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Quantifying Forest Structure Parameters and Their Changes from LiDAR Data and Satellite Imagery in the Sierra Nevada

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Quantifying Forest Structure Parameters and Their Changes from LiDAR Data and Satellite Imagery in the Sierra Nevada

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

in

Environmental Systems

by

Qin Ma

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2018
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Manuscripts in Submission
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Abstract

Quantifying Forest Structure Parameters and Their Changes from LiDAR Data and Satellite Imagery in the Sierra Nevada

by

Qin Ma

Doctor of Philosophy in Environmental Systems

University of California, Merced, 2018

Professor Qinghua Guo, Chair
Professor Roger C. Bales, Co-Chair

Sierra Nevada forests have provided many economic benefits and ecological services to people in California, and the rest of the world. Dramatic changes are occurring in the forests due to climate warming and long-term fire suppression. Accurate mapping and monitoring are increasingly important to understand and manage the forests. Light Detection and Range (LiDAR), an active remote sensing technique, can penetrate the canopy and provide three-dimensional estimates of forest structures. LiDAR-based forest structural estimation has been demonstrated to be more efficient than field measurements and more accurate than those from passive remote sensing, like satellite imagery. Research in this dissertation aims at mapping and monitoring structural changes in Sierra Nevada forests by taking the advantages of LiDAR. We first evaluated LiDAR and fine resolution imagery-derived canopy cover estimates using different algorithms and data acquisition parameters. We suggested that LiDAR data obtained at 1 point/m² with a scan angle smaller than 12°were sufficient for accurate canopy cover estimation in the Sierra Nevada mix-conifer forests. Fine resolution imagery is suitable for canopy cover estimation in forests with median density but may over or underestimate canopy cover in extremely coarse or dense forests. Then, a new LiDAR-based strategy was proposed to quantify tree growth and competition at individual tree and forest stand levels. Using this strategy, we illustrated how tree growth in two Sierra Nevada forests responded to tree competition, original tree sizes, forest density, and topography conditions; and identified that the tree volume growth was determined by the original tree sizes and competitions, but tree height and crown area growth were mostly influenced by water and space availability. Then, we calculated the forest biomass disturbance in a Sierra Nevada forest induced by fuel treatments using bi-temporal LiDAR data and field measurements. Using these results as references, we found that Landsat imagery-derived vegetation indices were suitable for quantifying canopy cover changes and biomass disturbances in forests with median density. Large uncertainties existed in applying the vegetation indices to quantify disturbance in extremely dense forests or forests only disturbed in the understory.
Last, we assessed vegetation losses caused by the American Fire in 2013 using a new LiDAR point based method. This method was able to quantify fire-induced forest structure changes in basal area and leaf area index with lower uncertainties, compared with traditional LiDAR metrics and satellite imagery-derived vegetation indices. The studies presented in this dissertation can provide guidance for forest management in the Sierra Nevada, and potentially serve as useful tools for forest structural change monitoring in the rest of the world.
Chapter 1  Introduction

The Sierra Nevada mountain range harbors one of Earth’s most diverse temperate conifer forests, which have provided people in California with various economic benefits and ecosystem services, such as timber goods, wildlife habitats, carbon sequestration, and water (Bales et al. 2011; Boisramé et al. 2017; Goulden et al. 2012; Hopkinson and Battles 2015; Hurteau et al. 2014; Zhao et al. 2012b). However, due to a warming climate and long-term fire suppression, the Sierra Nevada forests have experienced tremendous changes in species composition and tree density during the past century (Barth et al. 2015; Battles et al. 2008; Henn et al. 2018; Huning and Margulis ; Johnson et al. 2017; Stephens and Collins 2004). These forests are also facing new challenges, including high severity fires, droughts, and bark beetle attacks. Accurate mapping and modeling of forest attributes such as density, biomass, and competition, and their changes is essential for forest monitoring and management. How to quantify these forest attributes and their changes efficiently and precisely over this densely covered and rapidly changed mountainous area is the challenge addressed in this research.

1.1 Traditional methods for forest mapping and monitoring

Field measurements are the tradition methods for forest mapping, growth monitoring, and disturbance estimation. Basic forest structural parameters, such as canopy cover, leaf area index (LAI), tree height, and diameter at breast height (DBH) can be measured directly for individual trees, plots and line transects using instruments like Cajanus tube, fish-eye camera, and global positioning systems (Asner et al. 2002; Jennings et al. 1999; Korhonen et al. 2006; Naesset 2001). Aboveground biomass (AGB), an important indicator of forest carbon storage, can be measured by direct harvest methods, or allometric modeling with DBH, tree height, and species (Jenkins et al. 2003). Traditional forest growth models heavily rely on empirical relationships between site quality, tree sizes, and competition capacity for natural resources (competition indices) obtained from extensive field surveys (Battles et al. 2008; Biging and Dobbertin 1995; Biging and Wensel 1984; Cao 2000). The severity of forest disturbances (e.g. wildfire and fuel treatments) can be evaluated by measurements of vegetation survivors and mortality using severity classification systems, such as composition burn index (Kolden et al. 2015; Miller et al. 2009).

Field measurements have been long considered as the most accurate method for the applications above. However, most field measurements are conducted sparsely at sampled plots or line transects because the measurements are extremely labor intensive, time consuming, and sometime destructive to forests (Brienen et al. 2015; Condés and McRoberts 2017). Wall-to-wall measurements at forest stand and regional scales were relatively rare. Forest growth monitoring and disturbance estimation with field measurements are also limited by the spatial coverage and temporal frequency of the measurements. Research has indicated that the empirical relationships in forest growth models might be outdated if the field measurements are not updated frequently, particularly in areas with rapid environmental changes (Battles et al. 2008; Tompalski et al. 2018; Tompalski et al. 2016). Previous studies also indicated that forest disturbance
measures, such as the composition burn index-based fire severity evaluations, can be subjective to visual observation and need validation in multiple forest ecosystems (Smith et al. 2016).

1.2 Optical remote sensing for forest mapping and monitoring

Compared to traditional field measurements, remote sensing techniques have the advantages of broad coverage, frequent revisits, and potentially lower cost. Passive optical imagery is the most widely used remote sensing data in forest structural mapping and dynamics monitoring. Low-to-median spatial resolution images from optical sensors, such as Landsat and Moderate Resolution Imaging Spectroradiometer (MODIS), have been applied to mapping tree cover (Hansen et al. 2013), LAI (Chen and Cihlar 1996; Myneni et al. 2002), AGB (Lu 2005) at regional to global scales. A number of vegetation indices, such as normalized difference vegetation index (NDVI), normalized difference water index (NDWI), and normalized burn ratio (NBR), have been derived from these images and applied to map forest greenness (Gamon et al. 1995; Tucker 1979; Veraverbeke et al. 2012; Viedma et al. 1997), wetness (Su et al. 2017), and burn severity (Miller and Thode 2007). With the accumulation of long-term satellite imagery, particularly the ones from the Landsat program that started from 1970s, researchers have increasingly applied multi-temporal vegetation indices to monitor forest conditions and their responses to climate change, timber harvests, fuel treatments, and wildfires (Cohen et al. 2016; Hansen et al. 2013; Schroeder et al. 2011; White et al. 2016; White et al. 2017). High spatial resolution images from satellite sensors (e.g. Worldview, IKONOS, and QuickBird) and aerial photos (National Agriculture Imagery Program, NAIP) are valuable data sources for forest mapping, but are mainly applied at regional scales due to their higher cost and larger data size (Fujiki et al. 2016; Gonzalez et al. 2010; Maxwell et al. 2017; Pu and Landry 2012).

Although optical imagery is widely used for forestry applications, limitations of this passive remote sensing technique are also considerable. The spectral information from optical imagery is often contaminated by shadows and clouds, particularly in mountainous forests (Kennedy et al. 2010; Verbyla et al. 2008; Zhu and Woodcock 2012). The imagery-derived vegetation indices, such as NDVI, may fail to indicate vegetation’s structural variations in dense forests due to the saturation effect (Gamon et al. 1995; Gao et al. 2000; Mutanga and Skidmore 2004). Moreover, some forest structural attributes, such as total tree height, AGB, and understory vegetation conditions, are difficult to derive from optical imagery directly. Accurate estimation of these parameters often requires regression models with ground truth from other data sources such as field measurements (Su et al. 2016b; Zhang et al. 2014). These uncertainties of optical imagery in mapping and monitoring forest structural dynamics have not been fully investigated.

1.3 LiDAR data forest mapping and monitoring

Light Detection and Range (LiDAR) is an active remote sensing technique, which can penetrate forest canopy and delineate three-dimensional structures at fine resolution with high precision (Coops et al. 2007; Kelly and Di Tommaso 2015; Næsset and Økland...
2002). Compared with optical imagery, LiDAR data have stronger capability in characterizing tree canopy, understory, and terrain features in forests. A number of algorithms have been developed, either using original LiDAR points or LiDAR derived metrics, to estimate forest structural attributes, including canopy cover (Gatziolis 2012; Korhonen et al. 2015; Korhonen et al. 2011), tree height (Næsset 1997; Næsset and Bjerkenes 2001), LAI (Korhonen and Morsdorf 2014; Zheng and Moskal 2009), AGB (Dalponte et al. 2018; Li et al. 2015; Luo et al. 2017; Su et al. 2016b; Tao et al. 2014; Zhao et al. 2012a) and crown base height (Luo et al. 2018; Popescu and Zhao 2008). Studies have proven that most LiDAR-derived forest structural estimates are more accurate than the ones from imagery, and more efficient than field measurements (Chen et al. 2012; Smith et al. 2009; Su et al. 2014). LiDAR-derived forest structural estimates can be promising reference data to calibrate and evaluate satellite imagery-based estimates at larger scales. However, as the costs of obtaining high quality and density LiDAR data are still high (Hummel et al. 2011; Jakubowski et al. 2013), how to choose the optimal LiDAR acquisition parameters and the right estimation algorithms are valuable questions for economic and effective forest applications.

As the coverage of LiDAR data is growing both temporally and spatially, the applications of multi-temporal LiDAR data for forest dynamics monitoring have become a new research focus (McCarley et al. 2017; Su et al. 2016a; Zhao et al. 2017). However, previous studies mainly focused on a single feature of forest structural changes, for example tree height growth (Londo 2010; Song et al. 2016), crown growth (Frew et al. 2015), or fire-induced canopy cover disturbances (McCarley et al.), and at certain spatial scales, such as individual tree, forest plot, or stand. Comprehensively quantifying forest structural changes with multiple features (crown size, volume, and tree height) over different scales (individual tree, forest plot and stand) remains challenging. New algorithms and strategies using multi-temporal LiDAR applications are therefore necessary to address such challenges to comprehensive quantification. These algorithms and strategies can also help with better monitoring, modeling, and management of forests.

1.4 Objectives of this study
In this dissertation, we take the advantage of LiDAR data to access the uncertainties of optical imagery-based forestry applications, and develop new algorithms to investigate the potential of multi-temporal LiDAR in quantifying forest structural changes. Two main questions were addressed: what were the uncertainties of optical imagery in mapping and monitoring forest structures, comparing to LiDAR-based estimates? How can we improve the comprehensive quantification of forest structural changes using multi-temporal LiDAR data? This dissertation addressed these questions with four case studies in the Sierra Nevada forests:

1) Compare canopy cover estimation from airborne LiDAR, high resolution imagery, and field measurements. We estimated canopy cover from LiDAR data using various algorithms under different data acquisition parameters and validated the results with field measurements. We further assessed the accuracies of two high resolution imagery-based canopy cover estimates using the LiDAR-derived results. Some
practical guidance was provided for data source selection, sampling scheme, and estimation algorithms in canopy cover mapping.

2) Provide a strategy to quantify individual tree growth and tree competition using bi-temporal LiDAR data. We measured growth of over 114,000 trees in two Sierra Nevada forests by changes in tree height, crown area, and crown volume. We used bi-temporal LiDAR data to quantify tree growth and analyzed their relationships to factors including original tree size, tree competition, forest density, and topography. We performed this tree growth analysis at both individual tree and forest stand levels. The results provided some new insights for tree growth modeling and managements.

3) Evaluate the uncertainties in Landsat imagery-derived vegetation indices in quantifying disturbances due to forest fuel treatments. We quantified the disturbances as changes in AGB and canopy cover using LiDAR and field measurements collected from pre- and post-treatments. Using this LiDAR-based estimation as a reference, we quantified the uncertainties with the Landsat imagery-derived vegetation indices in indicating forest disturbances. We further discussed where the most uncertainties were found and how they were impacted by the pre-disturbance forest densities and treatment levels.

4) Develop a new metric, Profile Area Change (PAC), for quantifying fire severity from bi-temporal LiDAR data. We mapped the fire severity using the PAC metric at both individual tree and forest plot levels for the American Fire in 2013, and validated the results using field measured changes in basal area and LAI. Using PAC, we further classified the fire’s effects into two types: canopy and sub-canopy biomass disturbances. To evaluate the performances of PAC metrics in quantifying fire severity, we compared them with two commonly used LiDAR metrics and a Landsat imagery-derived vegetation index over different burn intensities and pre-fire vegetation conditions.

References
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Chapter 2  Comparison of canopy cover estimations from airborne LiDAR, aerial imagery, and satellite imagery

Abstract
Canopy cover is an important forest structure parameter for many applications in ecology, hydrology, and forest management. Light Detection and Ranging is a promising tool for estimating canopy cover because it can penetrate forest canopy. Various algorithms have been developed to calculate canopy cover from LiDAR data. However, little attention was paid to evaluating how different factors, such as estimation algorithm, LiDAR point density and scan angle, influence canopy cover estimates; and how LiDAR-derived canopy cover differs from estimates using traditional methods, such as field measurements, aerial and satellite imagery. In this study, we systematically compared canopy cover estimations from LiDAR data, quick field measurements, aerial imagery, and satellite imagery using different algorithms. The results show that LiDAR-derived canopy cover estimates are marginally influenced by the estimation algorithms. LiDAR data with a point density of 1 point/m² can generate comparable canopy cover estimates to data with a higher density. The uncertainty of canopy cover estimates from LiDAR data increased drastically as scan angles exceed 12°. The field measurements, averaged from 25 measurements in each 500m² plot, may not be as precise as canopy cover estimates from high density LiDAR data. Both the aerial imagery-derived and satellite imagery-derived canopy cover estimates are comparable to LiDAR-derived canopy cover estimates at the forest stand scale, but tend to be overestimated in sparse forests and be underestimated in dense forests, particularly for the aerial imagery-derived estimates. In sum, LiDAR data with 1 point/m² density obtained at a scan angle less than 12° are able to estimate canopy cover precisely, regardless of the estimation algorithm. High resolution imagery (approximately 1m resolution) is suitable for canopy cover estimation in forests with median density; uncertainties are larger in sparse or dense forests.

Keywords: Canopy cover; Light Detection and Ranging; National Agricultural Imagery Program; WorldView-2

2.1 Introduction
Canopy cover is defined as the percentage of an area occupied by the vertical projection of tree crowns (Jennings et al. 1999), and is directly related to water and carbon cycles and energy changes in terrestrial ecosystems (Hansen et al. 2013; Korhonen et al. 2006; Suganuma et al. 2006). Spatially explicit mapping of canopy cover is critical for carbon stock estimation (Blackard et al. 2008), wildfire behavior simulation (Rebain et al. 2010), and wildlife habitat modeling (Smart et al. 2012).

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Traditionally, canopy cover was determined by field measurements using labor-intensive techniques, such as Cajanus tube and line intersect sampling (Jennings et al. 1999; Korhonen et al. 2006). These are highly time-consuming and expensive, and thus, it is difficult to collect sufficient field measurements for estimating canopy cover over large areas. Remote sensing techniques can provide spatially continuous observations of the Earth’s surface with much higher efficiency and lower cost. Medium-to-coarse resolution multispectral data, such as Landsat and Moderate Resolution Imaging Spectroradiometer data, have been widely used to generate canopy cover products at national and global scales using regression-based methods (Hansen et al. 2013; Homer et al. 2007; Sexton et al. 2013). Very-high-resolution (VHR) satellite and aerial imagery, such as QuickBird, IKONOS, WorldView, and National Agriculture Imagery Program (NAIP), have also been used to map canopy cover at small areas or been used as reference data to validate large-area canopy cover products (Coulston et al. 2012; Toney et al. 2012; Verma et al. 2016; Yu et al. 2015; Zhao et al. 2011). However, previous studies have demonstrated shortcomings in canopy cover products derived from VHR imagery mainly because of its limited penetration capability in vegetated areas. Other effects, such as the shadow, viewing angle and bidirectional reflectance, may also influence the accuracy of the estimated canopy cover (Gatzios 2012a; Hart and Veblen 2015; Korpela and Korpilahti 2004).

Light Detection and Ranging (LiDAR), an active remote sensing technique, has been a robust tool for quantifying forest structural parameters (Jakubowski et al. 2013a; Tao et al. 2014; Xue et al. 2015). The narrow laser beams transmitted by a LiDAR sensor can penetrate forest canopy and generate detailed estimations of ground elevation and three-dimensional forest structures (Korhonen and Morsdorf 2014). Because of its penetration capability and independence from solar illumination (Cao et al. 2012; Korhonen et al. 2013; Li et al. 2015; Su et al. 2015; Wulder et al. 2012), LiDAR is superior to passive optical imagery in canopy cover estimation. Various algorithms have been developed to estimate canopy cover from LiDAR data (Korhonen et al. 2011; Korhonen and Morsdorf 2014). However, we currently lack a thorough understanding of how these algorithms may influence canopy cover estimations. Moreover, previous studies indicated that LiDAR-based estimations can be affected by many factors, such as LiDAR scan angle, LiDAR point density, and forest density (Holmgren et al. 2003; Hopkinson 2007; Korhonen et al. 2011). A systematic evaluation of how these parameters influence the accuracy of LiDAR-derived canopy cover is necessary to guide LiDAR data collection and processing.

This study aims to conduct a comprehensive evaluation of LiDAR-derived canopy cover estimations using different algorithms from LiDAR data with various point densities and scan angles. Moreover, we aim to further compare the LiDAR-derived canopy cover estimates with other estimates including those from quick field measurements, VHR aerial imagery, and VHR satellite imagery, in forests with various densities.
2.2 Data and methods

2.2.1 Study area

The study site (39°07'N, 120°36'W) is located within the Tahoe National Forest of California, U.S. (Figure 2-1), which occupies a mountainous area of 138 km². The complex terrain and forest composition makes this area an ideal site for assessing and comparing canopy cover estimations. The elevation ranges from 600 to 2190 m above the mean sea level. The site is dominated by mixed conifer trees accompanied by shrubs and annual grasslands. The main conifer species are ponderosa pine (*Pinus ponderosa*), incense cedar (*Calocedrus decurrens*), sugar pine (*Pinus lambertiana*), white fir (*Abies concolor*), California red fir (*Abies magnifica*), and Douglas fir (*Pseudotsuga menziesii*). Some hardwood species, such as black oak (*Quercus kelloggii*) and canyon live oak (*Quercus chrysolepis*), are also present, but only cover a small part of the study site. Forest fuel treatments have been conducted regularly in the study site to reduce forest fire risk. Accurate and spatially explicit forest structure mapping is critical for forest management and monitoring in this area.

2.2.2 Field survey

Field measurements were collected during the summer of 2013 using a quick field survey strategy. A total of 365 circular plots were surveyed, and each plot has an area of 500 m² (Figure 2-1). These plots were determined by first randomly selecting the center of a seed plot and then building a grid with 500-m spacing in the four cardinal directions of the seed plot. Plot locations were placed at the intersections of this grid. Sampling was intensified in certain areas with specific research purposes, such as modelling hydrological cycles (Su et al. 2016). Some plot centers were randomly shifted 25 m in one of the four cardinal directions if they were non-forested areas. Spatial locations of the plot centers were georeferenced using a Trimble™ GeoXH differential global positioning system receiver.

In each plot, the canopy cover was measured using a sighting tube following a quick field survey strategy. If the crosshair at the top of the tube was pointing at a tree crown, the observation was recorded as “1”; otherwise the observation was “0”. As shown in Figure 2-1, a total of 25 evenly distributed canopy observations were sampled in each plot using a sighting tube. The final canopy cover value for each plot was calculated as the average of the 25 observations. The sighting tube measurements were taken at the height of approximately 1.8 m.
Figure 2-1 Map of the study site and the location of 365 field plots. The field survey sampling strategy for canopy cover measurements is shown in the bottom of the figure.

2.2.3 LiDAR data
LiDAR data were obtained in November 2012, using an Optech GEMINI Airborne Laser Terrain Mapper system at a flying height of 600–800 m above the ground. This system transmitted laser beams with 1047 nm wavelength and recorded up to four discrete returns per pulse at a repetition frequency of 100–124 kHz. Each flight line was surveyed with a swath overlap of 67%. The scan angle of the LiDAR sensor ranged from $-15^\circ$ to $15^\circ$ off nadir, and the density of the collected LiDAR point cloud was 10 points/m$^2$ on average.

The raw LiDAR data were pre-processed using TerraSolid’s TerraScan software (Soininen 2004) to remove isolated outlier points. The remaining points were then classified into ground and non-ground points using an iterative triangulated surface filtering algorithm (Chang et al. 2008). We interpolated a digital elevation model (DEM) from the ground returns and a digital surface model (Kros et al.) from the first returns at a resolution of 1 m using the ordinary kriging method (Guo et al. 2010). The original LiDAR point cloud was further normalized using the derived DEM. Note that the LiDAR point cloud mentioned hereafter refers to the normalized LiDAR point cloud.

2.2.4 Multispectral Imagery
NAIP aerial imagery used in this study was acquired during the crop-growing season in 2012 by the U.S. Department of Agriculture (USDA) under qualified weather conditions with less than 10% cloud, haze, or snow cover. The NAIP imagery was composed of four spectral bands (i.e., red, green, blue and near infrared), with a spatial resolution of 1 m. The NAIP data used in this study were downloaded from the USDA Geospatial Data Gateway (https://gdg.sc.egov.usda.gov/). These data have been orthorectified before being released.
Spaceborne VHR data from the WorldView-2 satellite were also used to estimate canopy cover for comparison. The WorldView-2 imagery was obtained on September 2, 2012 over the study site with a clear sky (cloud cover <1%) and no snow cover. The WorldView-2 imagery contained eight multispectral bands and one panchromatic band, and their spatial resolutions were approximately 2 m and 0.5 m, respectively (Table 2-1). The WorldView-2 imagery was first radiometrically calibrated to top-of-atmosphere reflectance with parameters from the imagery metadata using the ENVI software (Exelis Visual Information Solutions, Boulder, CO, U.S.). Then, the multispectral bands were pan-sharpened to a 0.5 m resolution by fusing with the panchromatic band using the Gramm–Schmidt spectral sharpening algorithm (Ghosh and Joshi 2013; Pu and Landry 2012).

