M.D.A. (2009). Land-use and climate change within assessments of biodiversity change: A review. Global Environmental Change, 19, 306-315

Chen, G., & Hay, G.J. (2011). An airborne lidar sampling strategy to model forest canopy height from Quickbird imagery and GEOBIA. Remote Sensing of Environment, 115, 1532-1542

Chen, G., Hay, G.J., & St-Onge, B. (2012). A GEOBIA framework to estimate forest parameters from lidar transects, Quickbird imagery and machine learning : a case study in Quebec, Canada. International Journal of Applied Earth Observation and Geoinformation, 15, 28-37

Clinton, N., Holt, A., Scarborough, J., Yan, L., & Gong, P. (2010). Accuracy Assessment Measures for Object-based Image Segmentation Goodness. Photogrammetric Engineering & Remote Sensing, 76(3), 289-299

Cohen, W.B., & Goward, S.N. (2004). Landsat's Role in Ecological Applications of Remote Sensing BioScience, 54(6), 535-545

Culvenor, D.S. (2003). Extracting individual tree information A survey of techniques for high spatial resolution imagery. In M. Wulder & S. Franklin (Eds.), Remote Sensing of Forest Environments: Concepts and Case Studies (pp. 255-277): Springer

DeGomez, T. (2008). Determining Ponderosa Pine Tree Density on Small Lots. Backyards Beyond, 8-10

Donohue, R.J., Mcvicar, T.R., & Roderick, M.L. (2009). Climate-related trends in Australian vegetation cover as inferred from satellite observations, 1981-2006. Global Change Biology, 15(4), 1025-1039

Egbert, S.L., Lawrence, K.S., Martinez-Meyer, E., Ortega-Huerta, M., & Townsend Peterson, A. (2002). Use of datasets derived from time-series AVHRR imagery as surrogates for land cover maps in predicting species' distributions. In, Geoscience and Remote Sensing Symposium (pp. 2337-2339)

Federal Geographic Data Committee (2008). US National Vegetation Classification Systems. (http://usnvc.org)

Fitzgerald, S.A. (2005). Fire Ecology of Ponderosa Pine and the Rebuilding of Fire-Resilient Ponderosa Pine Ecosystems. In: USDA Forest Service

Flint, L.E., & Flint, A.L. (2012). Downscaling future climate scenarios to fine scales for hydrologic and ecological modeling and analysis Ecological Processes, 1(2), 1-15

Foody, G.M., Atkinson, P.M., Gething, P.W., Ravenhill, N.A., & Kelly, C.K. (2005). Identification of specific tree species in ancient semi-natural woodland from digital aerial sensor imagery. Ecological Applications, 15(4), 1233-1244

Franklin, J. (1995). Predictive vegetation mapping: geographic modelling of biospatial patterns in relation to environmental gradients. Progress in physical geography, 19(4), 474-499

Franklin, J. (2010). Mapping species distributions: spatial inference and prediction. New York: Cambridge University Press

Franklin, J., Davis, F.W., Ikegami, M., Syphard, A.D., Flint, L.E., Flint, A.L., & Hannah, L. (2013). Modeling plant species distributions under future climates: how fine scale do climate projections need to be? Global Change Biology, 19, 473-483

Franklin, J., Keeler-Wolf, T., Thomas, K.A., Shaari, D.A., Stine, P.A., Michaelsen, J., & Miller, J. (1999). Stratified sampling for field survey of environmental gradients in the Mojave desert ecoregion. In A.C. Millington, S.J. Walsh & P.E. Osborne (Eds.), GIS and Remote Sensing Application in Biogeography and Ecology. Massachusetts: Kluwer Academic Publishers

Franklin, J., Woodcock, C.E., & Warbington, R. (2000). Multi-Attribute Vegetation Maps of Forest Service Lands in California Supporting Resource Management Decisions. Photogrammetric Engineering & Remote Sensing, 66(10), 1209-1217

Franklin, S.E., Wulder, M.A., & Gerylo, G.R. (2001). Texture analysis of IKONOS panchromatic data for Douglas-fir forest age class separability in British Columbia. International Journal of Remote Sensing, 22(13), 2627-2632