To enable comparison with the NAIP imagery, we first resampled the pan-sharpened WorldView-2 imagery to 1 m resolution, and then geo-registered WorldView-2 imagery to the NAIP imagery using a nearest-neighbor method with manually selected ground control points. The absolute spatial difference between the two datasets was smaller than 0.5 m after the registration.

Table 2-1 WorldView-2 imagery parameters

<table>
<thead>
<tr>
<th>Band</th>
<th>Spectral range</th>
<th>Wavelength (nm)</th>
<th>Nadir resolution (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Coastal</td>
<td>400–450</td>
<td>1.85</td>
</tr>
<tr>
<td>2</td>
<td>Blue</td>
<td>450–510</td>
<td>1.85</td>
</tr>
<tr>
<td>3</td>
<td>Green</td>
<td>510–580</td>
<td>1.85</td>
</tr>
<tr>
<td>4</td>
<td>Yellow</td>
<td>585–625</td>
<td>1.85</td>
</tr>
<tr>
<td>5</td>
<td>Red</td>
<td>630–690</td>
<td>1.85</td>
</tr>
<tr>
<td>6</td>
<td>Red Edge</td>
<td>705–745</td>
<td>1.85</td>
</tr>
<tr>
<td>7</td>
<td>NIR 1</td>
<td>770–895</td>
<td>1.85</td>
</tr>
<tr>
<td>8</td>
<td>NIR 2</td>
<td>860–1040</td>
<td>1.85</td>
</tr>
<tr>
<td>9</td>
<td>PAN</td>
<td>450–800</td>
<td>0.46</td>
</tr>
</tbody>
</table>

2.2.5 Canopy cover estimation from LiDAR data

Three LiDAR-based canopy cover estimation methods were adopted, and their results were compared with quick field measurements and estimations from VHR imagery (Figure 2-2).
Figure 2-2 The flowcharts of canopy cover estimation and comparison. ARCI, FRCI, CHM, CC, WV2, SVM, ML, MD mean all-return cover index, first-return cover index, canopy height model, canopy cover, WorldView-2, support vector machine, maximum likelihood, and minimum distance to means, respectively.

### 2.2.5.1 LiDAR point-based method

Generally, LiDAR point-based algorithms for canopy cover estimations can be divided into two categories, all-return based methods and first-return based methods. All-return cover index (ARCI) is commonly defined as the ratio of LiDAR returns that intersect with the canopy (defined as a certain height above the ground), regardless of the return number (Ahmed et al. 2014; Barilotti et al. 2006; Hopkinson and Chasmer 2009). First-return cover index (FRCI) calculates the ratio only from the LiDAR first returns and single returns, because it assumes that last and intermediate returns can provide little additional information on canopy cover estimation (Korhonen et al. 2011). In this study, both methods were used to derive LiDAR point-based canopy cover estimations (2-1,2-2).

\[ \text{ARCI} = \frac{\sum \text{All}_{\text{canopy}}}{\sum \text{All}_{\text{total}}} \]  
\[ \text{FRCI} = \frac{\sum \text{First}_{\text{canopy}} + \sum \text{Single}_{\text{canopy}}}{\sum \text{First}_{\text{total}} + \sum \text{Single}_{\text{total}}} \]  

where \( \text{All} \) means all returns, \( \text{First} \) means first returns, and \( \text{Single} \) means single returns. The subscripts \( \text{total} \) and \( \text{canopy} \) represent the total number of returns and the number of returns intersecting the canopy, respectively. Note that a threshold of 2 m was used in this study to match the height of quick field measurements.

Scan angle may cause bias in canopy cover prediction because some oblique pulses transmitted at large scan angles can lead to uneven sampling of tree crowns (Holmgren et al. 2003). In this study, we evaluated the impact of the scan angle (\( \alpha \)) by categorizing...
LiDAR data into five scan-angle groups (15° ≤ |α| < 12°, 12° ≤ |α| < 9°, 9° ≤ |α| < 6°, 6° ≤ |α| < 3°, |α| < 3°). For each scan angle group, we computed the canopy cover estimations using ARCI and FRCI methods and compared them with the estimations from all LiDAR data.

LiDAR point density is another factor that can impact the estimation accuracy (He and Li 2012; Korhonen et al. 2011; Lim et al. 2008; Treitz et al. 2012). An increase in LiDAR point density may not necessarily improve the estimation accuracy due to the redundant information and the point clustering effect (Næsset 2009). We explored the sensitivity of canopy cover estimation to LiDAR point density by simulating lower density data. To thin LiDAR data, Jakubowski et al. (Jakubowski et al. 2013a) gridded the data at different spatial resolutions and chose a number of random points within each grid. This method was effective in keeping the LiDAR point density constant over the whole study area. However, in real situations, LiDAR point densities may not be homogenous because of heterogeneous land surfaces. To better simulate the real situation, we thinned LiDAR points by randomly reducing certain percentages of points in each plot. New LiDAR data were generated at 18 different densities by filtering out 10%, 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90%, 92.5%, 95%, 99%, 99.25%, 99.5%, 99.6%, 99.7%, 99.8%, and 99.9% of the original data. Thus, the averaged point density of the thinned datasets ranged from 9 points/m² to 0.01 point/m², and varied slightly among plots. We evaluated the canopy cover estimation accuracy by comparing them with the reference data derived from all LiDAR points using ARCI and FRCI methods.

2.2.5.2 LiDAR Canopy Height Model (CHM)-based method
LiDAR-derived Canopy Height Models (CHMs) have been widely used to estimate canopy cover (Chen et al. 2011; Jakubowski et al. 2013b; Korhonen et al. 2011; Korhonen and Morsdorf 2014). In this study, the 1-m resolution CHM was calculated as the difference between DSM and DEM. The CHM-based canopy cover can be calculated as the percentage of pixels with a CHM value larger than the tree height threshold (2 m) within a statistical unit (30×30 m grid) (3).

$$\text{Canopy Cover} = \frac{\sum CHM_{\text{canopy}}}{\sum CHM_{\text{total}}}$$

where $CHM_{\text{canopy}}$ represents the pixels of CHM belonging to canopy (with a CHM value above 2 m). $CHM_{\text{total}}$ means the total number of CHM pixels.

2.2.6 Canopy cover estimation from multispectral imagery
An image classification-based method was used to estimate canopy cover from WorldView-2 and NAIP data (Chen and Hay 2011; Chen et al. 2011; Chen et al. 2012; Samani Majd et al. 2013). Each pixel in the multispectral imagery was first classified as either tree canopy or non-tree canopy. Then canopy cover was calculated as the percentage of pixels classified as tree canopy within each 30×30 m statistic unit.

The same classification procedure was applied to both WorldView-2 and NAIP image datasets using the ENVI software. We first classified each image into six preliminary classes (i.e., bare soil, shadow, illuminated grass/shrub, shadowed
grass/shrub, illuminated tree, and shadowed tree) using supervised classification methods. In the final classification maps, illuminated and shadowed tree classes were aggregated into tree canopy, and other classes were labeled as non-tree canopy. The training samples were manually selected based on the knowledge from field surveys and image interpretation. A total of 700 sample objects (4 m² for each object on average) over the six classes were delineated from the imagery; 350 of them were randomly selected as training samples and the remaining samples were used for validation.

To choose the optimal classification algorithm, we compared three different supervised classifiers (i.e., the minimum distance to means, the maximum likelihood, and the support vector machine). These classifiers were selected for comparison because of their efficiency, robustness, and accuracy in image classification (Lillesand et al. 2014; Mountrakis et al. 2011; Otukei and Blaschke 2010). To better differentiate shadowed tree from shadowed grassland/shrub/bare earth and illuminated tree from illuminated grassland/shrub, we calculated seven texture layers (mean, variance, homogeneity, contrast, dissimilarity, entropy, and second moment) from each spectral band, and included them in the classification (Myeong et al. 2001; Zhang 2001). In this study, the texture layers were calculated using the gray-level co-occurrence matrix filtering method with a 3 × 3 moving window (Haralick and Shanmugam 1973; Su et al. 2016).

2.2.7 Comparison scheme and accuracy assessment

The cross-comparison scheme for canopy cover estimations obtained using different datasets and methods are presented in Figure 2-2. First, the three LiDAR-derived canopy cover estimates were compared with quick field measurements at the plot scale. Then the LiDAR CHM-derived canopy cover was estimated for the whole study area and compared with those generated from NAIP and WorldView-2 imagery at a 30 m resolution.

Canopy cover estimation accuracy was evaluated using the coefficient of correlation (R) and root mean squared error (RMSE), which can be calculated from the following equations,

\[
R = \frac{\sum_{i=1}^{n} (x_i - x_m)(y_i - y_m)}{\sqrt{\sum_{i=1}^{n} (x_i - x_m)^2} \sqrt{\sum_{i=1}^{n} (y_i - y_m)^2}}
\]

\[
RMSE = \sqrt{\frac{\sum_{i=1}^{n} (x_i - y_i)^2}{n}}
\]

where \(n\) is the number of plots, \(x_i\) and \(y_i\) are the values from \(i^{th}\) reference data and evaluated values, and \(x_m\) and \(y_m\) is the mean of all reference data.

The tree/non-tree classification accuracies achieved using NAIP and WorldView-2 data were evaluated using three indicators, i.e., the recall (r), the precision (p), and the F-score in the following equations.
\[ r = \frac{TP}{TP + FN} \]  \hspace{1cm} (2-6)

\[ p = \frac{TP}{TP + FP} \]  \hspace{1cm} (2-7)

\[ F \text{ score} = \frac{2(r \times p)}{r + p} \]  \hspace{1cm} (2-8)

where TP is true positive, indicating the number of tree samples accurately classified as tree cover; FP, false positive, is the amount of non-tree cover samples mistakenly classified as tree cover; and FN is false negative, indicating the amount of tree cover samples failed to be identified in the results.

2.3 Results

2.3.1 LiDAR derived canopy cover

2.3.1.1 Comparison of LiDAR estimations and field measurements

A comparison between canopy cover estimations from three LiDAR-based methods (i.e., ARCI, FRCI, and CHM) and field measurements are shown in Figure 2-3. No strong correlations were observed between field-measured and LiDAR-derived canopy cover estimations. The ARCI-generated canopy cover estimates were slightly more similar to the field measurements \((R = 0.57)\) than CHM and FRCI methods \((R = 0.56)\). Overall, the differences among the three LiDAR-based methods were small (Figure 2-4). The \(R\) among each two of the ARCI, FRCI, and CHM estimations ranged from 0.95 to 0.97. Figure 2-4 shows that CHM-derived canopy cover estimates were similar to those from FRCI, but slightly higher than ARCI-derived estimates. The mean CHM-derived canopy cover was 0.05 higher than that from ARCI.
Figure 2-3 Comparison of canopy cover estimations derived from field measurements and LiDAR data. Scatter plots with $R$, RMSE, and regression equations between field measurements ($y$) and LiDAR based estimations($x$) are shown in (a) for ARCI, (b) for FRCI, and (c) for CHM methods.
2.3.1.2 Impact of LiDAR point density on canopy cover estimation
Changes in $R$ and RMSE between ARCI estimations from the thinned LiDAR data and four reference datasets, i.e. three original LiDAR estimations and the field measurements, are presented in Figure 2-5a and Figure 2-5b as functions of point density. The $R$ increased as the LiDAR point density raised from 0.01 to 10 points/m$^2$, but the rate of increase in the $R$ varied at different density ranges (Figure 2-5a). The $R$ between thinned and all LiDAR points ARCI-derived estimations increased significantly from 0.74 to over 0.95 in the range of 0.01 to 0.1 point/m$^2$; the increase rate of $R$ was relatively smaller in the range of 0.1 to 1 point/m$^2$. After the point density passing 1 point/m$^2$, the $R$ value became relatively constant (0.95-0.98) with the increase of point density. The $R$ between thinned ARCI-derived estimations and field measurements were much lower, ranging from 0.18 to 0.31 (Figure 2-5a). As the LiDAR point density increased, the RMSE values diminished (Figure 2-5b). When the point density was larger than 1 point/m$^2$, the RMSE was almost constant (~0.21 for field measurement and 0.01 - 0.09 for original LiDAR estimations). The impact of LiDAR point density on canopy cover estimations using FRCI was similar to that using ARCI. As Figure 2-5c and 5d show, all $R$ values increased and RMSE decreased with the increase of point density; and their changes saturated when density reached 1 point/m$^2$. Thinned LiDAR estimations were the most similar (largest $R$ and smallest RMSE) to the reference data using the same method over all density ranges (Figure 2-5).
Figure 2-5 Changes in $R$ (a and c) and RMSE (b and d) between predicted canopy cover estimations from thinned LiDAR data and reference datasets using ARCI (a and b) and FRCI (c and d) methods. Results are plotted as functions of LiDAR point densities on a logarithmic scale. The reference datasets are canopy cover from field measurements, and original LiDAR data using CHM, ARCI, and FRCI methods.

2.3.1.3 Impact of LiDAR scan angle on canopy cover estimation

The differences between canopy cover estimations from each scan-angle group and the reference data from all LiDAR points are presented in Figure 2-6. Using the ARCI method (Figure 2-6a), canopy cover estimations from the smallest scan-angle ($|\alpha|<3^\circ$) group were the most similar to the reference data, while those from the largest scan-angle group ($12^\circ<|\alpha|\leq15^\circ$) were the most different from the reference data. The absolute difference can be up to 0.2 in the largest scan-angle group. The impacts of scan angle on canopy cover remained almost constant when the off-nadir scan angle increased from $3^\circ$ to $12^\circ$. In the majority of the sampling plots, the absolute differences were within 0.15. Our results also indicated that the mean canopy cover predictions from the largest scan-angle group tended to be slightly overestimated. The results from FRCI-based estimation in various scan-angle groups (Figure 2-6b) were similar to ARCI-derived results. Uncertainties in canopy cover estimations using the FRCI method were slightly
larger than those obtained using the ARCI method, particularly in the largest (12° < |α| ≤ 15°) and median (6° < |α| ≤ 9°) scan-angle groups. The differences from the reference data can be up to 0.25 and 0.2 in those two groups.

Figure 2-6 Changes in R (a and c) and RMSE (b and d) between predicted canopy cover estimations from thinned LiDAR data and reference datasets using ARCI (a and b) and FRCI (c and d) methods. Results are plotted as functions of LiDAR point densities on a logarithmic scale. The reference datasets are canopy cover from field measurements, and original LiDAR data using CHM, ARCI, and FRCI methods.

2.3.2 Comparison of LiDAR- and VHR imagery-derived canopy cover
3.3.2.1 Multispectral image classification
Accuracies of tree canopy classification from NAIP and WorldView-2 data using three different classifiers are presented in Table 2-2. Overall, the classification accuracies from both datasets are very similar. The F-scores for NAIP were slightly higher (1–5%) than those for WorldView-2. The order of accuracy among the classifiers in both datasets were consistent—the support vector machine gave the highest accuracies (F-scores 0.93, 0.94), followed by the maximum likelihood classifier (F-scores 0.86, 0.90), and the minimum distance to means classifier (F-scores 0.76, 0.81). Results obtained using the support vector machine classifier from both datasets were selected to estimate canopy cover for cross-comparison.

Table 2-2 Accuracy Assessments of Tree Canopy Classification Results from NAIP and WorldView-2 (WV2) Data

<table>
<thead>
<tr>
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<th></th>
<th>WV2</th>
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<tr>
<td></td>
<td>SVM</td>
<td>ML</td>
<td>MD</td>
<td>SVM</td>
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<tr>
<td>TP</td>
<td>305</td>
<td>279</td>
<td>233</td>
<td>301</td>
<td>261</td>
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<td>FP</td>
<td>3</td>
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<td>63</td>
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<td>FN</td>
<td>35</td>
<td>35</td>
<td>47</td>
<td>27</td>
<td>43</td>
</tr>
</tbody>
</table>
Recall | 0.90 | 0.89 | 0.83 | 0.92 | 0.86 | 0.86
Precision | 0.99 | 0.91 | 0.79 | 0.95 | 0.87 | 0.69
F-scores | 0.94 | 0.90 | 0.81 | 0.93 | 0.86 | 0.76

SVM: support vector machine; ML: maximum likelihood classification; MD: minimum distance to means; TP: true positive; FP: false positive; FN: false negative.

2.3.2.2 Comparison of canopy cover estimations from VHR imagery and LiDAR CHM

Results in Table 2-3 demonstrate that the averaged canopy cover estimations over the entire study site from NAIP and WorldView-2 were 0.10 and 0.04 lower than the CHM-derived canopy cover estimation. The standard deviation in canopy cover from WorldView-2 was closer to that from CHM than that from NAIP. The NAIP- and WorldView-2-derived canopy cover estimations were correlated with CHM-derived estimations, although the correlations were not very strong ($R$ 0.71 and 0.76, $p$ < 0.001). Canopy cover derived from WorldView-2 was slightly better than that from NAIP (12% higher in $R$ and 9.5% lower in RMSE).

<table>
<thead>
<tr>
<th>Mean</th>
<th>Standard deviation</th>
<th>$R$</th>
<th>RMSE</th>
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<tr>
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<td>0.71</td>
</tr>
<tr>
<td>NAIP</td>
<td>0.47</td>
<td>CHM,WV2</td>
<td>0.76</td>
</tr>
<tr>
<td>WV2</td>
<td>0.53</td>
<td>NAIP,WV2</td>
<td>0.72</td>
</tr>
</tbody>
</table>

Table 2-3 Comparisons of Canopy Cover Estimations from CHM, NAIP and WorldView-2 Data

Left: the mean and standard deviation values of canopy cover estimates derived from CHM, NAIP, and WorldView-2 (WV2) over the entire study site. Right: $R$ and RMSE among canopy cover estimations derived from CHM, NAIP, and WorldView-2 data.

A detailed comparison of the three canopy cover products from different canopy density groups is presented in Figure 2-7. Based on the CHM derived canopy cover dataset, the whole study area was divided into 11 levels with an interval of 0.1. Compared with the CHM-derived canopy cover, the NAIP-derived product was overestimated in low canopy cover areas (< 0.3), but was underestimated in high canopy cover areas (> 0.5) (Figure 2-7a). The mean differences of canopy cover estimations in each group varied from −0.1 to 0.2. The overestimates and underestimates in WorldVeiw-2-derived canopy cover were also observable (Figure 2-7b), but less obvious than those from NAIP. However, substantial underestimates and overestimates were observed from WorldView-2-derived results compared to CHM-derived ones in the median canopy cover groups (0.4-0.6).
Figure 2-7 Boxplots of the differences among canopy cover estimations in various canopy cover groups: (a) differences between CHM and NAIP derived canopy cover estimations; (b) difference between CHM and WorldView-2 derived canopy cover estimations. Red lines indicate median values, and blue ‘+’ marks indicate mean values.

2.4 Discussion
2.4.1 Differences among LiDAR-derived and field-measured canopy cover estimations
In this study, we compared canopy cover estimations from LiDAR data with field measurements, but no strong correlations were observed between them. The limitations
of the quick field survey adopted in this study might be the main cause of the disagreements.

In each quick surveyed field plot, merely 25 sighting tube observations were collected across a 500 m² area. In contrast, there were approximately 5000 LiDAR points in each plot. Therefore, the LiDAR-derived canopy cover contained more continuous values than field measurements (Figure 2-3a, b, c). Previous studies by Korhonen et al. (Korhonen et al. 2006) and Smith et al. (Smith et al. 2009) showed that using a quick field survey method with insufficient sampling can contribute up to 20% bias in canopy cover measurements. Korhonen et al. (Korhonen et al. 2006) suggested that an unbiased field measurement required at least 102 observations in a 500 m² plot using objective techniques, such as a Cajanus tube. However, limited by the time and budget, such robust field measurements were unable to conduct in this study. Moreover, since field measurements and LiDAR data were collected at different times using different GPS systems, there might be a substantial mismatch between them in the plot center locations. This mismatch could also lead to considerable discrepancies in the comparison with LiDAR-derived canopy cover estimates (Frazer et al. 2011). Considering time and labor costs, as well as uncertainties in field measurements, LiDAR data could be a promising alternative to measure canopy cover.

2.4.2 Comparisons of LiDAR estimation methods
Our results demonstrate that canopy cover estimations obtained using the CHM method were slightly higher than those using ARCI and FRCI methods (Figure 2-4). Similar results were reported by Korhonen et al. (Korhonen et al. 2011) that the differences could be 5% – 10% in various forest sites. Higher estimations obtained using the CHM method can be partly attributed to the rasterization procedure used for generating the CHM from LiDAR point data. In plots with most first returns reflected from the canopy rather than the ground, such as the plot shown in Figure 2-8, the CHM grids were more likely to be interpolated as canopy after rasterization. These situations were often occurred in areas covered by trees with some gaps in the crown where LiDAR pulses could penetrate and reach the ground surface. These gaps were accounted using the ARCI and FRCI methods, but were often neglected in the CHM-based method if gaps were smaller than the grid size. We chose the 1 m² CHM grid size because it was not only fine enough to characterize each tree crown, which had a 4 m² crown areas on average; but also accurate and efficient enough for LiDAR data processing considering its 15-cm horizontal accuracy. However, more studies are needed to determine the optimal CHM resolution for canopy cover estimation in different areas, so that gaps among tree crowns can be detected while gaps within crowns can be omitted.
Figure 2-8  A typical plot with all first-return LiDAR points overlaid on the CHM. Blue dots are first-return points from the ground (aboveground elevation < 2 m), red triangles indicate first-return points from the canopy (aboveground elevation ≥ 2 m). In this plot, the CHM-derived canopy cover was 11% higher than canopy cover derived from FRCI.

Results generated using the ARCI and FRCI methods were very similar. The slightly higher mean canopy cover obtained using FRCI can be explained by the penetration capability of LiDAR data in forest areas. Figure 2-9 shows that 42.5% of the first returns were lower than 2 m, whereas that proportion in the mid-last returns was 47.5%. This indicates that some of the LiDAR pulses, which initially intersected the canopy, could have also penetrated the canopy and even reached the understory or the ground. The additional information from the mid–last returns was related to the vegetation structure within and beneath the canopy, and thus may not be useful for canopy cover estimation (Korhonen et al. 2011; Morsdorf et al. 2006).
Figure 2-9  Cumulative frequency of LiDAR points aboveground heights grouped by all returns, first returns, and mid–last returns. Only LiDAR data from 0 to 5 m aboveground are presented since 2 m is the tree height threshold used for calculating canopy cover in this study.

2.4.3 Impacts of LiDAR point density and scan angle

Our study is based on a general assumption that LiDAR data with a higher density should yield a better canopy cover estimation. Using the canopy cover estimated from all LiDAR data (~10 points/m²) as a reference, we found that the results from 1% of the LiDAR point data (~0.1 point/m²) could explain over 90% of the variations in the reference data. The results generated from 10% of the data (~1 point/m²) were almost identical to the reference data, which indicated that any further increase in point density contributed very little to the estimation accuracy. Previous research (He and Li 2012; Jakubowski et al. 2013b; Korhonen et al. 2011; Singh et al. 2015; Singh et al. 2016; Treitz et al. 2012; Vauhkonen et al. 2008) also investigated the impact of LiDAR point density on forest structural parameter estimation. Although results varied slightly among the estimated parameters and methods, one conclusion was consistent: the increase of LiDAR point density does not always lead to a better forest structure parameter estimation. Similar or improved prediction accuracies can be achieved using LiDAR points at particular densities. In the mixed-conifer-dominated Sierra Nevada forests, reasonable canopy cover estimations can be achieved at 0.1 point/m² and very high accuracy can be obtained using 1 point/m² LiDAR data. These findings would be useful for forest canopy cover surveys using LiDAR data over broad areas, when time and budget are limited.

Our results showed that canopy cover estimated from LiDAR points with wide scan angles had larger uncertainties than those from narrow ones, and this is also consistent with previous study in the Pacific Northwest (Gatziolis and Andersen 2008). The increased uncertainty was mostly caused by the clustering effect of LiDAR points.
obtained at large scan angles. As the scan angle increases, canopies with long crowns gathered more LiDAR pulses than those with short crowns (Holmgren et al. 2003). This effect was the most significant when the scan angle exceeded a certain threshold. As a sample plot shown in Figure 2-10, when the scan zenith angle exceeded 12°, larger crowns were sampled more intensely than other areas, and thus tended to overestimate canopy cover (Figure 2-10). The mechanism of the scan angle effect can be complicated because it not only responded to forest structural characteristics, such as tree height, crown length, stem density; but also influenced by the LiDAR sensor configuration (sensor height and scan angle) (Holmgren et al. 2003; Korhonen et al. 2011). LiDAR data with large scan angle should be used with caution in canopy cover estimation, particularly in mountainous forested areas, where LiDAR data obtained with a narrower scan angle and larger overlap of adjacent flights are preferred.

![Figure 2-10](image)

Figure 2-10  Spatial distribution of LiDAR points in one plot at three different scan angle (SA) ranges: $0^\circ < |SA| < 3^\circ$ (up), $9^\circ < |SA| < 12^\circ$ (Petrakis et al.), and $12^\circ < |SA| < 15^\circ$ (down).
2.4.4 Difference among LiDAR-derived and VHR imagery-derived canopy cover estimations

Our results showed that canopy cover estimations from both WorldView-2 and NAIP image datasets were comparable to those from LiDAR estimations at a 30 m resolution, with the $R$ slightly higher than 0.7. Previous studies also indicated that the $R$ between LiDAR-derived and VHR imagery-derived canopy cover varied from 0.63 to 0.89, depending on the comparison scales, forest conditions, imagery qualities, and estimation methods (Ahmed et al. 2014; Gatziolis 2012b; Su et al. 2015).

One reason for the bias in the VHR imagery derived canopy cover was the misclassification between shrub/grass and tree canopy. Although satisfactory overall accuracies were achieved using the support vector machine classifier, 8%–10% of non-tree canopy pixels were misclassified as tree canopy in both datasets (Table 2-2). This misclassification mainly occurred in areas occupied by small trees and some clustered shrub/grass, because they have very similar spectral characteristics as tree canopy. This partly explains why estimations from VHR imagery were slightly higher than that from the CHM in low canopy cover areas (CC < 0.4). In the latter, shrub/grass and tree canopy were distinguishable by a constant vegetation height threshold (2 m), although the real threshold may not be uniform over the whole study area. Gatziolis (Gatziolis 2012b; Gatziolis and Andersen 2008) found that using thresholds ranging from 1 to 3 m could result in over 4% variance in the canopy cover estimation. The uncertainties resulting from the selection of a tree height threshold may also lead to the discrepancies between CHM- and VHR-imagery-based estimations.

The limitations of optical remote sensing techniques in obtaining VHR imagery may also contribute to the discrepancies in canopy cover estimations. One major constraint is the distortion of VHR imagery, particularly in the NAIP aerial photography where radial distortion, tilt displacement, and topographic displacement are common. These distortions in NAIP increase with off-nadir distance. In the distorted imagery, tilted tree crowns can obscure open gaps or neighboring tree crowns. In sparse areas, canopy cover was more likely to be overestimated because parts of the gaps are masked by tilted tree crowns. The other disadvantage of optical VHR imagery is the presence of shadows. The combination of tall trees, low sun elevation angle, and complex terrain in the study area resulted in numerous shadows in both WorldView-2 and NAIP images. Shadows occupied 8% to 12% of the study area, according to the classification results. In dense forest areas, parts of tree crowns were often shadowed by neighboring canopies, and were difficult to identify from imagery as canopy. Consequently, canopy cover is more likely to be underestimated in those dense forest areas.

The canopy cover estimated from WorldView-2 was more similar to the CHM derived estimations than that from NAIP. WorldView-2 satellite data, collected at high altitude, possess narrower viewing angles than NAIP, therefore, the distortion and shadow effects in WorldView-2 imagery were less obvious. Moreover, the metadata of the NAIP imagery, such as flight lines and times, were not publicly available, so it was difficult to analyze or correct the distortion and shadowing effects. Therefore, the canopy cover derived from NAIP had more bias than that from WorldView-2, particularly in areas with either sparse or dense forests (Figure 2-7). NAIP can still be a promising data source for large-scale canopy cover estimation, because of its continuous coverage across
the U.S., its free access to the public, and its frequent updates. However, more attention should be paid to the quality of NAIP data regarding the shadow and distortion effects. Future study on detecting tree crowns in the shadowed NAIP imagery will be helpful to improve canopy cover estimation.

2.5 Conclusions
This study provides the first comprehensive cross-comparison of canopy cover estimations from LiDAR data, quick field measurements, and high resolution aerial and satellite imagery at both plot and forest stand scales. At the plot level, we assessed how estimation algorithm, point density, and scan angle impact the LiDAR-based canopy cover estimations. Results show First-return cover index (FRCI) was more appropriate than All-return cover index (ARCI) and canopy height model (CHM) methods for canopy cover estimation. LiDAR data at 1 point/m² were sufficient for accurate canopy cover estimation, and further increases in the point density could hardly yield better results. Canopy cover estimations from LiDAR data with large off-nadir scan angles had considerable uncertainties, particularly when the angle exceeded 12°. Field measurements of canopy cover, averaged from 25 observations over each 500m² plot, were not adequately comparable with LiDAR-derived estimations. LiDAR based canopy cover estimation can be a promising alternative to “ground truth”, when unbiased measurements are difficult to obtain in the field.

At the forest stand scale, high resolution imagery, such as NAIP and WorldView-2, can be used to classify the tree crown cover using a support vector machine classifier with 93% overall accuracy. The imagery-derived canopy cover products were comparable to LiDAR-derived estimation in most areas at a 30 m resolution (R >0.7). However, using high resolution imagery tended to overestimate canopy cover in sparse forests and underestimate it in dense forests, particularly when using NAIP imagery. These findings can provide guidance for canopy cover estimations in mountainous forests at different scales, particularly in the LiDAR and high resolution imagery collection, as well as the selection of canopy cover estimation algorithms.

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Chapter 3  A Quantifying individual tree growth and tree competition using bi-temporal airborne laser scanning data: a case study in the Sierra Nevada mountains, California²

Abstract

Abstract: Improved monitoring and understanding of tree growth and its response to controlling factors are important for tree growth modeling. Airborne Laser Scanning (ALS) can be used to enhance the efficiency and accuracy of large-scale forest surveys in delineating three-dimensional forest structures and under-canopy terrains. This study proposed an ALS-based framework to quantify tree growth and competition. Bi-temporal ALS data were used to quantify tree growth in height, crown area, crown volume, and tree competition for 114,000 individual trees in two conifer-dominant Sierra Nevada forests. We analyzed the correlations between tree-growth attributes and controlling factors (i.e., tree sizes, competition, forest structure, and topographic parameters) at multiple levels. At the individual-tree level, tree height growth had no consistent correlations with controlling factors, growth in crown area and crown volume were positively related to original tree sizes ($R>0.3$) and negatively related to competition indices ($R<-0.3$). At the forest-stand level, growth in tree height and crown area were highly correlated to topographic wetness index ($|R|>0.7$), crown volume growth was positively related to original tree sizes ($|R|>0.8$). Multivariate regression models were simulated at individual-tree level for tree growth in the three attributes with the $R^2$ ranged from 0.1 to 0.43. The ALS-based tree height estimation and growth analysis results were consistent with field measurements.

Keywords: Airborne Laser Scanning; change detection; tree growth; tree competition; Sierra Nevada.

3.1 Introduction

The Sierra Nevada (SN) mountain range, covering an area of 63,100 km², is the home to one of the most diverse temperate conifer forests on Earth (Battles et al. 2001; Britting et al. 2012). The SN forests provide California with many forest services, including wildlife habitats, carbon stocks, water provision, and economic and cultural values (Bales et al. 2011). Spatially explicit and efficient quantification and modeling of tree growth are critical for SN forest resource evaluation, management, and protection (Battles et al. 2008).

Forest growth models, such as the California Conifer Timber Output Simulator (CACTOS) and the climate adjustment of CACTOS, have been developed either to

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simulate short-term timber yield (Wensel, Meerschaert, and Biging 1987) or to project tree growth under a changing climate (Battles et al. 2008) at individual-tree to landscape scales (Battles et al. 2008; Battles et al. 2006; Biging and Wensel 1984; Weiskittel et al. 2011; Wensel, Meerschaert, and Biging 1987). Tree growth models, particularly at the individual-tree level, relied heavily on forest inventory data (Weiskittel et al. 2011; Tompalski et al. 2016; Biging and Wensel 1984; Wensel, Meerschaert, and Biging 1987). However, taking in-situ measurements is often time consuming and labor intensive. Traditional models mainly focused on the growth in tree height and/or diameter at breast height (DBH) (Weiskittel et al. 2011; Pretsch 2009). Tree crown expansion, which is an essential part of tree growth in terms of light interception, gas exchange and water transpiration (Hardiman et al. 2013), has been rarely studied due to difficulties in obtaining direct field measurements (Weiskittel et al. 2011). Moreover, competition indices, which quantify competition among trees for resources, are important inputs in many tree growth models. The estimation of crown size for competition indices calculation were often based on indirect regression from tree height and DBH, which might be fraught with uncertainty issues (Wensel, Meerschaert, and Biging 1987; Biging and Dobbertin 1995). Therefore, accurate and efficient estimation of tree growth and tree competition at various scales has become an issue needed to be addressed for precise forest growth modeling and management (Olivier, Robert, and Fournier 2016).

Airborne Laser Scanner (ALS) data are playing an increasingly important role in forest surveys (Korhonen et al. 2011; Jakubowski et al. 2013; Su, Ma, and Guo 2016; Latifi et al. 2012; Tompalski et al. 2016) because of their capabilities in characterizing three-dimensional tree structures at forest-stand (Tao et al. 2014; Tempel et al. 2015; Su et al. 2015; Hyyppä et al. 2008; Coops et al. 2007; Næsset and Økland 2002) and individual-tree levels (Li et al. 2012; Lu et al. 2014; Zhen, Quackenbush, and Zhang 2016). Many studies have demonstrated the efficiency and accuracy of using ALS data to estimate forest structure parameters, including tree height (Breidenbach et al. 2008; Dubayah et al. 2010; Holmgren, Nilsson, and Olsson 2003; Yu et al. 2006), crown base height (Holmgren and Persson 2004; Popescu and Zhao 2008), crown area (Casas et al. 2016; Gonzalez-Benecke et al. 2014), crown volume (Kato et al. 2009), stem volume (Chen et al. 2007), canopy cover (Moeser et al. 2014; Korhonen et al. 2011), aboveground biomass (Tao et al. 2014; Cao et al. 2016; Singh et al. 2015; Singh et al. 2017), and basal area (Véga et al. 2016). Furthermore, ALS data have advantages over traditional in-situ measurements in estimating forest competition efficiently over large areas (Lo and Lin 2013; Pedersen et al. 2012).

Recently, techniques have been developed to detect tree growth from multi-temporal ALS data. At the forest-stand level, Yu et al. (2008) quantified mean tree height and volume growth in a boreal forest using multi-temporal ALS data; and Dubayah et al. (2010) estimated forest height and biomass changes in tropical forests. At the individual-tree level, several researchers have successfully used multi-temporal ALS data to detect tree height growth (Londo 2010; Song et al. 2016), canopy height growth (Yu et al. 2006) and crown growth (Frew et al. 2015). Moreover, studies have been increased on analyzing the relationships between tree growth and its controlling factors using multi-temporal ALS data. For example, Vepakomma (2011) assessed the responses of tree growth to canopy openings in a boreal forest. However, most previous studies either
estimated a single attribute of tree growth rather than multi-attributes (Londo 2010), or they focused on how tree growth was impacted by a single group of factors, such as competition index (Olivier, Robert, and Fournier 2016) and topographic condition (Adams, Barnard, and Loomis 2014). A comprehensive study is needed to systematically analyze how different factors influence tree growth in multi-attributes at various scales.

This study aimed to quantify tree growth and analyze its controlling factors in SN forests using bi-temporal ALS data. Three specific research questions were addressed. 1) How to quantify tree growth in height, crown area, and crown volume at individual-tree and forest-stand scales from bi-temporal ALS data? 2) How to estimate tree competition indices from ALS data? 3) How does tree growth respond to various factors, such as original tree sizes, density, competition, and topography, at different scales? Knowledge obtained in this study can provide guidance for tree growth modeling and forest management in SN forests.

3.2 Materials
3.2.1 Study areas
Our study areas, Last Chance (39° 07’ N, 120° 36’ W) and Sugar Pine (37° 25’ N, 119° 36’ W), are in the northern and southern SN (Figure 31). The elevation ranges from 730 m to 2190 m in Last Chance and from 730 m to 2650 m in Sugar Pine. Both areas have a Mediterranean climate. The annual total precipitation during the study period in Last Chance (2008–2013) was 1661 mm on average with a range from 255 mm to 2500 mm, and in Sugar Pine (2007–2012) was 1106 mm on average with a range from 589 mm to 1839 mm. Coniferous trees are the dominant species in both areas. In Last Chance, white fir (Abies concolor) and red fir (Pseudotsuga menziesii) are two most abundant species, followed by incense cedar (Calocedrus decurrens), sugar pine (Pinus lambertiana), ponderosa pine (Pinus ponderosa), and California black oak (Quercus kelloggii). Trees in Sugar Pine had similar species composition but slightly different species abundance.

Initially, we selected 25 study sites, which covered a range of forests with different dominant tree species, canopy densities, and topographic conditions. The selection of different forest types was guided by the vegetation map from the Classification and Assessment with Landsat of Visible Ecological Groupings system (CALVEG) (Franklin, Woodcock, and Warbington 2000). Originally, there were two Montane Hardwood (MHW), eight Ponderosa Pine (PPN), nine Sierran Mixed Conifer (SMC), four Red Fir (RFR), and two White Fir (WFR) forest sites selected from the CALVEG data. The 25 sites were evenly distributed over the elevation zones from 900 m to 2500 m. Since we mainly focused on the tree growth under natural conditions, study sites with observable disturbances, such as forest fires and treatments, were excluded. The disturbed areas were detected by calculating the stand-level average canopy cover differences between two sets of ALS data (Su et al, 2016). Finally, 17 sites were chosen for this study, which included one MHW, six PPN, seven SMC, two RFR, and one WFR forest stands (Figure 3-1). We manually delineated boundaries for each study site following two criteria: 1) each site should belong to the same forest type defined by CALVEG; and 2) each site should contain more than 4000 trees to guarantee enough samples for correlation analysis. Thus, the final study sites had different sizes, varied from 0.22 km² to 0.55 km². The
site-mean tree height ranged from 9.4 m to 31.2 m and the canopy cover varied from 38% to 97% (Table A1).

Figure 3-1 The geolocation of the Last Chance and Sugar Pine study areas and the distribution of 17 selected study sites and 61 field measured plots.

3.2.2 Field measurements
We obtained 61 in-situ plot measurements (~500 m² in a circle for each plot) in the study sites to validate ALS-based tree height and growth results (Figure 3-1). These measurements were taken in the summers of 2007 and 2008 and re-measured in 2012 and 2013. Plot center locations were measured using a Trimble™ GeoXH GPS. Within each plot, all live trees with a DBH larger than 5 cm were tagged for the repeated surveys. The tree vigor conditions for both surveys were recorded following the forest inventory and analysis standard (Schomaker et al. 2007). In total, 560 trees from six different species were measured, including 327 PPN, 76 WFR, 103 RFR, 15 ICD, 23 SPN, and 16 CBO (Table A2). The species and tree height information were used in the tree height growth analysis.

3.2.3 ALS data and pre-processing
Bi-temporal small footprint ALS data were acquired using the same scanner unit, the Optech GEMINI airborne laser terrain mapper (ALTM) system, in September 2008 and August 2013 for Last Chance, and in September 2007 and November 2012 for Sugar Pine. The ALS data were collected at 600–800 m above the ground, with a 67% swath overlap.
on average. The ALTM sensor was operated at 100 kHz with a scanning frequency of 40–60 Hz and a scan angle of 12–14° on either side of nadir. Up to four discrete returns were collected per shot. The delivered data had an averaged density of 10 points/m². To guarantee that the bi-temporal ALS flights could be aligned, we selected over 800 ground checkpoints using ground GPS to calibrate the ALS data both vertically and horizontally. The obtained spatial accuracy was around 10 cm horizontally and 5–35 cm vertically. Note that the 2007/2008 ALS data and 2012/2013 ALS data are referred as ALS1 and ALS2 hereafter.

The digital terrain model (DTM), digital surface model (Kros et al.) and canopy height model (CHM) were the three basic ALS derived metrics used to generate three tree growth metrics (i.e., tree height, crown area, and crown volume) and four sets of factors (i.e., original tree size, competition indices, forest structures, and topographic conditions) for this study. The DTM and DSM for each study period were interpolated from ALS ground returns and first returns using the ordinary kriging algorithm, respectively (Guo et al. 2010). CHM was calculated as the difference between the DSM and DTM. We chose 0.5 m as the resolution for DTM, DSM and CHM because it was a balance between accuracy and computational efficiency, and it was used in a similar study (Tao et al. 2014).

3.3 Methodology
The methodology for tree growth detection and analysis in tree height (ΔH), crown area (ΔA), and crown volume (ΔV) is shown in Figure 3-2 and introduced in the following sections.

![Flowchart of the methodology](image)

Figure 3-2 Flowchart of the methodology. ΔH, ΔA, and ΔV mean tree height, crown area, and crown volume.
3.3.1 Tree growth detection
3.3.1.1 Individual tree segmentation
We used the Marker-controlled Watershed Segmentation (MWS) algorithm to delineate individual tree crowns from all ALS-derived CHMs. MWS is a well-known image segmentation algorithm, which combined advantages in region-growing and edge-detection algorithms (Meyer and Beucher 1990). MWS has been successfully applied to segment individual tree crowns from ALS data in many studies (Chen et al. 2006; Tao et al. 2014). Before the segmentation, we applied the Gaussian filter with two times the standard deviation to suppress irrelevant local maxima and fill pits in CHM (Chen et al. 2006). Based on field surveys, a 2-m threshold was selected to separate shrubs from trees. The MWS segmentation was conducted with a 3 × 3 moving window in the System for Automated Geoscientific Analyses (SAGA) software (Tao et al. 2014). To refine results from auto-segmentation, we deleted small segments (area < 1 m²), and manually redrew extremely large-area (area > 150 m²) or elongate-shape (shape index > 4) (Li et al. 2012) segments through visual interpretation of CHM (Figure 3-3).

Figure 3-3 An example of tree crown segmentation results and the corresponding tree top locations. TPtl/2 are tree tops and TCtl/2 are tree crowns detected from ALS1/2, respectively.
3.3.1.2 Tree size metrics estimation

Three tree size metrics (i.e., tree height, crown area and crown volume) were estimated from the ALS data, because they are important indicators of tree vigor and competitiveness for natural resources (Burkhart and Tomé 2012). Each individual tree height was calculated as the maximum CHM value within its segmented tree crown, and tree crown area was represented by the area of each segment. The tree crown volume is usually defined as the volume between the CHM and crown base height (CBH), and many methods have been developed to quantify them from ALS data (Kato et al. 2009; Popescu and Zhao 2008; Vauhkonen et al. 2008; Vauhkonen et al. 2009). In this study, we approximated the crown volume by calculating the volume above the minimum CHM value within each segment (Tao et al. 2014). The minimum CHM value was used as a proxy of CBH, and the sum of CHM values above the CBH in each segment was multiplied by the pixel unit area (0.25 m$^2$) to estimate the crown volume.

3.3.1.3 Estimation of individual tree growth

Individual tree growth was estimated as the changes in tree size metrics estimated from ALS1 to ALS2. Precisely pairing up individual trees from ALS1 and ALS2 was a crucial step for accurate tree growth detection. In this study, each tree pair from ALS1 and ALS2 was recognized as the same tree only if the following two criteria were met simultaneously: 1) tree top from ALS1/ALS2 was the only tree top located in the tree crown from ALS2/ALS1; 2) the distance between the tree tops from ALS1 and ALS2 was less than 2 m. The second criterion was set to compensate for the mismatch of tree tops caused by ALS mis-registration. As shown in Figure 3-4, there were three scenarios that might fail to meet the above-mentioned criteria and needed manual pairing. Scenarios 1 and 2 represented conditions where small trees disappeared/appeared in ALS2 (Figure 3-4a and b). For these two scenarios, we manually removed small trees that disappeared/appeared and paired the two trees sharing the largest tree crown. Scenario 3 represented the condition that one tree top in ALS1 was mis-detected in ALS2 (Figure 3-4c). To pair these tree tops, we manually split the detected tree top in ALS2 into two tree tops by visual examination, and re-performed the tree segmentation to derive new ALS2 tree crowns. Besides, there were rare cases where the ASL1 and ALS2 tree tops satisfied the first rule, but were more than 2 m away from each other. We treated this situation as segmentation errors, and deleted them from tree segmentation results.
3.3.2 Calculation of tree growth factors
In this study, four sets of widely used tree growth modeling factors were calculated from ALS1, namely the original tree sizes, topographic parameters, competition indices, and forest structure indices (Adams, Barnard, and Loomis 2014; Biging and Dobbertin 1995; Das 2012; Goulden et al. 2016; Twery and Weiskittel 2013). The original tree sizes were derived using the above-mentioned tree growth detection procedure. The methods for calculating the other three sets of factors are described below.