Fu, K.S., & Mui, J.K. (1981). A survey on image segmentation. Pattern Recognition, 13(1), 3-16

Gougeon, F.A., & Leckie, D.G. (2006). The Individual Tree Crown Approach Applied to Ikonos Images of a Coniferous Plantation Area. Photogrammetric Engineering & Remote Sensing, 72(11), 1287-1297

Gracia, M., Retana, J., & Roig, P. (2002). Mid-term successional patterns after fire of mixed pine-oak forests in NE Spain. Acta Oecologica, 23, 405-411

Grady, L. (2006). Random Walks for Image Segmentation. IEEE Transactions on pattern analysis and machine intelligence, 28(11), 1768-1783

Haara, A., & Haarala, M. (2002). Tree Species Classifcation using Semi-automatic Delineation of Trees on Aerial Images. Scandinavian Journal of Forest Research, 17, 556-565

Habeck, R.J. (1992). Pinus ponderosa var. ponderosa. In: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station, Fire Sciences Laboratory

Haralick, R.M. (1979). Statistical and structural approach to texture. Proceedings of the IEEE, 67(5), 786-804

Haralick, R.M., Shanmugam, K., & Dinstein, I.h. (1973). Textural Features for image classification. IEEE Transactions on Systems, 3(6), 610-621

Hay, G.J., Blaschke, T., Marceau, D.J., & Bouchard, A. (2003). A comparison of three image-object methods for the multiscale analysis of landscape structure. ISPRS Journal of Photogrammetry & Remote Sensing, 57, 327-345

Hay, G.J., Castilla, G., Wulder, M.A., & Ruiz, J.R. (2005). An automated object-based approach for the multiscale image segmentation of forest scenes. International Journal of Applied Earth Observation and Geoinformation, 7, 339-359

Heumann, B.W. (2011). An Object-Based Classification of Mangroves Using a Hybrid Decision Tree—Support Vector Machine Approach. Remote Sensing, 3, 2440-2460

Hill, R.A., Wilson, A.K., George, M., & Hinsley, S.A. (2010). Mapping tree species in temperate deciduous woodland using time-series multi-spectral data. Applied Vegetation Science, 13, 86-99

Hoagland, S., Krieger, A., Moy, S., & Shepard, A. (2011). Ecology and Management of Oak Woodlands on Tejon Ranch: Recommendations for Conserving a Valuable California Ecosystem. In: Bren School of Environmental Science and Management, University of California, Santa Barbara

Huang, H., Wu, B., & Fan, J. (2003). Analysis to the relationship of classification accuracy, segmentation scale, image resolution. In, Geoscience and Remote Sensing Symposium, 2003. IGARSS '03. Proceedings. 2003 IEEE International

Jain, A.K., Murty, M.N., & Flynn, P.J. (1999). Data Clustering: A Review. ACM Computing Surveys (CSUR), 31(3), 264-323

Jarvis, A., Reuter, H.I., Nelson, A., & Guevara, E. (2008). Hole-filled seamless SRTM data V4, International Centre for Tropical Agriculture (CIAT). In: Consortium for Spatial Information (CGIAR-CSI)

Johnson, B., & Xie, Z. (2011). Unsupervised image segmentation evaluation and refinement using a multi-scale approach. ISPRS Journal of Photogrammetry and Remote Sensing, 66, 473-483

Katoh, M., Gougeon, F.A., & Leckie, D.G. (2009). Application of high-resolution airborne data using individual tree crowns in Japanese conifer plantations. Journal of Forest Research, 14, 10-19

Ke, Y., & Quackenbush, L.J. (2011a). A comparison of three methods for automatic tree crown detection and delineation from high spatial resolution imagery. International Journal of Remote Sensing, 32(13), 3625-3647

Ke, Y., & Quackenbush, L.J. (2011b). A review of methods for automatic individual tree-crown detection and delineation from passive remote sensing. International Journal of Remote Sensing, 32(17), 4725-4747