3.3.2.1 Topographic parameters
Variations in topographic conditions can result in different solar and water resource distributions, and consequently influence tree growth (Adams, Barnard, and Loomis 2014). In this study, we calculated four topographic parameters including elevation, slope, global insolation (GI), and topographic wetness index (TWI) from ALS1-derived DTM. GI indicates topographically-determined potential solar resources, and is defined as the sum of direct and diffused solar radiance per unit area in a year (Rich et al. 1994). In this study, slope and GI were calculated using the ESRI™ ArcMap software. TWI describes the probability of an area being saturated based on its catchment area and slope (Moore,
Grayson, and Ladson 1991), and it quantifies topographic determined soil moisture and water availability, which has been a major restriction of tree growth in the Sierra Nevada forests (Trujillo et al. 2012). In this study, TWI was calculated using SAGA software. Since the variations of these parameters within each site were small, we used the site-mean values to analyze their impacts on site-level tree growth (Figure 3-2).

3.3.2.2 Competition indices

Competition indices are designed to quantify competition among trees for resources in tree growth modeling (Wensel, Meerschaert, and Biging 1987; Twery and Weiskittel 2013; Biging and Dobbertin 1995). Generally, competition indices can be divided into three categories: distance-dependent indices, distance-independent indices, and semi-distance independent indices. Distance-dependent indices quantify fine-scale variation in competition by considering the distance from a tree to its neighbors, whereas distance-independent indices neglect the distance and treat every tree equally. Semi-distance-independent indices compromise the precision in distance-dependent indices and the efficiency in distance-independent indices (Contreras, Affleck, and Chung 2011), and thus have advantages in large-area applications. In this study, we calculated four semi-distance-independent indices from ALS1 data, including tree number (TN), crown competition of all tree crowns (CCT), crown competition of 66% tree height (CC66) and crown competition of higher trees (CCHT).

TN is the number of trees in a subject tree’s neighborhood (Reineke 1933). CCT, CC66 and CCHT are three crown-based indices, which quantify the percentages of competitive crown areas in a subject tree’s neighborhood under different definitions of competitive crown areas (Biging and Dobbertin 1995). As shown in equations 3-1 – 3-3, CCT counts the percentage of all tree crowns (CHM > 2 m) (Biging and Wensel 1990), CC66 counts the percentage of tree crowns taller than 66% of the subject tree (Krumland 1982), and CCHT counts the percentage of tree crowns taller the subject tree (Biging and Dobbertin 1995). The competition indices were calculated using R language (RCore 2013) programming based on equations 1-3, from individual tree crown and tree top segmentation results and CHM data.

\[
CCT = \frac{A_N(CHM>2) - A_S(CHM>2)}{A_N}, \quad (3-1)
\]

\[
CC66 = \frac{A_N(CHM>0.66H_s) - A_S(CHM>0.66H_s)}{A_N}, \quad (3-2)
\]

\[
CCHT = \frac{A_N(CHM>H_s)}{A_N}, \quad (3-3)
\]

where \( A_N \) is the area of the defined neighborhood, which is a circle with 15 m radius centered by the subject tree top in this study, \( A_S \) is the crown area of a subject tree, and
$H_s$ is the height of a subject tree. To avoid the edge effect, trees crowns within 15 m of site boundaries were excluded from the competition indices calculation.

### 3.3.2.3 Forest structure indices
We selected three forest structure indices including canopy cover (CC), density of tree (DT), and average nearest neighbor index (NNI) to quantify site-level tree competition. We calculated CC as the percentage of pixels with CHM higher than 2 m in each site. DT was defined as the total number of trees segmented from ALS data divided by the area of each site. NNI was the average distance of each tree to the nearest tree in a site divided by the average distance from a hypothetical random distribution. A site with a NNI smaller than one has a clustering tree distribution pattern, whereas the site with a NNI greater than one has a dispersed pattern (David 1985).

### 3.3.3 Correlation analysis and multivariate regression model
We assessed the correlations between tree growth and its controlling factors using the Pearson’s correlation coefficient ($R$). A natural-logarithm was applied on tree size and tree growth parameters to transform their distributions into normal ones. We also estimated the correlations among all impact factors to show the multicollinearity. Finally, we built multivariate linear regression models for tree growth in $\Delta H$, $\Delta A$, and $\Delta V$ from variables with substantial correlations to them. The stepwise variable selection based on the Akaike’s information criterion (Akaike 1974) method was applied to refine the model generation using the stepAIC function in R MASS package (Ripley 2002).

### 3.4 Accuracy assessment
Field-measured tree height was used to validate the ALS-based tree height estimation and growth analysis results. The tree height validation was conducted at the plot level, since the individual tree location was not available from the field in this study. We calculated the mean value of ALS-based tree height estimates in each plot, and compared them with field-measured plot mean tree height. The root-mean-square-error (RMSE) and bias were used to assess the accuracy of ALS-based estimations. Field-measured plot mean tree height growth ($\Delta fH$) and its correlations to original plot mean tree height ($fH_1$) and topographic parameters were also calculated to verify the correlations from ALS estimation. At the individual-tree level, the correlation between $\Delta fH$ and $fH_1$ was analyzed by species, instead of by site because there were only 33 trees measured in each site on average. As individual tree locations and crown sizes were not measured from the field, this study only provided a partial assessment of ALS-derived results.

### 3.4 Results
#### 3.4.1 Tree growth detection
There were 53,338 and 61,293 trees segmented and matched from bi-temporal ALS data in Last Chance and Sugar Pine, respectively. The mean value of tree height, crown area,
and crown volume from ALS1 was 15.6 m, 18.5 m², and 189.3 m³ in Last Chance, and 15.9 m, 26.5 m², and 198.5 m³ in Sugar Pine (Figure 3-5).

Figure 3-5 Distributions of tree height, crown area and crown volume at (a) Last Chance and (b) Sugar Pine from ALS1 and ALS2. The mean values of the changes from ALS1 to ALS2 are also labelled for each site.

On average, tree size increased on both areas, larger increase in tree crown area and volume was observed in Last Chance, and more tree height growth in Sugar Pine (Figure 3-5). More specifically, we categorized these changes into five classes (Figure 3-6). Most trees (83–97%) experienced increases in their sizes, and 1–6% experienced a sharp increase. Trees in Sugar Pine showed 7% more growth in tree height than in Last Chance, whereas trees in Last Chance showed 3–5% more crown expansions.
Figure 3-6 Comparison of the cumulative proportions of tree size changes from ALS1 to ALS2 in Last Chance and Sugar Pine in five classes: sharp increase (ΔH ≥ 10 m, ΔA ≥ 20 m$^2$, and ΔV ≥ 200 m$^3$), median increase (1 m ≤ ΔH < 10 m, 10 m$^2$ ≤ ΔA < 20 m$^2$, and 50 m$^3$ ≤ ΔV < 200 m$^3$), minor/no increase (0 m ≤ ΔH < 1 m, 0 m$^2$ ≤ ΔA < 10 m$^2$, and 0 m$^3$ ≤ ΔV < 50 m$^3$), minor/median decrease (−10 m ≤ ΔH < 0 m, −20 m$^2$ ≤ ΔA < 0 m$^2$, and −200 m$^3$ ≤ ΔV < 0 m$^3$), and sharp decrease (ΔH < −10 m, ΔA < −20 m$^2$, and ΔV < −200 m$^3$).

The mean and standard deviation of tree sizes for each study site differed substantially (Figure 3-7). Among the 17 sites, L3 and S2 sites were young PPN forest stands with small variations in size. The SMC sites in L1, S5, and S6 had relatively large mean values and standard deviations.
3.4.2 Individual-tree level tree growth responses to controlling factors
Correlations between tree growth in height and controlling factors were relatively weak (Figure 3-8a). The maximum absolute $R (|R|)$ was lower than 0.4 among all sites, albeit most of them were significant. Factors with the strongest correlation changed from site to site. In general, $\Delta H$ was the most influential factor to $\Delta H$ in 8 out of 17 sites. Competition indices could be either negatively or positively correlated with $\Delta H$ among different study sites and indices.

The correlations between tree crown area growth and controlling factors were stronger and more consistent than those with tree height growth (Figure 3-8b). $A_1$ had the strongest positive correlations with $\Delta A$ in most sites (averaged $R$: 0.41), followed by $V_1$ (averaged $R$: 0.39) and $H_1$ (averaged $R$: 0.32). $CC66$ and $CCHT$ were the most influential competition indices, which were negatively correlated with $\Delta A$. On average, the $|R|$ with $\Delta A$ for $CC66$ (0.31) and $CCHT$ (0.31) were 505% and 93% higher than that for the CCT and TN, respectively.
As expected, tree growth in crown volume was positively related with original tree sizes, and negatively impacted by competition indices, but the correlations were stronger than those in crown area (Figure 3-8c). The average $|R|$ in $\Delta V$ was approximately 53% higher than $\Delta A$, and 308% higher than $\Delta H$. $\Delta V$ had the strongest correlation with $V_1$ ($R$: 0.48 to 0.76), and CCHT is the most influential competition indices on $\Delta V$ among most sites ($R$: -0.39 to -0.59).
3.4.3 Site level tree growth responses to controlling factors
Site level tree height growth had the strongest correlation with TWI ($R = 0.82$), followed by Slope ($R = -0.53$), but no significant correlation with other factors. Site mean crown area growth had the strongest correlation with TWI ($R = -0.78$), followed by slope ($R = 0.65$) and NNI ($R = -0.6$), but no significant correlation with original tree sizes. Site mean crown volume growth, on the contrary, was strongly controlled by the original tree sizes ($0.85 \leq R \leq 0.9$), but had no correlation with topographic parameters (Figure 3-9).

3.4.4 Multivariate regression modeling of tree growth
Multivariate linear regressions for individual tree growth in height, crown area, and crown volume from original tree sizes, competitions, and site level impact factors are shown in equations 3-4 – 3-6. Variables in the models were selected from those with significant correlations with tree growth (Figure 3-8 and Figure 3-9) and determined by the adjusted $R^2$ (Appendix B) and Akaike's An Information Criterion (AIC) of the final models (Appendix C). We also filtered out the variables with strong multicollinearity based on the correlation matrix among all factors. All variables were normalized using their mean and standardize deviation to reduce the scale effects before regression. The coefficients of determination ($R^2$) for these models were 0.24 for $\Delta H$, 0.10 for $\Delta A$, and 0.43 for $\Delta V$, and they were significant at the confidence level of 99.9%. The RMSE and relative RMSE of predicted $\Delta H$, $\Delta A$, and $\Delta V$ were 0.94 m (53.9%), 4.87 m$^2$ (77.9%), and 51.99 m$^3$ (63.2%), respectively.

\[
\Delta H = 0.109 H1 - 0.102 A1 - 0.077 CCHT - 0.205 TN + 0.430 TWI \quad (3-4)
\]

\[
\Delta A = 0.183 H1 - 0.115 C66 - 0.128 TN - 0.133 NNI - 0.175 DEM - 0.146 TWI \quad (3-5)
\]

\[
\Delta V = 0.421 H1 + 0.245 A1 - 0.051 CCHT + 0.085 Slope \quad (3-6)
\]

3.4.5 Validation using tree height field measurements
Mean tree height in all the 61 plots from two ALS estimates was validated using field measurements (Figure 3-10). The $R^2$ between ALS estimation and field measurements were both 0.96, the RMSE were 0.82 m and 0.85 m from the data collected in the first and second time periods, respectively. The field measured tree heights were slightly higher (0.63 m and 0.11 m on average) than values from ALS estimation. Overall, the ALS-based tree height was consistent to tree height measured in the field.
Figure 3-9 Scatter plots between site-level tree growth in ΔH, ΔA, ΔV and 10 factors from original tree sizes (H1, A1, and V1); forest structure indices (CC, DT, and NNI); and topographic parameters (slope, elevation, GI, and TWI). Each dot presents a site mean value and its color indicates the number of trees in each site. The regression line is presented in the black line. $R$ is labeled as significant at the confidence level of 99.9 %(***), 99% (**), and 95%(*).
Figure 3-10 Comparison between ALS estimated tree height and field measured tree height at plot level. Subfigure (a) and (b) show data collected in the first and second time periods over 61 plots.

At the individual-tree level, correlations between field measured tree height growth (ΔfH) and original tree height (fH1) were positive for PPN (R = 0.27); but negative for RFR (R = −0.32) and WFR (R = −0.21) species. No significant correlation was found when combining all species. At the plot level, the ΔfH had the strongest correlation with TWI (R = 0.51), and was also responsive to fH1 with a lower correlation (R = 0.27). No significant relationship was found between ΔfH and any other environmental parameters. These results were consistent with the correlations observed from ALS-based estimates.

3.5 Discussion
Previous studies have found that individual tree growth was positively determined by internal tree competitiveness, such as original tree sizes, and negatively influenced by external tree competition, owing to limited solar and water resources (Wensel, Meerschaert, and Biging 1987; Weiskittel et al. 2011; Biging and Dobbertin 1995; Aakala et al. 2013). Our results generally agreed with these arguments, but the correlations between impact factors and tree growth in ΔH, ΔA, and ΔV varied by factors and sites.

ΔV had a stronger correlation with the original tree sizes than ΔA and ΔH (Figure 3-8). Ideally, absolute crown growth of a vigorous tree should be proportional to its original crown size if the same amount of elongation occurs in the main stem and branches (Pretzsch 2014, Weiskittel et al. 2011). However, the horizontal elongation of a tree crown, quantified by ΔA in this study, was also constrained by the space availability between trees, and thus was less linearly related to the original size than ΔV. Studies have shown that ΔH was determined more by genetics and environmental conditions rather
than original tree sizes and competition conditions (Wensel, Meerschaert, and Biging 1987; Weiskittel et al. 2011). Our results also indicated that $\Delta H$ had the lowest correlations with the original sizes. Among the four competition indices, CCHT and CC66 had stronger correlations with tree size growth (Figure 3-7). This might be because tree height information was included in CCHT and CC66 calculation, but not in the CC and TN (Biging and Dobbertin 1995; Wensel, Meerschaert, and Biging 1987). For example, CC66 used the 66% tree height to calculate the competition in “light crown”, which was critical to tree growth for most tree species in the SN forests. (Wensel, Meerschaert, and Biging 1987).

The correlations between tree size growth and impact factors varied among sites (Figure 3-8). For example, $\Delta H$ in L3 site had the strongest correlation with original tree sizes, which might be because L3 was dominated by juvenile trees (interpreted from the relatively small tree height) of a single species (PPN) (Figure 3-7). $\Delta H$ in sites with mixed tree species (SMC) generally had lower $|R|$ than single species forests. This was also consistent with field measurements, as no significant correlation was observed when combining all trees species. Moreover, the relative tree growth decreased as tree sizes increased (Table A3). Tree sizes can be a good indicator of tree ages in a single-species forest (Weiskittel et al. 2011). Zeide et al. (1993) has suggested that there was a sigmoidal curve relationship between tree age and tree height growth rate, which changed from positive in juvenile trees to negative in mature ones. This partly explained why the correlation was positive in L3 (small tree dominated site), and negative in S8, S9, and L8 (large tree dominated sites). $\Delta A$ in L8 had the strongest correlation to original tree sizes among all sites (Figure 3-8), which was probably because it was dominated by WFR (Figure 3-7). WFR has the strongest tolerance to shadow and root competition among SN conifer species (Gersonde and O’Hara 2005). Their expansion may be less sensitive to external factors, such as solar radiation and water availability, and thus more related to the original sizes. $\Delta V$ in L4 showed the weakest correlations among all sites (Figure 3-8). The relatively small variation of tree sizes in L4 (Figure 3-7) may lead to similar $\Delta V$ among trees, which ultimately resulted in its poor prediction using original tree sizes.

At the site level, both $\Delta H$ and $\Delta A$ were strongly correlated with TWI, but the correlations were positive in $\Delta H$ and negative in $\Delta A$. TWI describes the topography-related indicator of soil moisture condition (Beven and Kirkby 1979). The positive correlation between $\Delta H$ and TWI was consistent with plot level field measurements ($R = 0.51$) and previous studies (Adams, Barnard, and Loomis 2014). High soil moisture is beneficial for tree height growth, particularly in the water-limited low-elevation forests of the SN (Trujillo et al. 2012). The negative correlation between $\Delta A$ and TWI might be because sites with higher TWI were often occupied by well-grown dense forests, and the lack of space for tree crown expansion in dense forests could constrain, instead of promoting, tree crown growth.

By integrating all the controlling variables, multivariate regression models (Equation 3-5 - 3-7) also suggested that TWI was the most important variable to $\Delta H$, and original tree sizes contributed most to $\Delta V$. The $\Delta A$ model had relatively lower accuracy, probably because $\Delta A$ were influenced by several factors simultaneously, including tree sizes, competition indices, and solar water conditions. The modelling results were consistent with correlation analysis at both individual-tree and site levels, although the model
accuracy was relatively low. Limited by the scope of this study, the random-effect in the sampled sites were not addressed in these simple multivariate regression models (Hao et al. 2015). Multi-level mixed-effects regression is expected to be used in the future study to generate more robust tree growth models.

At the study-area level, ∆H in Sugar Pine was about 64% larger than that in Last Chance, whereas ∆A was about 25% lower (Figure 3-5). This may be because the TWI and GI in Sugar Pine were 157% and 8.7% higher than those in Last Chance (Table A1). The abundance in topographic wetness and solar radiance were more likely to promote height growth but constrain crown area expansion, as suggested by site level correlation results (Figure 3-9). The volume growth was a combined effect of tree height growth and crown area expansion, which may lead ∆V to be similar in both sites.

We view this study as the first step of quantifying forest tree growth from multi-temporal ALS data. The correlation analysis and regression model given in this study can help researchers to build more robust and accurate models for forest growth at multiple scales and guide forest managers to distribute the limited resources for conducting forest management activities. This study also demonstrates the possibility of using ALS data to estimate tree competition indices. However, there are still limitations in the current study. First, the validation from field measurements mainly focused on plot-level tree height, but the validations for crown area and crown volume were not available. Slight underestimation (11 cm and 43 cm in ALS1 and ALS2) was observed in ALS-based tree height estimation. This may be caused by two reasons: 1) ALS sensor may fail to detect some tree tops and thus underestimated the true height (Yu et al., 2006); and 2) small trees (DBH < 5 cm) were not measured in the field but some of them were detected from the ALS data in the sparse plots. Second, certain uncertainties still existed in tree crown and height estimation and matching between two flights. The relatively large tree height decrease (17%) in Last Chance may be partly explained by the field survey results, in which 18.4% and 10.0% of surveyed trees in Last Chance and Sugar Pine were tagged as senescence, dead, or removed during the second survey. Although we manually edited the tree segmentation and pairing results, biases in ALS-based estimation were still unavoidable due to the segmentation accuracy, and the different weather conditions between two ALS scans (Sumnall et al. 2016; Londo 2010; Lo and Lin 2013). Third, this study only evaluated four semi-distance-independent competition indices. Newly developed competition indices from ALS data (Lo and Lin 2013; Pedersen et al. 2012) should be considered in the future study. Fourth, many other tree growth-related environmental factors, such as soil type and nutrition, were not included because they were less important in this study area, but might be necessary in other areas.

3.6 Conclusions
Efficient and accurate tree growth monitoring and modeling are critical for SN forest resource evaluation and management. This study proposed a strategy to quantify tree growth in height, crown area, and crown volume at both individual-tree and forest-stand levels using bi-temporal airborne LiDAR data. The high accuracy of LiDAR-based tree height estimation was validated by field measurements. Four sets of tree growth impact factors were estimated using the LiDAR data including original tree size, forest density,
four competition indices, and topography. Analysis of their correlations to tree growth indicated that individual tree growth was positively related to original tree sizes and negatively influenced by competition indices. These correlations were strongest in crown volume growth and lowest in tree height growth. At the forest-stand level, the crown volume growth was highly related to original sizes, whereas the growth in crown area and tree height were more controlled by water accessibility quantified by TWI and the spaces availability for crown expansion. These findings were consistent with multivariate regression results and field measurements, which demonstrated the accuracy and robustness of using multi-temporal LiDAR data for large-area tree growth quantification in the Sierra Nevada forest. The strategy proposed in this study could potentially be a useful tool for forest monitoring, modeling, and management in other areas.

References


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Chapter 4  Evaluating the uncertainty of Landsat-derived vegetation indices in quantifying forest fuel treatments using bi-temporal LiDAR data

Abstract
Forest ecosystems in the American west have long been influenced by timber harvests and fire suppression, and recently through treatments that reduce fuel for fire management. Precisely quantifying the structural changes to forests caused by fuel treatments is an essential step to evaluate their impacts. Satellite imagery-derived vegetation indices, such as the normalized difference vegetation index (NDVI), have been widely used to map forest changes of attributes. However, uncertainties in using these vegetation indices to quantify forest structural changes have not been thoroughly studied, mainly due to the lack of wall-to-wall validation data. In this study we generated forest structural changes in aboveground biomass (AGB) and canopy cover as a result of fuel treatments using bi-temporal airborne light detection and ranging (LiDAR) data and field measurements in a mixed coniferous forest of northern Sierra Nevada, California, USA. These LiDAR-derived forest structural measures were used to evaluate the uncertainties of using Landsat-derived vegetation indices to quantify treatments. Our results confirmed that vegetation indices can accurately map the extent of forest disturbance and canopy cover changes caused by fuel treatments, but the accuracy in quantifying AGB changes varied by the pre-treatment forest densities and treatment intensity. Changes in vegetation indices had relatively weaker correlations (coefficient of determination < 0.45) to biomass changes in forests with sparse (AGB<100 Mg/ha) or dense pre-treatment biomass (AGB >700 Mg/ha), than in forests with moderate-density (AGB between 100 Mg/ha and 700 Mg/ha). Moreover, understory treatments (height<10m) were poorly indicated by changes in Landsat-derived vegetation indices. Our results suggest that when relating vegetation indices to AGB changes, researchers and managers should be cautious about their uncertainties in extremely dense or sparse forests, particularly when treatments mainly removed small trees or understory fuels. 

Keywords: forest fuel treatment, vegetation index, aboveground biomass, LiDAR.

4.1 Introduction
Selective removal of forest fuels (i.e. fuel treatment) is a widely used forest management and restoration practice with both economic and ecological goals (Agee and Skinner 2005; Kerr and Haufe 2011; Mitchell et al. 2009; Park et al. 2018). In the Sierra Nevada, California, forest fuel treatments including logging, thinning, and mastication have been conducted for many years (Knapp et al. 2013). The United States Department of Agriculture Forest Service (referred to as USFS hereafter) spent 52% of its annual budget on wildfire suppression and management in fiscal year 2015, and this percentage is expected to increase in the coming decades (Stephens et al. 2016a; Stephens et al. 2018). These long-term and broad-area treatments have significantly altered tree species and age composition, as well as forest landscape structures (Agee and Skinner 2005; Collins et al. 2011a; Mitchell et al. 2009; Parsons and DeBenedetti 1979). Consequently, forest ecosystem services and ecological functions have also changed, including forest...
carbon stocks, vegetation water use, wildlife habitat, and forest fire frequency and severity (Bales et al. 2011; Battles et al. 2001; Stephens et al. 2009; Tempel et al. 2014). Because these management practices are so impactful on forest structure, accurate measurement of the changes to forest structure as a result of fuel treatments is necessary, but doing so remains challenging.

Accurate and timely quantification of forest changes in abundance, production, and spatial pattern is a necessary step for forest fuel treatment evaluation (Huang et al. 2009; Su et al. 2016a). Traditional forest fuel treatment evaluation has relied heavily on in-situ measurements of tree height, diameter at breast height (DBH), tree density, and distribution (Collins et al. 2015; Knapp et al. 2013). Due to the high cost of field measurements in both time and labor, forest inventory data were often limited to selected plots or transects. When these local measures are scaled to landscapes or regions with auxiliary data, large uncertainties can be introduced (Schroeder et al. 2014).

Remote sensing techniques have been widely used in forestry to map and monitor forest dynamics (Cohen et al. 2016; Hansen et al. 2013; Schroeder et al. 2011; White et al. 2016; White et al. 2017). The applications of optical satellite imagery in forestry have increased dramatically at both temporal and spatial scales, particularly in the recent decade, with open access to Landsat satellite imagery (Schroeder et al. 2017; Vogelmann et al. 2017; Wang et al. 2016; White et al. 2017; Wulder et al. 2012a). A number of satellite imagery-derived vegetation indices, such as normalized difference vegetation index (NDVI), normalized difference water index (NDWI), and normalized burn ratio (NBR) have been developed to monitor forest dynamics. Among them, NDVI has demonstrated to be a strong indicator of vegetation greenness, biomass and water use, and has been widely used to quantify forest disturbances and their recoveries (Gamon et al. 1995; Tucker 1979; Viedma et al. 1997). NBR, a combination of the near infrared and short wave infrared bands, has many applications for forest disturbance detection, but is mainly emphasized for forest fire severity mapping (Key and Benson 2006; Miller and Thode 2007). The Tasseled Cap Transformation (TCT) is another widely applied method for quantifying the vegetation vigor, coverage, and density by extracting the greenness, brightness, and wetness of the land surface from multispectral satellite imagery (Crist 1985; Crist and Cicone 1984; Huang et al. 2002). The Tasseled Cap Angle (TCA), calculated from the ratio of greenness and brightness components in the TCT, has been successfully used to characterize the spatio-temporal forest dynamics in northwestern Alberta, Canada (Gómez et al. 2011). Although these vegetation indices were widely used to map forest dynamics, their accuracies in quantifying change in forest structures, such as canopy cover and biomass, have not been fully studied. Some issues with these applications have been reported in previous studies. For example, the saturation effect of vegetation indices, like NDVI, may cause its failure to indicate the increase or decrease of structure parameters, such as aboveground biomass (AGB) in forests with extremely high density and large biomass, and thus may lead to the underestimation of forest treatment (Gamon et al. 1995; Gao et al. 2000; Mutanga and Skidmore 2004). Moreover, shadows in mountainous areas and cloud cover in satellite imagery may result in the spatio-temporal variations in vegetation indices, which are unnecessarily related to forest disturbances (Kennedy et al. 2010; Verbyla et al. 2008; Zhu and Woodcock 2012). A systematic evaluation of these uncertainties is necessary to
precisely assess the impacts of forest fuel treatments. However, these evaluations are challenging, mainly due to the lack of accurate and timely ground reference data for validation.

Light detection and range (LiDAR) is an active remote sensing technique which can characterize three-dimensional forest structure parameters with high accuracy (Coops et al. 2007; Kelly and Di Tommaso 2015; Næsset and Økland 2002). Laser pulses emitted by LiDAR sensor can penetrate through the forest canopy, and therefore, are less impacted by the shadowing or saturation effects (Ma et al. 2017a; Su et al. 2016a). Airborne LiDAR data combined with field measurements have been successfully applied to map tree height (Næsset 1997; Næsset and Bjerknes 2001), large tree density(Kramer et al. 2016), crown base height (Popescu and Zhao 2008), canopy cover (Korhonen et al. 2011; Ma et al. 2017a), leaf area index (Korhonen and Morsdorf 2014; Zheng and Moskal 2009), fire-related forest stand structure metrics (Blanchard et al. 2011; Jakubowksy et al. 2013; Kelly et al. 2017; Kramer et al. 2014), and aboveground biomass (AGB) (Dalponte et al. 2018; Li et al. 2015; Luo et al. 2017; Su et al. 2016b; Tao et al. 2014; Zhao et al. 2012) from the individual tree to forest stand scale. LiDAR data have been increasingly used as an alternative or auxiliary data source in forest inventory (Korhonen et al. 2011; Wulder et al. 2012b). With continued accumulation of LiDAR data over time and space, studies focusing on detecting and monitoring forest structure changes from multi-temporal LiDAR data have increased in the recent years (Ma et al. 2017b; McCarley et al. 2017; Su et al. 2016a; Zhao et al. 2017). These successful applications demonstrated the strong potential of using airborne LiDAR, combined with field measurements, to provide a wall-to-wall validation data for evaluating the accuracies of satellite imagery-based quantification of forest structure dynamics.

The objective of this study is to systematically assess the uncertainties of satellite imagery-based vegetation indices in characterizing fuel treatment-induced forest structural changes. The uncertainty analysis focused on the capabilities of Landsat-derived vegetation indices in quantifying the forest structural changes, resulted from fuel treatments conducted at various intensities over different forest densities. LiDAR data and field measurements derived forest structural changes, primarily in AGB and canopy cover, were used as ground references to evaluate the performances of four widely used Landsat-derived vegetation indices in detecting and quantifying forest fuel treatment in a conifer-dominated forest in the Sierra Nevada, California. Results from this study can help to understand the effectiveness of and uncertainties related to Landsat-derived vegetation indices in forest treatment quantification and to provide guidance for forest management and monitoring.

4.2 Materials
4.2.1 Study area
The study site (39° 07’ N, 120° 36’ W) covers an area of 99.5 km² and locates within the Tahoe National forest of the Sierra Nevada, California. It is a mountainous area with the elevation ranging from 579 m to 2184 m above sea level (Figure 4-1). This forest is dominated by five major tree species: white fir (Abies concolor), red fir (Pseudotsuga menziesii), incense cedar (Calocedrus decurrens), sugar pine (Pinus lambertiana), and
ponderosa pine (*Pinus ponderosa*). Broadleaf trees and chaparral, primarily California black oak (*Quercus kelloggii*) and manzanita (*Arctostaphylos spp*), co-exist with the conifers, but in smaller numbers. The climate is Mediterranean with an annual total precipitation of 1,661 mm/yr (averaged from water years from 2008 to 2013).

Fuel treatments were implemented in the study area as part of the Sierra Nevada Adaptive Management Project, which was designed to study how fuel treatments can affect fire risk, wildlife habitat, and the water cycle (Hopkinson et al. 2017; Saksa et al. 2017). The majority of the treatments were conducted between 2008 and 2013 within a treatment boundary proposed by the USFS (the blue boundary in Figure 4-1). This area of forest was dominated by small to mid-sized conifers with relatively high density (approximately 67% of canopy cover before the treatment) as a result of long-term fire suppression before treatments (Tempel et al. 2015). The fuel treatments were designed to reduce ladder fuels, or the forest fuels that provide vertical fuel continuity and can preheat unignited canopy fuels in a fire (Kramer et al. 2016; Kramer et al. 2014; Menning and Stephens 2007). Thus, the treatments concentrated on mechanical thinning at selected locations (Collins et al. 2011b) and focused on low and mid-strata of canopy, with small to medium sized trees removed. The study area and fuel treatments provide a natural experiment to evaluate the effectiveness of Landsat-derived indices in quantifying forest structure in two ways. First, the complex terrain and fine-scale selective thinning likely provided a challenge for Landsat-derived vegetation indices to quantify structural changes, and second, the availability of detailed before and after treatment LiDAR data provided detailed reference data with which to evaluate the accuracies and uncertainties in measuring structure from Landsat.
4.2.2 Data and Methods

4.2.2.1 Field data

A total of 328 plots were surveyed in the field during the summer of 2008 and 2013 to characterize the forest structural changes from pre- to post-treatment. The plot distribution started from a random point and covered the entire study area in a 500m spaced grid. The plot density was intensified (250m or 125m spacing) in two small instrumented catchments for hydrological studies. Each plot was in circular shape with an area of 500 m². In the pre-treatment (2008) plot survey, tree height, diameter at breast height (DBH), species, and height to live crown base were measured for individual trees in the plot, and the measurements of trees with a DBH larger than 5 cm were recorded. In the post-treatment (2013) survey, the DBH and tree height were re-measured for individual trees in the sampled plots.

Table 4-1 A summary of field measurements by tree species. Parameters include the number of trees, DBH, tree height from both pre- and post-treatment. The values are presented as mean ± standard deviation.

<table>
<thead>
<tr>
<th>Tree Species</th>
<th>No. of trees</th>
<th>DBH, cm</th>
<th>Tree height, m</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pre</td>
<td>Post</td>
<td>Pre</td>
</tr>
<tr>
<td>White fir</td>
<td>3013</td>
<td>2250</td>
<td>25 ±18</td>
</tr>
<tr>
<td>Red fir</td>
<td>304</td>
<td>251</td>
<td>34 ±19</td>
</tr>
<tr>
<td>Incense cedar</td>
<td>568</td>
<td>452</td>
<td>26 ±20</td>
</tr>
<tr>
<td>Mountain dogwood</td>
<td>14</td>
<td>12</td>
<td>7 ±2</td>
</tr>
<tr>
<td>Live oak</td>
<td>53</td>
<td>40</td>
<td>12±6</td>
</tr>
<tr>
<td>Sugar Pine</td>
<td>691</td>
<td>558</td>
<td>38 ±32</td>
</tr>
<tr>
<td>Western white pine</td>
<td>16</td>
<td>11</td>
<td>25±19</td>
</tr>
<tr>
<td>Ponderosa pine</td>
<td>887</td>
<td>874</td>
<td>27 ±20</td>
</tr>
<tr>
<td>Douglas fir</td>
<td>1205</td>
<td>1061</td>
<td>28 ±22</td>
</tr>
<tr>
<td>Black oak</td>
<td>178</td>
<td>127</td>
<td>26 ±19</td>
</tr>
<tr>
<td>Sequoia</td>
<td>3</td>
<td>2</td>
<td>20±16</td>
</tr>
</tbody>
</table>

Plot-level aboveground biomass (AGB) was estimated using the Jenkins allometric equations (Jenkins et al. 2003) based on tree DBH. The total aboveground biomass for each individual tree was calculated following the general form in equation 4-1. Each species has specific equation coefficient (b0, b1).

\[
AGB = \exp(b0 + b1 \ln(DBH))
\]  \hspace{1cm} (4 - 1)

The AGB (Mg ha⁻¹) in the plot location was the sum of the total aboveground biomass over all field measured trees, and then divided by the area of the plot (500 m²).
Detailed coefficients for each species can be found in Jenkins et al. (2003). The same equations were applied to estimate the plot-level AGB for both pre- and post-treatments.

4.2.2.2 LiDAR data

An Optech GEMINI airborne laser terrain mapper system was used to acquire both pre- and post-treatment airborne LiDAR data within the study area. The pre- and post-treatment LiDAR data were collected in September 2008 and August 2013, respectively. The LiDAR data were collected with a 67% swath overlap. The flight heights were between 600m to 800m aboveground. The LiDAR sensor has a scanning frequency of 40-60 Hz and a scan angle of 12-14° on either side of nadir. It collected up to four discrete returns per shot. The final LiDAR point cloud had a total density of 10 points/m² and first return density of 8.2 points/m² on average. A total of 800 ground GPS points were collected to calibrate the two airborne LiDAR flights as well as to assess the spatial accuracy. The spatial accuracy was similar between the two LiDAR datasets, with around 10 cm in horizontal and 5-35 cm in vertical.

Forest structure parameters, including AGB and canopy cover, were generated from the LiDAR data and field plot measurements for both pre- and post-treatment forest. First, the ground returns were classified from all LiDAR returns using a filter algorithm (Zhao et al. 2016) in LiDAR360 software. Then a digital terrain model (DTM) was generated from LiDAR ground returns at 1m spatial resolution using the ordinary Kriging algorithm (Guo et al. 2010). The digital surface model was interpolated from the LiDAR first returns using a similar method as the DTM. The canopy height model (CHM) was then calculated as the difference between DSM and DTM for both pre- and post-treatment LiDAR data. The wall-to-wall AGB estimate was generated by applying the plot-level relationship between field measured AGB and LiDAR CHM metrics to the whole study area, as suggested in (Li et al. 2015; Ni-Meister et al. 2010). The details of AGB estimation are introduced in 2.2.3. The canopy cover was calculated directly from LiDAR data as the ratio of LiDAR first returns that were higher than the tree crown threshold (Ma et al. 2017a) within each statistic grid. We used the 2m as the height threshold of tree crowns as it is a commonly used threshold to separate trees from non-tree vegetation (Ma et al. 2017a; Ma et al. 2017b; Nilsson 1996), and also suitable for this study site according to field measurements. For comparison, both AGB and canopy cover were calculated at the same spatial resolution as Landsat imagery (30m by 30m).

4.2.2.3 AGB estimations

The wall-to-wall vegetation AGB maps were estimated using plot-level relationships between LiDAR derived tree height metrics and field measured AGB. Various methods have been developed for AGB estimation from LiDAR data and field measurements (Valbuena et al. 2017), including linear regression (Li et al. 2015; Magnussen et al. 2015), exponential regression (Lim and Treitz 2004), plot-aggregate allometry (Asner and Mascaro 2014), and machine learning (Gleason and Im 2012). Among them, the linear regression has advantages of simplicity and relatively low risk of overfitting, while being
able to predict the majority of the variations in field-measured AGB, according to a comparison study conducted using the same pre-fire LiDAR dataset (Li et al. 2015). Therefore, in this study we implemented linear regression following the equation:

\[ AGB = aH^2 + bH + c \]  \hspace{1cm} (4-2)

Where H is the LiDAR-derived the mean tree height (the averaged CHM value within each plot), as suggested by Li et al. (2015); Ni - Meister et al. (2010); a, b, and c are coefficients regressed from plot-measurements and LiDAR metrics using the least-squares method. The linear regression models were generated for pre- and post-treatment independently and applied to the study area. For comparison, we resampled the AGB maps estimated from LiDAR and field measurements into 30m resolution (referred as AGB maps, hereafter) and co-registered them to the satellite imagery. The AGB change was generated by subtracting post-treatment AGB map from pre-treatment AGB map for each pixel.

4.2.2.4 Satellite imagery

The pre- and post-treatment satellite images were obtained from Landsat-5 TM and Landsat-8 OLI sensors in 2008 and 2013, respectively. These surface reflectance images over the whole growing season (June 1st to October 1st) were collected from the high-level top-of-atmosphere product in Google Earth Engine (Gorelick et al. 2017). The pixels with cloud or snow cover were excluded from all images using the mask developed by (Zhu and Woodcock 2012). A maximum-value composite (MVC) was applied to the annual images from both pre- and post-treatments. The MVC method composited the annual images by mosaicking the land-surface reflectance with the highest NDVI values for each pixel (Holben 1986). Comparing to using single-date imagery, vegetation indices derived from MVC can better present variations in vegetation greenness and less likely to be influenced by the atmospheric effects or the difference in solar-sensor-geometry (Delbart et al. 2006). Moreover, we homogenized surface-reflectance from Landsat-5 TM to Landsat-8 OLI sensors using the regression-based method introduced in (Su et al. 2017; Sulla-Menashe et al. 2016). The MVC of Landsat-7 ETM+ surface reflectance images obtained in both pre- (2008) and post-treatment (2013) were calculated as a reference for sensor homogenization. We randomly selected 100 samples (1km by 1km) over the study area. Samples located in any black (no Landsat data) strip were moved 10 km in a random direction to avoid the impacts from the failed Landsat-7 ETM+ sensor on homogenization. The mean values of MVC of surface-reflectance images within each sample were used to build regression equations. These regression equations were then applied to calibrate the whole MVC images from Landsat-5 TM (2008) and Landsat-8 OLI (2013) into Landat-7 ETM+ in the corresponding years for better comparison in vegetation indices between pre- and post-treatment.
Vegetation indices calculation

Four vegetation indices were calculated to quantify structural changes resulting from fuel treatments. They were: normalized difference vegetation index (NDVI), normalized difference water index (NDWI), normalized burn ratio, and Tasseled Cap Angle (TCA). NDVI, NDWI, and NBR are based on normalized differences between two given surface-reflectance bands, which characterized the greenness (Tucker 1979), wetness (Su et al. 2017), and the ratio between the photosynthesis vegetation and the bare ground (Miller and Thode 2007), respectively (Equation 4-3, 4-4, 4-5). The TCA was calculated as the angle formed by the greenness and brightness components (Gómez et al. 2011) derived from the Tasseled Cap Transformation of six surface-reflectance bands (Equation 4-6). All the four vegetation indices were generated from the homogenized MVC Landsat surface-reflectance images for both pre- and post-treatment. The differences in Landsat-derived vegetation indices (referred as vegetation indices, hereafter) between the post- and pre-treatment were compared with AGB changes.

\[
\begin{align*}
\text{NDVI} &= \frac{(R_{\text{nir}} - R_{\text{red}})}{(R_{\text{nir}} + R_{\text{red}})} \quad (4-3) \\
\text{NDWI} &= \frac{(R_{\text{nir}} - R_{\text{swir1}})}{(R_{\text{nir}} + R_{\text{swir1}})} \quad (4-4) \\
\text{NBR} &= \frac{(R_{\text{nir}} - R_{\text{swir2}})}{(R_{\text{nir}} + R_{\text{swir2}})} \quad (4-5) \\
\text{TCA} &= \arctan\left(\frac{TCT_{\text{Greenness}}}{TCT_{\text{Brightness}}}\right) \quad (4-6)
\end{align*}
\]

where \(R_{\text{nir}}, R_{\text{red}}, R_{\text{swir1}}, R_{\text{swir2}}\) are homogenized MVC surface-reflectance in near infrared band, red band, shortwave infrared band 1, and shortwave infrared band 2, respectively. \(TCT_{\text{Greenness}}\) and \(TCT_{\text{Brightness}}\) are the greenness and brightness components from the Tasseled Cap Transformation (Crist 1985) of homogenized MVC surface-reflectance.

Comparison between vegetation indices and AGB maps

The accuracies and uncertainties of vegetation indices in quantifying forest biomass disturbances were evaluated by comparing them to LiDAR-derived AGB maps. First, we compared the changes of vegetation indices and AGB maps qualitatively, in terms of their spatial extents and distributions of detected changes. We then quantified the correlations between changes in vegetation indices and AGB maps at a pixel-level using the Pearson’s correlation coefficients. The correlations were evaluated over three different regions: (1) within the USFS proposed treated boundary, (2) in the untreated area outside of the treatment boundary, and (3) over the entire study area, including both treated and untreated areas. The first two regions represented changes either driven by human treatment, or caused by natural disturbances, respectively; and the third region included changes induced by multiple potential causes. The comparison among the three regions enabled us to evaluate the effectiveness of vegetation indices in quantifying changes induced by different sources.

To assess the capability of vegetation indices in quantifying biomass disturbances over forests with different densities, we categorized each region into seven pre-treatment AGB groups, and compared their correlations to AGB and canopy cover changes among groups. In addition to forest density, the differences in the height level where the
treatment was conducted might also influence the usefulness of vegetation indices. To evaluate this influence, we classified the treated area into four height classes determined by the level where the majority of forest structural loss occurred. The four height strata were defined as: 1-5m, 5-10m, 10-20m, >20m, which represented the small tree/shrub, small-mid tree, mid-large tree, and large tree, respectively. The selection of the height strata was made empirically by referring to in-situ tree height measurements. We identified the height stratum of tree structure loss from the changes in LiDAR point density for each 30m pixel: first, we calculated the ratios of LiDAR points in each height strata according to their aboveground height (z values); then we recorded the height stratum where the LiDAR point ratio experienced the largest reduction from pre- to post-treatment; finally, we labelled the treatment height level as the recorded height stratum for each pixel in the treated boundary.

4.3 Results
4.3.1 AGB and vegetation indices maps
The plot-level AGB estimation from LiDAR-derived height metrics showed strong correlations with field measurements in both pre- and post-treatment datasets (Figure 4-2). The correlation coefficients were similar between the two datasets, 0.784 for pre-treatment and 0.783 for post-treatment. The root-mean-squared-error between simulated and measured plot total AGB were 4.881Mg and 4.822 Mg for pre- and post-treatment, respectively. Most of the LiDAR simulated AGB matched well with field measurements, except for one plot where the LiDAR-based total AGB was 10 Mg lower than the field measurement in the pre-treatment data.

Figure 4-2 Scatter plots of total AGB from LiDAR data against field measurements at plot-level for both pre-treatment (left) and post-treatment (right) datasets. The dashed line indicates the 1:1 line.
The final LiDAR-derived AGB maps presented a wide range of biomass varying from 0 Mg/ha to 1500 Mg/ha in the study area (Figure 4-3). Trees with large AGB values mainly clustered in the southwest (500-1500 Mg/ha), whereas the northeast of the study area had smaller AGB values (0-200 Mg/ha) (Figure 4-3a, b). Within the USFS proposed treatment boundaries, the majority of the area (65.11%) observed AGB reduction after treatment (Figure 4-3c). The mean AGB values within the treatment boundary decreased from 265.64 Mg/ha to 220.36 Mg/ha, and the standard deviation of AGB values also dropped from 183.53 Mg/ha to 150.82 Mg/ha. The AGB values in the remainder of the proposed treated area (approximately 35%) remained unchanged or slightly increased during the five-year period. Some areas outside the treatment boundary (21.86%) also experienced obvious AGB decreases, potentially up to 100 Mg/ha during the past five years.