Kerr, J.T., & Ostrovsky, M. (2003). From space to species: ecological applications for remote sensing. TRENDS in Ecology and Evolution, 18(6), 299-305

Kim, M., Madden, M., & Warner, T. (2008). Estimation of optimal image object size for the segmentation of forest stands with multispectral IKONOS imagery. In T. Blaschke, S. Lang & G.J. Hay (Eds.), Object-Based Image Analysis: Spatial Concepts for Knowledge-Driven Remote Sensing Applications (pp. 91-110). Berlin Heidelberg: Springer-Verlag

Kim, M., Madden, M., & Warner, T.A. (2009). Forest T ype Mapping using Object-specific Texture Measur es from Multispectral Ikonos Imagery: Segmentation Quality and Image Classification Issues. Photogrammetric Engineering & Remote Sensing, 75(7), 819-829

Kim, M., Warner, T.A., Madden, M., & Atkinson, D.S. (2011). Multi-scale GEOBIA with very high spatial resolution digital aerial imagery: scale, texture and image objects. International Journal of Remote Sensing, 32(10), 2825-2850

King, D.A. (1996). Allometry and life history of tropical trees. Journal of Tropical Ecology, 12, 25-44

Klobučar, D., Subašić, M., & Pernar, R. (2011). Estimation of stands parameters from IKONOS satellite images using textural features. In, 7th International Symposium on Image and Signal Processing and Analysis (ISPA 2011). Dubrovnik, Croatia

Laliberte, A.S., Fredrickson, E.L., & Rango, A. (2007). Combining Decision Trees with Hierarchical Object-oriented Image Analysis for Mapping Arid Rangelands. Photogrammetric Engineering & Remote Sensing, 73(2), 197-207

Leckie, D.G., Gougeon, F.A., Tinis, S., Nelson, T., Burnett, C.N., & Paradine, D. (2005). Automated tree recognition in old growth conifer stands with high resolution digital imagery. Remote Sensing of Environment, 94, 311-326

Leckie, D.G., Gougeon, F.A., Walsworth, N., & Paradine, D. (2003). Stand delineation and composition estimation using semi-automated individual tree crown analysis. Remote Sensing of Environment, 85, 355-369

Li, Z., Hayward, R.F., Zhang, J., & Liu, Y. (2008). Individual Tree Crown Delineation Techniques for Vegetation Management in Power Line Corridor. In, 10th International Conference on Digital Image Computing: Techniques and Applications. Canberra, Australia

Lillesand, T.M., Kiefer, R.W., & Chipman, J.W. (2004). Remote Sensing and image interpretation: Wiley

Lines, E.R., Zavala, M.A., Purves, D.W., & Coomes, D.A. (2012). Predictable changes in aboveground allometry of trees along gradients of temperature, aridity and competition. Global Ecology and Biogeography, 21, 1017-1028

Liu, D., & Xia, F. (2010). Asscssinu Asscssing object-based classification: advantages and limitations. Remote Sensing Letters, 1(4), 187-194

Loh, J., Green, R.E., Ricketts, T., Lamoreux, J., Jenkins, M., Kapos, V., & Randers, J. (2005). The Living Planet Index: using species population time series to track trends in biodiversity. Philosophical Transactions of the Royal Society B: Biological Sciences, 360, 289-295

Ma, Z., Tavares, J.M.R.S., Jorge, R.N., & Mascarenhas, T. (2010). A Review of Algorithms for Medical Image Segmentation and their Applications to the Female Pelvic Cavity. Computer Methods in Biomechanics and Biomedical Engineering, 13(2), 235-246

Mallinis, G., Koutsias, N., Tsakiri-Strati, M., & Karteris, M. (2008). Object-based classification using Quickbird imagery for delineating forest vegetation polygons in a Mediterranean test site. ISPRS Journal of Photogrammetry & Remote Sensing, 63, 237-250

Mateo, R.G., Vanderpoorten, A., Muñoz, J., Laenen, B., & Désamoré, A. (2013). Modeling Species Distributions from Heterogeneous Data for the Biogeographic Regionalization of the European Bryophyte Flora. PLOS, 8(2), 1-11