Figure 4-3 LiDAR-derived AGB maps for: (a) pre-treatment (2008); (b) post-treatment (2013); and (c) the difference between post- and pre-treatment. Landsat-derived NDVI maps for: (d) pre-treatment (2008); (e) post-treatment (2013); and (f) the difference between post- and pre-treatment.

The NDVI maps and their changes show similar patterns to AGB maps (Figure 4-3), with higher values in the southwest and lower values in the northeast. A significant drop in NDVI values can be observed within the proposed treatment boundary, with the mean NDVI values changed from 0.76 in the pre-treatment to 0.59 after treatment. The mean NDVI value outside the treatment boundary indicated a marginal decrease in AGB, which was ten times smaller than that inside the boundary. Overall, the spatial extent and distribution of NDVI reduction matched well with AGB changes. However, the NDVI change map failed to capture some fine-scale isolated changes in forest biomass which were obvious from the AGB change map.
The histograms of NDVI and AGB show different shapes, both in the original values (Figure 4-4a, 4-4c), and in the change values over the treated areas (Figure 4-4b, 4-4d). The AGB histograms over the whole area (Figure 4-4a) were right-skewed and peaked at low values (approximately 200 Mg/ha), whereas the NDVI histograms (Figure 4-4c) peaked at large values (approximately at 0.8) for both pre- and post-treatment datasets. Within the treatment boundary, the histogram of AGB changes had a single peak (around 0 Mg/ha) and a long left-tail (Figure 4-4b), but the histogram of NDVI changes presented double-peak at -0.2 and 0, respectively.

Figure 4-4 Histograms of AGB values: (a) over the study area from pre-and post-treatment; and (b) AGB changes within and outside the treatment boundary. Histograms of NDVI values: (c) over the study area from pre-and post-treatment; and (d) NDVI changes within and outside the treatment boundary.

4.3.2 Overall correlations between changes in AGB and vegetation indices
The correlations between changes in two LiDAR-derived forest structural metrics (AGB and canopy cover) and Landsat-derived vegetation indices were significantly positive among all the four indices (NDVI, NDWI, TCA, and NBR) (Figure 4-5).
Pearson’s correlation coefficients (R) among the four vegetation indices were consistent over the whole area, varying from 0.42 to 0.43 in AGB and from 0.7 to 0.73 in canopy cover. Vegetation indices were more sensitive to structural changes in canopy cover than AGB, as R was 70% higher in canopy cover than in AGB on average. The four vegetation indices demonstrated strong linear correlations, particularly between NDWI and NBR (R=0.97), and between NDVI and TCA (R=0.97).

The correlation matrixes derived from inside and outside the treatment boundary were generally similar to that over the whole area. Changes in vegetation indices are more sensitive to canopy cover than AGB. However, the correlations were the strongest within the treatment boundary (Figure 4-5b), followed by the whole area (Figure 4-5a), and were the weakest outside the treatment boundary (Figure 4-5c). On average, the correlations between vegetation indices and canopy cover within the treatment boundary were 100% higher than that outside the treatment boundary. The correlation coefficient between NDVI and AGB was 0.54 inside the treatment boundary, but was as low as 0.11 outside the boundary, although both correlations were significant at 99.9% level. Since the four vegetation indices demonstrated similar responses to forest structural changes, we chose the most widely used vegetation index, NDVI, to further analyze its sensitivess to AGB changes in different scenarios.
Figure 4-5 Correlation matrices between changes in two LiDAR-derived structural parameters (AGB and canopy cover (CC)) and four vegetation indices (NDVI, TAC, NDWI, NBR) for (a) the entire study area; (b) within the treatment boundary; and (c) outside the treatment boundary (untreated area).

4.3.3 Correlations among various forest densities and treatment levels
Changes in NDVI can partly predict the spatial variations in the AGB change map, and the strength of the prediction varied substantially among forests with different biomass densities before treatments (Figure 4-6). Over the whole area, the coefficient of determination ($R^2$) between NDVI changes and AGB changes increased from
low-biomass forest ($R^2 = 0.21$ at 0-100 Mg/ha) to medium-biomass forest ($R^2 = 0.49$, 200-300 Mg/ha), and the $R^2$ declined between forests with 300-400 Mg/ha and forests with 700-2000 Mg/ha. A similar trend was observed among AGB groups in the treated area, but the highest $R^2$ was achieved in a slightly large AGB group ($R^2 = 0.68$ at 300-400 Mg/ha) compared to the whole area. More significantly, the NDVI changes in the treated area demonstrated stronger prediction of AGB changes: the $R^2$ in the treated area was 81% higher than the whole area, and 500% higher than the untreated area on average among all pre-treatment AGB groups. Even in the largest pre-treatment AGB group, the $R^2$ was as high as 0.37 inside the treated area. Outside the treated area, the sensitivity of NDVI changes to AGB changes were low in general ($R^2 <0.2$), and the correlations were lower in forests with largest biomass. It should be noted that the area of forests varied among AGB groups, as well as between treated/untreated areas: the low-to-mid pre-treatment AGB groups (0-400 Mg/ha) occupied larger proportions of the study area than the large groups (400-2000 Mg/ha).

![Figure 4-6 Correlations between changes in NDVI and AGB grouping by pre-treatment AGB values in whole area (light blue), inside the treatment boundary (dark blue) and outside the treatment boundary (green). The numbers on the bar indicate the Landsat pixels in each group.](image)
A further examination of the capability of NDVI to represent AGB and canopy cover over forests of different densities for both pre- and post-treatment are presented in Figure 4-7. Before the treatment, NDVI was barely sensitive to AGB change in the densest forests (i.e. pre-treatment AGB greater than 600 Mg/ha in Figure 4-7a), which indicated the saturation effect of NDVI when relating to AGB in dense forests. The NDVI saturation effect in NDVI was less severe within the treated area, particularly when relating post-treatment NDVI to AGB values (Figure 4-7c). In contrast, the saturation effect when relating NDVI to canopy cover was marginal until the forest canopy cover approached full coverage (100%) for all areas from both pre- and post-treatment datasets (Figure 4-7b and 4-7d).
Figure 4-7 Boxplots comparing: (a) NDVI and grouped AGB over the entire study area pre-treatment; (b) NDVI and grouped canopy cover over the entire study area pre-treatment; and (c) NDVI and grouped AGB for the treated area post-treatment; (d) NDVI and grouped canopy cover for the treated area post-treatment. The width of box is proportional to the number of observations in each group.

The effectiveness of NDVI in quantifying fuel treatments was also influenced by the height of the treatments. In this study, as there were no detailed in-situ records on how forest treatments were conducted, or what sizes of trees were removed, we used the relative changes in LiDAR point density to classify treatments into different height strata. In the highest stratum, most of the tall trees (height>20m) were removed; whereas in the lower ones, treatments were mainly focused on small trees, shrubs, or understory fuels. An example from two typical sites is shown in Figure 4-8 depicting the difference between clear cutting of large trees in >20m height class (Figure 4-8a, 4-8b) and understory fuel removing in the 5-10m height class (Figure 4-8c, d) is apparent from the LiDAR point clouds. A correlation analysis between changes in NDVI and AGB among the four treatment classes indicated that the strongest correlation ($R^2 = 0.43$) was observed in treated areas where the majority of LiDAR point density reduction occurred in the highest stratum (height>20m). The $R^2$ dropped dramatically when the treatment occurred in the lower canopy or closer to the ground surface (Figure 4-9). Overall, NDVI changes can better quantify AGB decrease induced by the removal of larger trees rather than smaller trees or understory treatments.
Figure 4-8 Examples of the changes in LiDAR point clouds after fuel treatments conducted in high canopy levels (Site 1 (a) and (b)) and low canopy levels (Site 2 (c) and (d)).
Figure 4-9 Correlations between changes in NDVI and AGB grouping by treatments conducted at different height strata. The numbers on each bar indicate the Landsat pixels in each class.

The sensitivity of NDVI to forest fuel treatments was influenced by the combined effect of both pre-treatment forest density and treatment intensity. To illustrate this combined effect, we further categorized the decreased AGB pixels into four classes with similar pixel numbers but different pre-treatment biomass densities and examined how NDVI responded to various amounts of AGB decrease among the four groups (Figure 4-10). Results indicated that in the low pre-treatment AGB group (0-250 Mg/ha) a slight reduction in AGB (40 Mg/ha) could lead to substantial decreased in NDVI (0.2 on average), whereas in the high pre-treatment AGB groups (400-500 Mg/ha and 500-1500 Mg/ha), the mean NDVI changes did not respond to AGB disturbances until the reduction exceeded 80 Mg/ha and 100 Mg/ha, respectively. Overall, the NDVI was barely sensitive to fuel treatments in extremely dense forests, but tended to be over-sensitive in sparse forests, even to mild treatments.
Figure 4-10 Boxplots of NDVI changes in different AGB change groups. The four boxplots represent (a) pre-treatment AGB in small (0-250 Mg/ha); (b) small-mid (250-400 Mg/ha); (c) mid-large (400-500 Mg/ha); and (d) large (500-2000 Mg/ha) groups. The width of box is proportional to the number of observations in each group.

4.4 Discussion

4.4.1 Comparison between vegetation indices and forest structural changes

Four widely used Landsat-derived vegetation indices were evaluated regarding their effectiveness in quantifying treatment induced forest structural changes. We found the difference among them was marginal (<10%); this suggests that the high collinearity among them (e.g. Figure 4-5) was partly due to the fact that all indices were generated from the annual MVC surface reflectance data. MVC removed most of the seasonal changes in vegetation (Delbart et al. 2006), and consequently may also reduce the overall variations among the four vegetation indices. NDWI was designed to detect the water availability (Gao 1996; Gu et al. 2007), whereas NBR was developed to indicate fire severity (Key and Benson 2006; Miller and Thode 2007). Their applications in monitoring forest biomass changes induced by treatments have been less common than NDVI because NDVI is a stronger indicator of forest greenness and biomass (Gamon et al. 1995; Tucker 1979; Veraverbeke et al. 2012; Viedma et al. 1997). The TCA integrated information from six bands of Landsat data rather than two bands as the other three indices (Gómez et al. 2011). Due to the higher complexity in TCA calculation, the TCA-derived change does require more normalization from field measurements to enable comparisons among sites (Gómez et al. 2011), and thus may limit its applications in broad areas. Some other indices, such as the enhanced vegetation index and reduced simple ratio have also been used to monitor forest changes (Chen et al. 2005; Jin and Sader 2005), but less frequently in previous studies, and thus their performances were not evaluated in this study. Overall, NDVI has a longer history and broader usage in representing the forest greenness, biomass, and leaf area index, and thus is more pervasive in forest changes monitoring than the other indices (Gamon et al. 1995; Tucker 1979; Veraverbeke et al. 2012; Viedma et al. 1997).

Our results indicated that all the vegetation indices showed higher correlations to changes in canopy cover than AGB (Figure 4-5). Similar conclusions have been suggested in some previous studies (Gamon et al. 1995; Gao et al. 2000; Mutanga and Skidmore 2004). Their less sensitivity to AGB is mainly because vegetation indices often fail to indicate the further increase of AGB in forests denser than a certain amount. This phenomenon has been described as the saturation effect of vegetation indices in previous studies (Mutanga and Skidmore 2004). Gamon et al. (1995) found that the saturation effect in NDVI when relating it to AGB and other structural parameters could be influenced by many factors, including vegetation type, canopy senescence, soil background, and sensor and sun geometry. In this study, the saturation effect of NDVI was apparent in relation to AGB, particularly in the forests where pre-treatment AGB was larger than 600 Mg/ha (Figure 4-7). In contrast, the saturation effect was marginal in relation to canopy cover even if the canopy cover approached 100% (Figure 4-7). The stronger saturation effect in AGB might also be due to the larger uncertainty in AGB
estimation comparing to canopy cover. Although one of the most accurate wall-to-wall AGB estimation methods was adopted in this study (e.g. regression based on LiDAR-metrics and plot-measured biomass), uncertainties could have been introduced from bias in field measurements, as well as the generation of the relationship between field-measured AGB and LiDAR metrics. The bias in AGB estimation could be up to 25%, according to a study conducted in the same location (Li et al. 2015). The canopy cover map, on the contrary, was generated directly from LiDAR data, and thus had less sources of uncertainties (Ma et al. 2017a).

In this study area, the NDVI saturation effect was less severe within the treated area after the fuel treatment (Figure 4-8), mostly due to the decreased canopy density, and this also explained why the relationships between changes in NDVI and AGB in the treated area were stronger than that over the whole area. Gamon et al. (1995) mentioned that satellite-derived vegetation indices, such as NDVI and Simple Ratio Index, were stronger indicators of green-biomass rather than total biomass. It is possible that the correlations between NDVI and green-AGB could be stronger than current NDVI and total-AGB relationships. However, due to the lack of explicit information on whether the sampled trees were dead or alive, with yellow, red or green leaves, it was difficult to distinguish green-AGB from total-AGB purely using LiDAR measurements.

4.4.2 Uncertainties related to forest densities

In this paper we analyze the uncertainty by comparing responses of NDVI to AGB and canopy cover changes under different forest densities and treatment intensities. The uncertainty of using NDVI to quantify the forest biomass changes was smaller in the medium-biomass groups (200-300 Mg/ha and 300-400 Mg/ha) than the extremely low (0-100 Mg/ha) or high (700-2000 Mg/ha) pre-treatment AGB groups, as indicated by the variations in the correlations between changes in NDVI and AGB in different forest density groups (Figure 4-6). The larger uncertainty can partly be explained by the over-sensitivity of NDVI to AGB disturbance in sparse forests, and its saturation effect in extremely dense forest. A minor AGB reduction in sparse forests can lead to a substantial decrease in NDVI, whereas in extremely dense forests, NDVI might not be responsive even to a large amount of biomass removal.

Vegetation indices from time series satellite imagery have been used to map forest treatments and evaluate their hydrologic and ecological impacts through relating changes in vegetation indices to reductions in basal area and/or biomass (DeVries et al. 2015; Huang et al. 2010; Masek et al. 2008). However, our results showed that the robustness of the relationships varied substantially by the pre-treatment forest densities. In the low AGB areas, a small reduction (<30 Mg/ha) in biomass could result in large amount of NDVI decrease (up to 0.4). The removal of some small trees in sparse forests may expose the ground surface and even bare earth, and result in the sharp decrease of NDVI to extremely low values (close to 0). In contrast, the NDVI values in extremely dense forests may remain unchanged after fuel treatments because NDVI is saturated even after removing some large trees. Therefore, caution should be paid to the over-sensitivity and saturation effects in Landsat-derived vegetation indices when using them to quantify forest biomass changes in either extremely sparse or dense forests. Due to the limited
coverage of LiDAR and field measurement in this study, we only evaluated the Landsat-derived vegetation indices in a typical mixed-conifer dominated forest. Results drawn from this forest stand may be representative of Sierra Nevada mixed-conifer forests, but not necessarily applicable to other regions with different biomes and/or climates. More studies are needed to thoroughly evaluate the capabilities and limitations of Landsat-derived vegetation and clarify its uncertainties in biomass change quantification over large areas.

4.4.3 Uncertainties related to different treatments

Forest fuel treatments are a common management practice in Sierra Nevada forests for many reasons, including wildlife habitat protection, fire risk reduction, and drought resistance improvement (Knapp et al. 2013; Knapp et al. 2017; Park et al. 2018; Battles et al. 2001; Stephens et al. 2009). Depending on the purposes, fuel treatments can be achieved in many ways. Some fuel treatments focused on the removal of overstory trees, particularly large trees (>20 inch dbh), in order to reduce overstory canopy cover and increase sunlight exposure in understory. Increasing the forest heterogeneity both vertically and horizontally was critically important for wildlife habitation protection; because spatial variations are desirable for sustaining adequate food and biodiversity at different scales from forest stand to landscape (Franklin et al. 2002; North et al. 2009). For example, the spotted owl prefers forests with snags and large trees for prey and nesting (Stephens et al. 2016b; Tempel et al. 2014). In contrast, fire suppression often focuses on thinning the surface fuel, tree ladders, or small understory trees, because they are more likely to cause the spread of fires, whereas large trees (dbh>20 inches) are less impacted in forest fires (Stephens et al. 2009). Responding to different forest management goals, treatments are often conducted using a range of equipment and methods, i.e. mechanical treatment, hand thinning, piling, and chain removing (Knapp et al. 2017). Their impacts on forest structures will vary accordingly, which could be challenging for treatment mapping and biomass change quantification at regional scales using remote sensing techniques.

In this study, we categorized fuel treatment levels by referencing to the changes in point density over various height strata (Figure 4-10) because we lacked detailed documentation regarding treatment strategies. The LiDAR data may not fully delineate forest structure changes due to limitations in point density and laser penetration capability in extremely dense forests (Jakubowski et al. 2013). However, by comparing the two LiDAR datasets, obtained using similar flight parameters and in the same season, we considered the comparison of the point clouds as an appropriate reference to categorize different treatment strategies. Forest stands that were treated at high strata by removing most of the tall and big trees were better quantified using vegetation indices, whereas the biomass reduction caused by understory thinning on small trees (<10 m) or understory fuels was more difficult to quantify. Our results suggest that using Landsat-derived vegetation indices to monitor forest fuel treatments or to assess the impacts on forest structures is most reliable when the objectives were the removal of overstory trees. Landsat-derived vegetation indices can be used to detect some of the understory thinning or fuel reduction at certain levels, but the uncertainties can be huge when the major biomass reduction occurred lower than 10m. Our study characterized treatments merely
based on the changes in LiDAR-point density, more studies with detailed documentation of treatment methods are needed to fully illustrate how well Landsat-derived vegetation indices can quantify biomass changes.

4.5 Conclusions

Landsat-derived vegetation indices have been widely used to map and monitor forest disturbances over long-term periods from regional to global scales. Our study evaluated their uncertainties in indicating the forest structural loss induced by forest fuel treatments using wall-to-wall validation data derived from LiDAR and field measurements. The four widely used vegetation indices, NDVI, NDWI, NBR, and TCA, performed equally well in characterizing canopy cover loss due to forest fuel treatments, but their capabilities in predicting aboveground biomass loss were less satisfactory. Focusing on the most widely used vegetation index, NDVI, we found that uncertainties mainly resulted from the saturation and over-sensitivity of NDVI in representing the biomass changes at extremely dense or sparse forests, respectively. In conclusion, vegetation indices like NDVI are more suitable for quantifying biomass changes in forests with mid-density ranges (aboveground biomass: 100-700 Mg/ha) rather than extremely sparse or dense forests in the Sierra Nevada. The accuracy of NDVI in predicting aboveground biomass changes were also influenced by the treatment types, which decreased sequentially as the treatments implemented from the overstory to the ground surface. Overall, vegetation indices from satellite imagery can detect and map changes in canopy cover and land cover types induced by treatments and other disturbances. However, researchers and managers should be cautious about their uncertainties in quantifying biomass disturbance. Vegetation indices might not be responsive to a large amount of biomass reduction (>200Mg/ha) in an extremely dense forest (aboveground biomass>700 Mg/ha). Information about the pre-treatment forest density and treatment boundary can help improve the quantification accuracies. Moreover, forest fuel treatments, such as surface fuel clearing and understory thinning, are difficult to monitor precisely from Landsat-derived vegetation indices alone. Active remote sensing techniques, such as LiDAR, are needed to improve the accuracy of quantifying biomass loss induced by understory fuel treatments.

References


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Chapter 5  A simple and integrated approach for fire severity assessment using bi-temporal airborne LiDAR data

Abstract
This study proposed a new method (profile area change, PAC) to quantify fire severity at the individual-tree and forest-plot scales using pre- and post-fire LiDAR data. We applied the PAC method to assess the 2013 American Fire in the Sierra Nevada, California, USA. Our LiDAR PAC metrics were compared to changes in two commonly used LiDAR metrics (canopy cover and tree height) at the tree level, and to Landsat-8 imagery derived Relative differenced Normalized Burn Ratio (RdNBR). A quantitative validation using field measured changes in basal area and leaf area index (LAI) confirmed that correlations between PAC metrics and field measurements ($R^2 \geq 0.67$) were significantly higher than those from canopy cover or tree height metrics ($R^2 \leq 0.41$), and much stronger than that from RdNBR ($R^2 \leq 0.26$). The PAC metrics can also be used to infer the extent of tree canopy disturbance caused by fire, based on whether the majority of biomass loss occurred above or below the tree crown base height. Mapping of canopy disturbance indicated that over half (57.0%) of the American Fire region had tree canopy loss from fire, 22.5% of trees had mainly sub-canopy loss, and the rest were barely affected by the fire. A visual evaluation using aerial imagery also confirmed that our method outperformed commonly used LiDAR metrics in forests burned at diverse fire severities with different pre-fire biomass densities. Overall, the LiDAR PAC metric, as a simple and integrated method, demonstrated promising potential in characterizing changes in forest structure. The method can help forest managers to evaluate fire-induced forest structural losses and assess their ecosystem and economic losses efficiently and effectively.

Keywords: fire severity; airborne LiDAR; tree crown and canopy; surface and crown fire; profile area change

5.1 Introduction
Forest fires play increasingly important roles in shaping forest structure, composition, and ecological functions due to climate change and intensive anthropogenic activities in the American West (Collins et al. 2017a; Westerling 2016). Fire can be categorized into different severities by the amount of tree mortality and biomass lost (Jain and Graham 2004). Studies have shown that fires burning primarily on the forest floor, i.e., surface fires, can be beneficial to forest ecosystems by reducing tree density and ladder fuels (Ager et al. 2013; Kramer et al. 2016), and promoting seed germination and sprouting (Lamont et al. 1993). These fires are referred to as low or moderate severity. In contrast, high severity fires affect both the forest floor and dominant tree canopies, which can significantly alter forest habitat (Jones et al. 2016; Stephens et al. 2016), reduce soil organic matter (Certini 2005), and increase carbon emissions (Garcia et al. 2017). Accurate quantification of fire severity and spatially explicit fire-type mapping are necessary for assessing fire impacts, understanding fire behaviors, and designing restoration strategies.
Field-based assessments of fire severity can provide accurate measurements of changes in vegetation and soil, such as the Composite Burn Index (CBI), which has been a primary fire inventory protocol for a decade (Key and Benson 2006). However, the CBI method is usually limited to plot-level studies due to labor and time demands. Moreover, CBI assessments can sometimes be biased as they rely on visual observations of forest changes using relative scales without reference to pre-fire data (Smith et al. 2016).

Satellite remote sensing imagery has been widely used to map fire extent and severity, from regional to national scales, due to its broad and frequent coverage (Miller and Thode 2007; Parks et al. 2018). The removal of vegetation and the exposure of soil caused by forest fires can decrease the near-infrared reflectance and increase shortwave infrared reflectance in burned areas. Satellite imagery derived spectral indices, including the Normalized Burn Ratio, difference between pre- and post-fire NBR (dNBR), and the relative difference between pre- and post-fire NBR (RDNBR), were developed to quantify these spectral changes in surface reflectance caused by fire and to relate them to field measurements (Miller and Thode 2007). These indices have been successfully applied to classify fire severities into general types (Lydersen et al. 2016; Miller et al. 2009a; Roy et al. 2006). However, quantifying forest structure changes, such as canopy cover, leaf area index (LAI), basal area, and aboveground biomass, directly using these indices can be problematic due to the passive nature of optical imagery (Veraverbeke and Hook 2013). Shadows in the mountainous areas or cloud cover can bias fire severity estimates (Verbyla et al. 2008). Moreover, the correlations between spectral indices and forest structure changes can vary by pre-fire forest conditions and fire types (McCarley et al. 2017).

Light Detection and Ranging (LiDAR) is an active remote sensing technique using a focused laser pulse, which can penetrate the forest canopy and provide detailed three-dimensional forest structure information. Studies have shown that LiDAR data can be used to estimate forest structure parameters at multiple scales with high accuracy, including tree height (Clark et al. 2004; Jakubowski et al. 2013; Su et al. 2016b), canopy cover (Ma et al. 2017a), LAI (Morsdorf et al. 2006; Zhao and Popescu 2009), aboveground biomass (Popescu et al. 2011; Su et al. 2016a; Tao et al. 2014), and forest fuel parameters (Blanchard et al. 2011; Jakubowski et al. 2013; Kelly and Di Tommaso 2015; Kelly et al. 2017; Kramer et al. 2014). Post-fire forest structure information derived from LiDAR data have been adopted to map post-fire residual vegetation, assess fire severities by comparing with unburned areas, and evaluate the post-fire recovery when combined with multi-temporal satellite imagery (Bishop et al. 2014; Meng et al. 2018; Michael et al. 2017; Wang and Glenn 2009; Wulder et al. 2009). Multi-temporal LiDAR data show promise in quantifying fire severity and classifying fire types because the fire-induced tree structure changes can be delineated directly at various height strata from the ground surface to the crown tops. Similar ideas have been successfully applied to quantify tree growth (Ma et al. 2017b; Vepakomma et al. 2011; Zhao et al. 2018) and canopy dynamics caused by multiple disturbances (Vepakomma et al. 2010; Vepakomma et al. 2008).

While multi-temporal LiDAR data show great potential in quantifying fire-induced forest changes, there remain operational challenges such as obtaining both pre- and post-fire LiDAR with comparable data quality. Some recent studies have used basic
LiDAR metrics to estimate changes to forest structure, but most have been applied at the plot level. Among them, Bishop et al. (2014) combined LiDAR percentile metrics with aerial imagery to classify tree mortality at the plot level; McCarley et al. (2017) and Wulder et al. (2009) calculated forest structure changes from multiple LiDAR metrics (canopy cover, mean height, and point densities at different height strata) and evaluated their correlations to Landsat-derived spectral changes at Landsat pixel and segment levels. However, to the best of our knowledge, there remains a need to develop metrics that quantify forest structure changes directly from multi-temporal LiDAR data at diverse scales from individual trees to forest plots.

The objective of this study is to propose a new LiDAR-based method for fire severity and type mapping, fire-caused ecosystem and economic loss assessment, and providing useful information for fire behavior modeling. Using the American Fire burned in California as a case study, we aimed to address two specific research questions: 1) How to quantify fire-induced forest structural changes from LiDAR point data at both individual tree and forest plot scales? 2) What are the advantages and disadvantages of this method in fire severity quantification, comparing to traditional LiDAR metrics and satellite imagery-based fire mapping techniques?

5.2 Data and methods

5.2.1 The American Fire and study area

The American Fire started in a steep canyon in the Tahoe National Forest, California, USA (39°04′53″N, 120°34′30″W) on August 10th, 2013, and was contained on August 29th, 2013. It burned an area of 111 km², and 78% of it was inside a study site of the Sierra Nevada Adaptive Management Project (SNAMP) (Hopkinson and Battles 2015), where field measurements and LiDAR data were available (Figure 5-1). This area is characterized as a Mediterranean climate with an average precipitation of 1182 mm/year, primarily in the form of snow. Historically, this forest experienced frequent, low-to-moderate severity fires with a median fire return interval of 15 years (Collins et al. 2011; Krasnow et al. 2016; Stephens and Collins 2004). The terrain is mainly characterized by steep slopes with an elevation range of 658 m to 2184 m. This study site had a mean tree canopy cover of 67% before the fire (assessed from LiDAR), which was primarily dominated by mixed conifer forest. The main tree species included white fir (Abies concolor), ponderosa pine (Pinus ponderosa), incense-cedar (Calocedrus decurrens), sugar pine (Pinus lambertiana), and Douglas-fir (Pseudotsuga menziesii). Within the mixed conifer stands, the major hardwoods included California black oak (Quercus kelloggii) and canyon live oak (Quercus chrysolepis).

Fuel treatments were completed by United States Forest Service (USFS) in the southeastern portion of the study area just before the American Fire (Figure 5-1). As part of the SNAMP project, these treatments were designed to reduce forest fuels that provide the vertical fuel continuity that can preheat and ignite canopy fuels (Agee and Skinner 2005). This study area and fuel treatments provide a natural experiment to test the robustness of our proposed method in quantifying fire severity over forests with diverse topography, tree densities, and pre-fire management strategies.
Figure 5-1 The study area with the American Fire perimeter overlaid with the LiDAR scan boundary. The distribution of field-measured plots and five sample sites were highlighted using black dots and green polygons. The blue polygon indicates the boundary of fuel treatments provided by the USFS. The blank box indicates no useful LiDAR data obtained due to a failure in data collection.

5.2.2 LiDAR data acquisition and pre-processing
The pre-fire airborne LiDAR data were acquired in August 2013, a few days before the American Fire; and collected again in October 2013. The raw LiDAR data were generated in 1km by 1km tiles in LAS format. A total of 87 km$^2$ of the LiDAR scanned area interacted with the fire perimeter in this study (Figure 5-1). Post-fire LiDAR data were obtained using the same equipment and method as the pre-fire data collection for a fair comparison. The Optech GEMINI airborne laser terrain mapper from the National Center of Airborne Laser Mapping was used to collect both pre- and post-LiDAR data. The sensor was operated at 100 kHz with a scanning frequency of 40-60 Hz and a scan angle of 12-14° on both sides of nadir for both flights. They flew at 600-700 m above the ground, with a swath width of approximately 510 m and over 50% overlap between two adjacent flight lines. The point densities for both datasets were approximately 10
points/m², the horizontal accuracies were approximately 10 cm, and the vertical accuracies varied from 5 to 35 cm by location.

The classification of ground from non-ground LiDAR points was performed in LiDAR360 software (https://greenvalleyintl.com/software/lidar360/). We generated the digital elevation model (DEM) and digital surface model (DSM) at 1 m resolution from the ground returns and first returns using the ordinary kriging interpolation method (Guo et al. 2010). A Canopy Height Model (CHM) was then computed as the difference between the DSM and the DEM. The LiDAR point clouds were normalized by DEM to calculate the aboveground height. LiDAR points with above ground height greater than 100m were considered as outliers and removed from further analyses.

5.2.3 Field measurement
Plots were established on a 500 x 500 m grid across both the control and treated firesheds based on a random starting location. In some areas, sampling was intensified to 250 m spacing in order to accommodate concurrent studies and to increase the sample size of plots in treated areas. There were a total of 408 circular plots across the study area of SNAMP, each 0.05 ha in size. Initial sampling occurred in the summers of 2007 and 2008 before fuel treatments were installed. Measurements taken on each plot included tree species, height, vigor (live or dead), and diameter at breast height (DBH) for trees >= 5.0 cm DBH. Canopy trees (trees with DBH >= 19.5 cm) were tagged for long-term monitoring. The cover and average height of shrubs were measured by species using the line intercept method (total length sampled = 37.8 m). In 2013, plots were re-measured to capture post-treatment conditions, following the pre-treatment measurement protocol. The American Fire began burning in August of 2013, cutting short field measurements, so that 369 of the 408 plots were re-measured before the fire. In 2014, we re-measured 162 plots within the American Fire perimeter. For all canopy trees in the post-fire survey, we estimated the amount of char on the stem and scorch in the crown.

5.2.4 Spectral index from satellite imagery
The spectral indices from satellite imagery have been extensively used in the fire community to map wildfire effects (Eidenshink et al. 2007; Miller et al. 2009a; Miller and Thode 2007). In this study, we chose RdNBR, a relative difference change in Normalized Burn Ratio, as a spectral indicator of fire severity from Landsat satellite imagery to compare with the LiDAR derived fire severity index. RdNBR was selected because it has been reported to be superior to other spectral indices, such as dNBR and NBR, as it can remove the biasing effect of the pre-fire condition (Miller et al. 2009a). For fair comparison, we collected pre- and post-fire Landsat-8 OLI imagery on July 30, 2013, and September 16, 2013, respectively, since they were closest to the LiDAR flight dates among all cloud and snow free images. These two Landsat-8 OLI images were atmospherically corrected and converted to surface reflectance using the software of Environment for Visualizing Images (ENVI, Version 5.0 SP1, Exelis Visual Information Solutions, Boulder, CO, USA). RdNBR is the relative difference of pre- and post-fire NBR, calculated from the surface reflectance in near infrared (band 5) and
shortwave-infrared (band 7) bands of Landat-8 OLI images following the equations (Equation 1 and 2) introduced by (Miller et al. 2009a).

\[
NBR = \frac{(Band_{NIR} - Band_{SWIR2})}{(Band_{NIR} + Band_{SWIR2})}
\]

\[
RdNBR = \frac{1000 \times (NBR_{pre-fire} - NBR_{post-fire})}{\sqrt{ABS(NBR_{pre-fire})}}
\]

5.2.5 LiDAR-based fire severity estimation: Profile Area Change

We developed a new LiDAR-based metric, profile area change (PAC), to quantify fire severity at multiple scales. The design of PAC is based on the assumption that patterns of fire effects are inherently heterogeneous in forests (Collins et al. 2017b), resulting in varying amounts of biomass loss at different height strata from individual tree to forest stand levels. These losses alter the structure of the canopy that in turn changes the vertical distribution of LiDAR points. For example, consider the two tree clusters shown in Figure 5-2. Site A had a denser canopy than Site B before the American Fire; but higher severity fire in Site A resulted in the reduction of LiDAR point density over the whole canopy, whereas lower severity fire in Site B only reduced the point density in the lower canopy and ground surface. LiDAR height percentiles are able to characterize the vertical distribution of LiDAR points. Quantifying changes in height percentile is critical to better representation of fire caused biomass loss. In this study, we used the area delineated by the height percentile curves to describe the overall changes, rather than focusing on height changes at any specific percentile/s as adopted in previous LiDAR forestry studies (Bolton et al. 2015; Dalponte et al. 2012; Gleason and Im 2012; Zhao et al. 2009).
First, we normalized the aboveground height of LiDAR points into the range of 0 to 1 for each statistical unit using the maximum height from both pre- and post-fire LiDAR data. This normalization is necessary to make the metric comparable among trees at different heights. Normalized points were then ranked in ascending order, and their height percentiles were calculated for each statistical unit. Local polynomial regression was used to fit the height percentiles into a profile curve, \( f(\text{percentile}) \) in Equation 5-3), since the curve was usually non-linear. Next, the area delineated by the percentile profile curve and x-axis (LiDAR point percentile, % in Figure 5-3) was calculated using a definite integral of \( f(\text{percentile}) \) from 0 to 100%, and denoted as the Profile Area (PA in Equation 3). Finally we calculated the PAC as the difference between pre-fire PA and post-fire PA for each statistical unit (the PAC in Equation 5-4).

\[
PA = \int_0^{100\%} f(\text{percentile})d(\text{percentile})
\]

(5-3)

Where PA is the profile area, calculated as the integrated area below the percentile profile curve, simulated by polynomial regression equation \( f \).

\[
PAC = PA_{\text{pre}} - PA_{\text{post}}
\]

(5-4)

Where PAC is the profile area change, PApre and PApnext are profile area calculated from pre- and post-fire LiDAR data.
Theoretically, the PAC value can range from -100 to 100. A positive PAC value indicates more LiDAR points have penetrated the burned canopy and reached the understory/ground. The larger the positive PAC value is, the higher severity the fire could be. As the examples show in Figure 5-3, the PAC values increased gradually from 1 to 10, 15, and 25, which represent a non-burned tree crown, a relatively low-severity burned tree, a moderate-severity burned tree, and a severely burned tree, respectively. In contrast, a negative value indicates the canopy has become denser and fewer LiDAR points have penetrated it in the post-fire LiDAR scan.

Figure 5-3 Profile area change (PAC) of individual trees at different fire severity levels. The (a), (b), (c), (d) stand for unburned tree, low-severity burn tree, moderate-severity burn, and high-severity burn, respectively. The grey and black lines indicate the percentile curves generated from pre- and post-fire LiDAR point clouds. The blue area indicates the PAC.

In this study, the fire severity was evaluated using the PAC metric at both the individual tree and forest plot scales following the schematic procedure shown in Figure 5-4. The PAC at individual tree scale (PACtree) was calculated for each tree crown,
segmented from the pre-fire LiDAR CHM. We used the marker-controlled watershed segmentation (MWS) algorithm to delineate individual tree crowns. MWS is a classic image segmentation algorithm, which combines the ideas of region-growing and edge-detection (Meyer and Beucher 1990). It has been widely used in LiDAR CHM based individual tree segmentation due to its efficiency and accuracy (Chen et al. 2006; Ma et al. 2017b; Tao et al. 2014). Before the segmentation, we applied a Gaussian filter to CHM with a 5m search radius to suppress irrelevant local maxima and fill pits, as recommended by Chen et al. (2006). Then, the local maxima points were identified from the filtered CHM and used as markers. The MWS algorithm was applied to segment the filtered CHM data through LiDAR360 software (https://greenvalleyintl.com/software/lidar360/). We used the pre-fire CHM to generate individual tree segments, since some tree crowns might be diminished or even disappear in the post-fire CHM. The PACtree was calculated for each tree segments over the entire study area.

The PAC was also calculated at 900m² (PACpixel) for comparison with Landsat-derived RdNBR, as well as to approximate the forest plot (500m²). The pre- and post-LiDAR points were first grouped by Landsat grids, and then PACpixel was calculated for each pixel following the same method as PACtree.

Figure 5-4 Workflow for data processing and analysis in this study, including the LiDAR-based fire severity estimation and fire type classification at individual (indiv.) tree level; the comparison of pixel-level LiDAR profile area change to Landsat-derived spectral index; and the validation from field measured forest structure changes. PAC is profile area change, and PAC50% was the height level where the accumulated profile area change reaches 50% of the total change for each tree. CBH is crown base height.
5.2.6 LiDAR PAC-based fire type classification

At the individual tree scale, we classified the segmented trees into three types: unburned, burned at surface, and burned in crown based on the PACtree values (Figure 5-4). Due to the unavoidable difference in pre- and post-fire LiDAR scans, variations in relatively small amounts existed in the height profiles even if the tree structure was unchanged. To distinguish unburned trees from burned trees, we used the PACtree values outside the American Fire perimeter as a reference for unburned trees. The mean ($\mu$) and standard deviation ($\sigma$) of PACtree for these trees outside the American Fire perimeter were calculated. We assumed that trees with a PACtree value smaller than $\mu + 1.0\sigma$ can be recognized as unburned. In this study, the $\mu$ and $\sigma$ of PACtree outside the fire perimeter were 0.0 and 4.0, respectively, and thus the PACtree value of 4.0 was used as a threshold to separate burned and unburned trees. In sum, burned trees were defined as trees (height>5m) with a PACtree $> 4$. The other segments were labelled as unburned, either because the vegetation was below the commonly used tree height threshold (FAO 2015), or the changes were too marginal to be recognized as burned trees.

The profile area delineated in this study is able to reflect tree structure changes at various height strata, and thus, is capable of distinguishing canopy vs. sub-canopy fire effects. Here, we used the height where 50% of accumulated profile area change (PACtree50%) occurred as the threshold to determine the fire types. If the PACtree50% was lower than the crown base height (CBH), then the tree was burned at the surface, otherwise the tree was considered to have fire-cause canopy reduction. However, due to difficulties in identifying the CBH for individual trees, we adopted a mean CBH at 20m spatial resolution generated by Jakubowski et al. (2013) from field measurements and pre-fire LiDAR metrics. The generated CBH varied from 0 to 16.24m, with a mean value of 4.55m. The estimated CBH value showed satisfactory accuracy with a root mean squared error of 2.0 m, and a strong correlation to field measurements (coefficient of determination $R^2 = 0.81$).

5.2.7 Data comparison and validation

The accuracies of our LiDAR-derived PAC metrics in fire severity quantification were evaluated at both individual tree and forest plot scales using references from field measurements and high resolution aerial imagery (Fig. 4). The PACtree was compared with changes in two commonly used LiDAR metrics, canopy cover and tree height, at the individual tree scale. PACpixel was compared with Landsat-derived RdNBR at the forest plot scale. Canopy cover was calculated as the ratio of LiDAR first-returns above 2m, a height threshold used to distinguish tree from non-tree vegetation type (Korhonen et al. 2011; Ma et al. 2017a). Tree height was defined as the maximal value of CHM pixels in each tree segment (Ma et al. 2017b). The changes in these two metrics were calculated as the difference between pre- and post-fire for each tree.

The accuracies of our PAC metrics and other metrics were evaluated using field-measured changes in LAI and basal area from 162 sample plots. Field estimates of leaf area were calculated from species-specific allometric models (Jones et al. 2015). Independent variables used to predict leaf area were species, DBH, height, and live crown ratio. The projected leaf area of the all the trees was summed and then divided by the plot area to calculate LAI. Considering the uncertainties in plot spatial locations, we used a 15m radius circle rather than the original 12.5m radius to calculate the areal weighted plot-mean fire severity values. We calculated the coefficient of determination ($R^2$) to evaluate the linear relationships between field-measured changes in basal area and LAI, and plot-mean fire severity metrics estimated at both individual tree-level (PACtree, changes in canopy cover and tree height), and pixel-level (PACpixel and RdNBR). The fire severity metrics with higher $R^2$ indicated stronger capabilities in predicting the spatial variations of forest structure losses.
In addition to field plots, five sample sites (1 km² for each) were selected as representative of the study area for detailed comparison (Figure 5-1). Two of the five sites experienced pre-fire fuel treatments (Table 5-1). The five sites covered a wide range of topographic conditions in elevations and slopes. The main vegetation type was Sierran Mixed Conifer (https://www.fs.usda.gov/detail/r5/landmanagement/resourcemanagement/?cid=stelprdb5347192). The pre-fire canopy cover varied from 48.7% to 72.8%, and mean tree height ranged from 11.6 to 14.8 m. High-resolution aerial imagery in these sites was used as a visual reference of vegetation disturbances because of its fine resolution (1 m), multi-spectral information (4 bands), frequent revisit (1-2 year return), and free access (Liang et al. 2016; Ma et al. 2017a; Schroeder et al. 2014). The aerial imagery was obtained by the National Agriculture Imagery Program (NAIP) and downloaded from USDA Geospatial Data Gateway (https://gdg.sc.egov.usda.gov/). We collected the aerial imagery obtained in the growing season of 2012 and 2014 to represent the pre- and post-fire vegetation conditions. The fire severity maps from PACtree, PACpixel and other metrics were qualitatively examined using the vegetation changes observed from aerial imagery. We also compared PACtree values to changes in canopy cover and tree height for all trees in the five sample sites using density scatter plots and evaluated their correlations using linear regression. The values of PACpixel and RdNBR over the entire American Fire perimeter were also compared in the same way.

Table 5-1. Sample site information calculated from pre-fire LiDAR-derived DEM and CHM. Elevation and slope are plot mean values from DEM. Vegetation type is derived from California vegetation classification under the Wildlife Habitat Relationships. SMC = Sierran Mixed Conifer, MC = Montane Chaparral, MHC = Montane Hardwood Conifer, and WF = White Fire. Canopy cover and tree height was generated from CHM using each sample site boundary as statistic unit.

<table>
<thead>
<tr>
<th>Site ID</th>
<th>Pre-fire treatment</th>
<th>Elevation (m)</th>
<th>Slope, degree</th>
<th>Vegetation type</th>
<th>Canopy cover</th>
<th>Tree height (m)</th>
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</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Dominant</td>
<td>Secondary</td>
<td></td>
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<tr>
<td>S1</td>
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<td>16.0</td>
<td>SMC</td>
<td>MC</td>
<td>50.8%</td>
</tr>
<tr>
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<td>22.7</td>
<td>SMC</td>
<td>MC</td>
<td>61.6%</td>
</tr>
<tr>
<td>S3</td>
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<td>MC</td>
<td>72.8%</td>
</tr>
<tr>
<td>S4</td>
<td>Yes</td>
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<td>13.7</td>
<td>SMC</td>
<td>MHC</td>
<td>48.7%</td>
</tr>
<tr>
<td>S5</td>
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<td>1697.1</td>
<td>15.3</td>
<td>SMC</td>
<td>WF</td>
<td>58.0%</td>
</tr>
</tbody>
</table>

5.3 Results
5.3.1 PAC-derived fire maps of the American Fire
The spatial extents of the area impacted by the American Fire matched well between LiDAR-derived PACtree, PACpixel, and Landsat-8 derived RdNBR. However, the RdNBR map indicated that a majority of this area was burned at homogenously high intensity, whereas maps from PAC metrics showed more fine scale variations in fire severity. The mean RdNBR value of American Fire burned area was 488 (Figure 5-5a). According to the fire severity classification system based on RdNBR and CBI relationships (Miller et al. 2009b; Miller and Thode 2007), 14.0% of the American Fire perimeter was burned at high severity (CBI>2.25 high to complete vegetation mortality), 30.7% at moderate severity (1.25<CBI≤2.25 mixed effects of unchanged to high), 29.5% at low severity (0.1<CBI≤1.25 little change or mortality), and 25.8% was unburned (CBI≤0.1). From the PACtree fire severity estimates, the mean value of burned trees was
Trees that experienced canopy biomass loss showed higher fire severity with 24.3% larger in PACtree values than sub-canopy disturbed ones. For the trees that experienced canopy loss, the clustered ones generally showed higher severities (higher PACtree values) than the areas with scattered trees. Among all the segmented trees, 57.0% experienced fire-caused canopy reductions, 22.5% had sub-canopy biomass loss, and 20.5% were unburned (Figure 5-5d), according to our fire effect classification. The percentage of trees that experienced sub-canopy fire disturbances (22.5% from PACtree) was slightly lower than the area burned by low severity fire (29.5% from RdNBR), whereas the percentage of canopy-loss trees (57.0% from PACtree) was higher than the moderate-to-high severity burned area (44.7% from RdNBR).