Menne, M.J., C.N. Williams, J., & Vose, R.S. (2013). Long-Term Daily and Monthly Climate Records from Stations Across the Contiguous United States. In, United States Historical Climatology Network: National Climatic Data Center, National Oceanic and Atmospheric Administration

Morgan, J.L., Gergel, S.E., & Coops, N.C. (2010). Aerial Photography: A Rapidly Evolving Tool for Ecological Management. BioScience, 60(1), 47-59

Myint, S.W., Giri, C.P., Wang, L., Zhu, Z., & Gillette, S.C. (2008). Identifying Mangrove Species and Their Surrounding Land Use and Land Cover Classes Using an Object-Oriented Approach with a Lacunarity Spatial Measure. GIScience & Remote Sensing, 45(2), 188-208

Nagendra, H., & Rocchini, D. (2008). High resolution satellite imagery for tropical biodiversity studies: the devil is in the detail. Biodiversity and Conservation, 17, 3431-3442

Osborne, P.E., & Suárez-Seoane, S. (2002). Should data be partitioned spatially before building large-scale distribution models? Ecological Modelling, 157, 249-259

Otsu, N. (1979). A Tlreshold Selection Method from Gray-Level Histograms. IEEE Transactions on systems, man and cybernetics, 9(1), 62-66

Ozdemir, I., & Karnieli, A. (2011). Predicting forest structural parameters using the image texture derived from WorldView-2 multispectral imagery in a dryland forest, Israel. International Journal of Applied Earth Observation and Geoinformation, 13, 701-710

Pal, N.R., & Pal, S.K. (1993). A review on image segmentation techniques. Pattern Recognition, 26(9), 1277-1294

Pearson, R.G., & Dawson, T.P. (2003). Predicting the impacts of climate change on the distribution of species: are bioclimate envelope models useful? Global Ecology & Biogeography, 12, 361-371

Peres-Neto, P.R., Legendre, P., Dray, S., & Borcard, D. (2006). Variation partitioning of species data matrices: estimation and comparison of fractions. Ecology, 87(10), 2614-2625

Pettorelli, N., Vik, J.O., Mysterud, A., Gaillard, J.-M., Tucker, C.J., & Stenseth, N.C. (2005). Using the satellite-derived NDVI to assess ecological responses to environmental change. TRENDS in Ecology and Evolution, 20(9), 503-510

Pham, D.L., Xu, C., & Prince, J.L. (2000). Current Methods in Medical Image Segmentation. Annual Review of Biomedical Engineering, 2, 315-337

Pontius Jr, R.G., & Millones, M. (2011). Death to Kappa birth of quantity disagreement and allocation disagreement for accuracy assessment. International Journal of Remote Sensing, 32(15), 4407-4429

Poorter, L., Lianes, E., Heras, M.M.-d.l., & Zavala, M.A. (2012). Architecture of Iberian canopy tree species in relation to wood density, shade tolerance and climate. Plant Ecology, 213, 707-722

Randin, C.F., Engler, R., Normand, S., Zappa, M., Zimmermann, N.E., Pearman, P.B., Vittoz, P., Thuiller, W., & Guisan, A. (2009). Climate change and plant distribution: local models predict high-elevation persistence. Global Change Biology, 15, 1557-1569

Roerdink, J.B.T.M., & Meijster, A. (2001). The Watershed Transform: Definitions, Algorithms and Parallelization Strategies. Fundamenta Informaticae, 41, 187-228

Ryherd, S., & Woodcock, C. (1996). Combining Spectral and Texture Data in the Segmentation of Remotely Sensed Images. Photogrammetric Engineering & Remote Sensing, 62(2), 181-194

Sekercioglu, C.H., Schneider, S.H., Fay, J.P., & Loarie, S.R. (2007). Climate Change, Elevational Range Shifts, and Bird Extinctions. Conservation Biology, 22(1), 140-150

Seo, C., Thorne, J.H., Hannah, L., & Thuiller, W. (2009). Scale effects in species distribution models: implications for conservation planning under climate change. Biology Letter, 5, 39-43

Sezgin, M., & Sankur, B. (2004). Survey over image thresholding techniques and quantitative performance evaluation. Journal of Electronic Imaging, 13(1), 146-165

Shandley, J., Franklin, J., & White, T. (1996). Testing the Woodcock-Harward image segmentation algorithm in an area of southern California chaparral and woodland vegetation. International Journal of Remote Sensing, 17(5), 983-1004

Sonka, M., Hlavac, V., & Boyle, R. (2008). Image Processing, Analysis, and Machine Vision. Toronto: Thomson

Strahler, A.H. (1981). Stratification of natural vegetation for forest and rangeland inventory using Landsat digital imagery and collateral data. International Journal of Remote Sensing, 2(1), 15-41

Strahler, A.H., Woodcock, C.E., & Smith, J.A. (1986). On the Nature of Models in Remote Sensing. Remote Sensing of Environment, 20, 121-139

Thuiller, W., Albert, C., Araújo, M.B., Berry, P.M., Cabeza, M., Guisan, A., Hickler, T., Midgley, G.F., Paterson, J., Schurr, F.M., Sykes, M.T., & Zimmermann, N.E. (2008). Predicting global change impacts on plant species' distributions: Future challenges. Perspectives in Plant Ecology, Evolution and Systematics, 9, 137-152

Treitz, P., & Howarth, P. (2000). High Spatial Resolution Remote Sensing Data for Forest Ecosystem Classification: An Examination of Spatial Scale. Remote Sensing of Environment, 72, 268-289

Trier, Ø.D., & Taxt, T. (1995). Evaluation of Binarization Methods for Document Images. IEEE Transactions on pattern analysis and machine intelligence, 17(3), 312-315

Turner, M.G., & Dale, V.H. (1998). Comparing Large, Infrequent Disturbances: What Have We Learned? Ecosystems, 1, 493-496

Tyler, C.M., Kuhn, B., & Davis, F.W. (2006). Demography and Recruitment Limitations of Three Oak Species in California. The Quarterly Review of Biology, 81(2), 127-152

United States Geological Survey (2001). Digital Orthophoto Quadrangles Fact Sheet 057-01.

van Gelder, H.A., Poorter, L., & Sterck, F.J. (2006). Wood mechanics, allometry, and life-history variation in a tropical rain forest tree community. New Phytologist, 171(2), 367-378

Varela, R.A.D., Rego, P.R., Iglesias, S.C., & Sobrino, C.M. (2008). Automatic habitat classification methods based on satellite images: A practical assessment in the NW Iberia coastal mountains. Environmental Monitoring and Assessment, 144, 229-250

Wang, D. (1997). A multiscale gradient algorithm for image segmentation using watershelds. Pattern Recognition, 30(12), 2043-2052

Woodcock, C.E., & Harward, V.J. (1992). Nested-hierarchical scene models and image segmentation. International Journal of Remote Sensing, 13(16), 3167-3187

Woodcock, C.E., & Strachler, A.H. (1987). The Factor of Scale in Remote Sensing. Remote Sensing of Environment, 21, 311-332

Xie, Z., Roberts, C., & Johnson, B. (2008). Object-based target search using remotely sensed data: A case study in detecting invasive exotic Australian Pine in south Florida. ISPRS Journal of Photogrammetry & Remote Sensing, 63, 647-660

Yan, G., Mas, J.-F., Maathuis, B.H.P., Xiangmin, Z., & Dijk, P.M.V. (2006). Comparison of pixel-based and object-oriented image classification approaches—a case study in a coal fire area, Wuda, Inner Mongolia, China. International Journal of Remote Sensing, 27(18), 4039-4055

Yu, Q., Gong, P., Clinton, N., Biging, G., Kelly, M., & Schirokauer, D. (2006). Object-based Detailed Vegetation Classification with Airborne High Spatial Resolution Remote Sensing Imagery. Photogrammetric Engineering & Remote Sensing, 72(7), 799-811

Zavala, M.A., & Zea, E. (2004). Mechanisms maintaining biodiversity in Mediterranean pine-oak forests: insights from a spatial simulation model. Plant Ecology, 171, 197-207