Figure 5-5 Fire severity map of the American Fire in the area covered by LiDAR: (a) RdNBR calculated from Landsat-8; (b) PACpixel calculated from pre- and post- fire LiDAR data; (c) PACtree calculated from pre- and post- fire LiDAR data; and (d) fire
A detailed analysis on the 1km² Sample Site S1 (S1 in Figure 5-1) showed that over the 12,184 segmented trees (height > 5m), 51.7% were burned (PACtree > 4) by the fire. The distribution of PACtree values in each tree height group was similar and most of their PACtree values belonged to 0~10 and 10~20 categories (Figure 5-6). Among all the burned trees, 59.5% experienced canopy loss. The ratio of trees with canopy loss increased from short to tall tree groups. From field measurements, 72% of the measured canopy trees (height >= 10 m) in all plots had evidence of some crown scorch. This ratio was similar to PACtree based estimation in S1, where 65.7% of trees taller than 10m had canopy-loss. The mean PACtree value of canopy-loss trees (mean PACtree=15.2) was 31.0% higher than those burned at the surface (mean PACtree=11.6).

Figure 5-6 The distributions of trees at different PACtree categories for each tree height groups binned by 5m intervals: (a) number of trees burned by PAC; (b) number of trees experienced sub-canopy vs. canopy biomass loss during the fire.

5.3.2 Comparing PACtree with canopy cover and tree height changes

The comparison between PACtree and canopy cover changes in five sample sites (Figure 5-7) show that both metrics successfully detected high-severity-fire scars where trees were combusted and bare earth was exposed in the post-fire aerial images. However, the canopy cover change metric performed slightly worse than PACtree in detecting low-severity and surface-fire burns. Visually, more low-severity-fire induced tree disturbances have been mapped from PACtree than canopy cover changes Figure 5-7. A direct comparison in values between PACtree and canopy cover change of all trees in the five sample sites (Figure 5-8a) also indicated that a large portion of (71.1%) canopy
cover has no/negative changes whereas only 36.2% PACtree values was lower than the burn/unburned threshold (PACtree<4). The linear correlation between these two metrics was still positive, with a $R^2$ at 0.22. The less sensitivity of the canopy cover change metric in detecting low severity fires can also be confirmed by field measurements. As shown in Figure 5-9, the canopy cover metric was unchanged or even slightly increased after fire in plots with tree disturbances of up to 15 m²/ha in basal area and 1.5 in LAI.

The fire severity maps derived from tree height changes only detected several isolated burned trees, and poorly differentiated fire severities between sample sites with (S4, S5) and without (S1, S2, and S3) pre-fire fuel treatments (Figure 5-7). In contrast, the variations in fires severities between fuel-treated and untreated sites were obvious in maps derived from PACtree and canopy cover changes. The comparison of values between PACtree and change in tree height (Figure 5-8b) also indicated that tree height metric only decreased in a few trees burned at high severity, whereas a majority of them (81.7%) showed no response to the fire. The linear correlation between PACtree and change in tree height was still positive, but much lower ($R^2 = 0.1$) than that with canopy cover. The insensitivity of tree height metric to low-to-moderate-fire severity was also demonstrated in field measurements (Figure 5-9), in that tree height metric only decreased in some plots, with huge amounts of reduction in basal area and LAI. Overall, all the three metrics were able to detect the high-severity fires, but PACtree demonstrated the strongest capability to quantify vegetation disturbances at low-to-moderate severities.
Figure 5.7 Fire severity metrics derived from LiDAR and Landsat data in comparison with aerial imagery over 5 sample sites. The (a) and (b) columns are NAIP aerial imagery obtained in pre-fire (2012) and post-fire (2014). The (c), (d), and (e) columns are LiDAR derived PACtree, canopy cover change, and tree height change at the individual tree scale. The (f) and (g) columns are PACpixel and RdNBR metrics at 30m spatial resolution. S1-3 includes three sample sites without treatments, and S4-5 includes two sample sites with treatments.

Figure 5.8 Smoothed density plots between: (a) PACtree and changes in canopy cover over individual tree segments in the five sample sites; (b) PACtree and changes in tree height over individual tree segments in the five sample sites; and (c) smoothed density plot between PACpixel and RdNBR over the whole study area.
The quantitative evaluation using field measurements (Figure 5-9) indicated that the PACtree metric showed the strongest linear correlation with field-measured changes in both basal area and LAI, with the $R^2$ at 0.7 and 0.67, respectively. The canopy cover changes also demonstrated significant positive correlations with field measurements of basal area and LAI, but at lower strength, with the $R^2$ at 0.37 and 0.41, respectively. Even lower correlations were observed between tree height changes and field measurements, with $R^2$ values of 0.31 for basal area and 0.33 for LAI. These evaluation results from field measurements were generally consistent with those from sample sites in that our PACtree metrics outperformed the two commonly used LiDAR change metrics; whereas canopy cover was slightly better than tree height.

![Figure 5-9 Correlating fire severity quantified by LiDAR derived changes in CHM, canopy cover, profile area, and Landsat 8 derived dNBR with basal area and leaf area index changes over 162 field plots. The changes are calculated as the difference between pre- and post-fire.](image)

5.3.3 Comparing PACpixel with RdNBR
At the forest plot level, fire severity maps from both PACpixel (Figure 5-7f) and RdNBR (Figure 5-7g) successfully captured the variations among sample sites burned at different severities, particularly between those with and without pre-fire fuel treatments. However, the RdNBR performed poorly in quantifying the variations of fire severities within each site. For example, in the S1 sample site, a majority of the area was burned at high
intensity, but the pre-fire tree biomass varied considerably (as interpreted from aerial imagery). The severities of vegetation disturbances in S1 should vary accordingly. However, the RdNBR map only showed a homogenously high fire severity with extremely large RdNBR values (RdNBR>1000). In contrast, the PACpixel was able to characterize the differences among vegetation disturbances in the heavily burned site.

The scatter plot between values in RdNBR and PACpixel over the entire study area (Figure 5-8c) indicated that RdNBR can easily achieve high values (RdNBR>1000), whereas the PACpixel only indicated low-to-moderate severities (PAC<10), although the relationship between them was significantly positive (R² = 0.32). This result was consistent with the validation using field measurements in Figure 5-9. The RdNBR corresponded positively to the changes in field measurements, but RdNBR values could be extremely large (RdNBR > 1000) in plots burned with slight reductions in basal area (changes in basal area < 10 m²/ha) and LAI (changes in LAI < 1). The R² between RdNBR and field measurements (0.26 for basal area, 0.25 for LAI) were less than 40% of that between PACpixel and field measurements (0.65 for basal area, 0.67 for LAI). Compared to PACtree calculated at individual tree level, the PACpixel showed a slightly lower correlation (R² = 0.65) to changes in basal area, but similar correlation (R² = 0.67) to changes in LAI. Overall, PACpixel was capable of characterizing the variations in fire severity at the forest plot (~900 m²) scale with similar accuracy to individual tree PACtree estimate, and PACpixel was superior to RdNBR in differentiating the variations in biomass loss caused by fires at different severities.

5.4 Discussion
5.4.1 Advantages of PAC in fire severity estimation

The newly proposed PACtree metric outperformed the other two commonly used LiDAR metrics in both mapping fire severity and quantifying forest structure changes. The advantages of PACtree lie in its capability to quantify the tree structure changes from the land surface to tree tops using all the information from changes in LiDAR point densities. Other LiDAR metrics, such as tree height change, merely accounts for changes to tree structure at the top-canopy layer, calculated as the difference of the maximum CHM values in each tree crown. Changes below this top layer are ignored. Vegetation height changes have been used to map fire severity and quantify biomass combustion, but mostly in ecosystems dominated by shrubs or grasses (Wang and Glenn, 2009). The applications of vegetation height change were less successful in forest ecosystems, like mixed-conifer forests in this study. Some of the top canopy layer could either remain unchanged (if fires only burned the sub-canopy), or where dead trees remain standing after fire (which is often the case for 5-20 years). In those cases, the fire-caused biomass change cannot be accurately quantified merely based on tree height changes.

The canopy cover change metric performed similarly to PACtree at detecting high severity fires, but was greatly outperformed by PACtree in forests burned at low severities (Figure 5-7, 5-8, 5-9). LiDAR-derived canopy cover metrics have been widely used in fire severity mapping in many forest ecosystems (Bolton et al. 2015; Kane et al. 2015; Kane et al. 2014b; McCarley et al. 2017). However, since one canopy cover metric can only measure structural change above the given height, such as the 2 m in this study,
it does not capture the biomass combustion below it. This explains why the canopy cover change metric often failed to detect low severity fires that burned over understory or at the ground surface (Figure 5-7, 5-8), as well as the substantially weaker correlations between canopy cover change and field-measured changes in LAI and basal area (Figure 5-9). To overcome this disadvantage, Kane et al. (2014a) evaluated fire induced forest structure changes using canopy cover changes at multiple height strata (e.g., 2m, 8m, 16m, and 32m), and gave a more comprehensive assessment of fire impacts. The PACtree metric, in contrast, is a simple and integrated method that can quantify biomass loss at various height levels and pre-fire forest conditions caused by different fire intensities.

The fire severity maps at the forest plot scale (~900 m²) generated by RdNBR matched well with the aerial imagery burn scars and the PACpixel metric (Figure 5-7). However, the accuracy in quantifying forest structure changes was significantly lower in RdNBR than PACpixel (Figure 5-9). RdNBR, along with many other Landsat-derived spectral indices (dNBR, NBR) have been used to map fire perimeters and general classes of fire severity at regional to national scales (Fernández-García et al. 2018; Miller et al. 2009a; Miller and Thode 2007; Petrakis et al. 2018; Verbyla et al. 2008; White et al. 2017). However, since RdNBR is mainly sensitive to the spectral changes in land surface, its capabilities to indicate forest structure changes are limited. This partly explained the differences between RdNBR and PAC metrics and the fire-type classification results generated from them (Figure 5-5 and 5-7). For example, the fire-caused biomass loss in lands covered by small trees should be significantly lower than those covered by mature trees when both were burned to the ground. However, the spectral differences in Landsat imagery could be less apparent, as both of them turned to bare earth from continuous green vegetation coverage. The difference between them could be marginal in RdNBR derived fire maps, but vary substantially in PACpixel, as shown in S1 in Figure 5-7. The oversensitivity of RdNBR to low severity fire and its limitation for precise quantification of forest structure changes have also been reported in previous studies (French et al. 2008; Verbyla et al. 2008). Verbyla et al. (2008) suggested that more field measurements should be collected for calibration when using RdNBR and dNBR for fire severity mapping over different locations and ecosystems. In contrast, the PACpixel metric, calculated as a direct comparison between pre- and post-fire forest structure characteristics, showed strong capabilities in quantifying forest structure changes caused by diverse fire severities.

Another advantage of PAC metrics lies in its robustness for multiscale applications. The PAC metrics, regardless in individual tree or forest plot scale, demonstrated stronger capability than the commonly used LiDAR metrics and RdNBR in quantifying fire severities at various fire intensities and pre-fire conditions (Figure 5-5, 5-7). The comparisons with field measurements also indicated that the PACtree (tree level) and PACpixel (forest plot level) showed equally strong correlations to changes in LAI and basal area. The consistently strong capability of PAC metrics in quantifying forest structure changes indicates their potential to measure the spatial dimensions of forest disturbance.
5.4.2 Advantages in canopy disturbance mapping and applications

Mapping of fire-caused canopy loss could help inform fire behavior modeling, improve fire suppression effectiveness, and evaluate fire effects (Mitri and Gitas 2006; Rogan and Yool 2001; Scott and Reinhardt 2001). Mitri and Gitas (2006) classified surface from crown fires using spectral indices and texture information derived from fine resolution satellite imagery. This imagery-based method can achieve high accuracies in areas burned with larger patches of crown fires, whereas omission errors were often observed in areas burned with isolated crown fire patches. In this study, we innovatively applied the LiDAR derived PACtree metric to map tree canopy disturbance according to the height level where major tree structural loss occurred. The fire type mapping results in Figure 5-5 indicated that our method identified canopy loss in both large homogeneous patches and small isolated tree crowns, and that the clustering of canopy loss often occurred in areas burned at high intensity. This method could be expanded on in future studies to differentiate crown and surface fires, classified by the stratum of fuel burnt, and thus was more appropriate for fire type mapping.

The initiation of crown fire depends both on the intensity of surface fire and the CBH (Wagner 1977). Due to the lack of detailed information on CBH for individual trees, we adopted the mean CBH estimated at 20m resolution using a regression method. A finer estimation of CBH at individual tree level (Luo et al. 2018) may help improve the classification of fire types. Overall, our fire disturbance type mapping showed that more tree canopy disturbances were observed in forests with pre-fire fuel treatments, which confirmed the success of the fuel treatments in suppressing the spread of crown fires in the American Fire. This PAC-based fire disturbance mapping method can be applied to examine the effect of fire suppression, understand where and how crown fires occur, and provide useful information to mitigate uncontrollable fire in the future.

5.4.3 Limitations and future studies

The LiDAR-based PAC metrics proposed in this study showed strong capabilities to quantify fire severity and map fire types in forests, but three primary deficiencies were identified. First, this method requires acquisitions of both pre- and post-fire LiDAR data with consistent, good quality, particularly for individual tree analysis. The high cost of airborne LiDAR scans could restrict its broader application. A new airborne platform, UAV-borne (Unmanned Aerial Vehicle) or mini-UAV-borne LiDAR can significantly reduce the LiDAR data acquisition cost compared to the traditional airborne platform, and make the periodical acquisition of LiDAR data feasible (Lin et al. 2011; Wallace et al. 2012). With a reduced cost in LiDAR data acquisition, PAC metrics could be applied to forest disturbances other than forest fires, such as wind, insect attack, timber harvesting, and fuel treatment.

Second, the difference in pre- and post-fire LiDAR scans, linked to each flight parameters and weather conditions, can introduce uncertainties to PAC estimation. For example, some tree-crown segments observed a PACtree value as small as -20, indicating misinformation about the large increase in tree biomass (Figure 5-5). Such problems were more severe and common at the individual tree scale (PACtree) rather than in forest plot-scale (PACpixel). Small trees located either at the edges of LiDAR flight lines, or
fully blocked by the neighboring large trees, might not be scanned completely in the pre-fire scans, but fully exposed to the sensor in the post-fire LiDAR scans. The difference in PACtree detected in such cases were not necessarily related to the tree structure changes, but mainly induced by the mismatch in LiDAR scans and/or errors in tree crown segmentation. Many new algorithms have been developed to improve the accuracy of individual tree segmentation (Li et al. 2012; Lu et al. 2014; Marinelli et al. 2018; Paris et al. 2016), but the watershed method was adopted in this study because of its efficiency in large-scale applications. More studies are needed to fully evaluate the uncertainties induced by mismatch in LiDAR scans and individual tree segmentation on the applications of PACtree for fire severity mapping and quantification.

Lastly, the lack of spectral information limits LiDAR-based methods to only describing structural changes. PAC metrics alone can neither distinguish live biomass from dead, nor present the changes in leaf greenness, species composition, or other biochemical attributes. However, these changes are also important for fire severity assessments in terms of the tree mortality rates and other ecological losses (Karavani et al. 2018; Meng et al. 2018; Romero Ramirez et al. 2018). More studies are needed to explore the potential of combining LiDAR and optical remote sensing in assessing fire severity in both structural and bio-chemical attributes.

5.5 Conclusion
Accurate assessments of fire severity are essential for understanding and evaluating the ecological and economic impacts of fires. The multi-temporal LiDAR based profile area change (PAC) metrics introduced in this study demonstrated strong capabilities to quantify fire severity at the individual tree to forest plot scales. Evaluated by field measurements and high-resolution aerial imagery, our method outperformed other commonly used LiDAR metrics, such as tree height and canopy cover, in quantifying the overall biomass loss, both at overstory and understory, caused by fires at different severities over forests with diverse pre-fire densities. Moreover, using the PACtree metric, we successfully mapped fire-caused disturbance types, as canopy and sub-canopy loss, for individual trees. The spatial pattern of the various fire severities and types can better illustrate the fire spread mechanisms and provide useful information for fire modeling, impact assessment, as well as the design of fire control and restoration strategies. At the forest plot scale, our newly proposed PACpixel metric is superior to Landsat-8 imagery derived RdNBR in capturing structure changes at higher accuracy. Overall, PAC metrics can not only be directly applied for fire assessment at the individual tree level, but also used as validation or reference data for satellite imagery based regional studies when the full coverage of pre- and post-fire LiDAR data are unavailable. With the increasing spatial and temporal coverage of airborne LiDAR data, our PAC metrics have promising potential to be applied to assess many other forest disturbances beyond fires and in broader areas.
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Chapter 6 Conclusions

This dissertation focused on applying LiDAR data to map forest structural parameters, quantify their changes, and validate remote sensing imagery-based forest structural estimates. Using two Sierra Nevada forests as the study area, we demonstrated the advantages of LiDAR data in forest mapping and monitoring at individual tree, forest plot, and forest stand scales. We also evaluated the effectiveness and uncertainties of remote sensing imagery in regional scale forest applications.

Chapter 2 provided the first comprehensive comparison of canopy cover estimation between LiDAR data, field measurements, and high resolution imagery. The accuracy of LiDAR-based canopy cover estimates was marginally impacted by the estimation algorithm, but sensitive to LiDAR point density and off-nadir scan angles. LiDAR data obtained at 1 point/m² within the scan angle of 12° were sufficient for accurate canopy cover estimation. At forest stand scale, high resolution imagery was able to identify tree crown with 93% overall accuracy when using support vector machine classifier. At 30 m resolution, the canopy cover estimates from the high resolution imagery were comparable to LiDAR-based estimates in most areas with the R²>0.52. However, high resolution imagery tended to overestimate canopy cover in sparse forests and underestimate it in dense forest. These biases were more salient with aerial photos than satellite imagery. These comparison results can provide some practical guidance for canopy cover estimation in the Sierra Nevada forests, regarding the design of data collection and estimation method.

Chapter 3 demonstrated that LiDAR data can improve forest growth model by precisely quantifying the tree growth and competition indices, and comprehensively analyzing the relationships between tree growth and controlling factors from individual tree to forest stand scales. Our results indicated that individual tree growth in Sierra Nevada forests was positively related to their original sizes and negatively impacted by competition from the neighboring trees. These relationships were strongest in tree volume growth and weakest in tree height changes. At the forest-stand level, the tree volume growth was still highly related to original sizes, but growth in height and crown size were mostly controlled by water and space availability. This study showed the strong capability of LiDAR as a valuable data to update the tree growth models as an auxiliary data, if not replacement, for in-situ forest inventory, and provided resourceful tools for forest monitoring, modeling, and management.

Chapter 4 evaluated the uncertainties of using Landsat imagery-derived vegetation indices to quantify forest fuel treatments, by comparing the disturbance estimates from vegetation indices with the references derived from LiDAR and field measurements. Results show that the four widely used vegetation indices performed equally well in quantifying canopy cover changes, but much weaker in aboveground biomass (AGB) reduction. A detailed analysis on the widely used vegetation index, NDVI, showed that uncertainties were mainly resulted from the saturation and over-sensitivity of NDVI in representing AGB changes in extremely dense and sparse forests. NDVI was more applicable to quantify AGB losses in Sierra Nevada forests with mid-density (100 to 700 Mg/ha). Moreover, the study also indicated that understory treatments, in which disturbances mainly occurred below 10m, were difficult to be quantified from vegetation
indices. These results suggested that when relating Landsat imagery-derived vegetation indices to AGB changes, researchers and managers should be cautious about their uncertainties in extremely dense or sparse forests, especially when treatments were mainly conducted in understory.

Chapter 5 introduced a new LiDAR point-based method for assessing fire severity at both individual tree and forest plot scales. This method addressed the limitations of commonly used LiDAR metrics, such as canopy cover and tree height, in quantifying low severity burns at understory or ground surface. At the forest plot scale, our method outperformed Landsat imagery-derived index in characterizing the fine-scale variations in fire severities. Validation from field measurements showed that our method was a stronger indicator of fire-induced forest structural loss in basal area and leaf area index, \( R^2 > 0.67 \) than commonly used LiDAR metrics and Landsat imagery-derived vegetation index \( R^2 \leq 0.41 \). Our method can be used to help forest managers evaluate fire-induced environmental and economic loss and provide useful information for post-fire restoration.

Overall, this dissertation illustrated the capability of LiDAR data in quantifying forest structure and their change induced by forest growth and disturbances. However, the four studies in this dissertation mainly focused on the conifer-dominated forests in the Sierra Nevada. With the development of LiDAR technologies, the spatial coverage of LiDAR data is increasing dramatically. We need to extend our studies to other forest ecosystems, so that we can evaluate our LiDAR-based methods for a spectrum of tree species and environmental conditions. Moreover, as LiDAR data are accumulated over time, studies on monitoring tree growth and vegetation recovery over longer time are becoming more applicable in the future. Finally, this study only assessed the performance of optical remote sensing data against LiDAR-based estimates. How to combine of these two datasets for forest monitoring and modeling could be another study question to investigate in the near future.
Appendix A

Table A1 A summary of the selected 17 study sites information, including site area, elevation, slope, topographic wetness index (TWI), canopy cover, tree height, and dominant tree species.

<table>
<thead>
<tr>
<th>Study area</th>
<th>Site ID</th>
<th>Site area, km²</th>
<th>Terrain conditions</th>
<th>Vegetation conditions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td>Elevation, m</td>
<td>Slope, degree</td>
</tr>
<tr>
<td>Last Chance</td>
<td>L1</td>
<td>0.22</td>
<td>940.8</td>
<td>30.1</td>
</tr>
<tr>
<td></td>
<td>L2</td>
<td>0.31</td>
<td>911.8</td>
<td>43.9</td>
</tr>
<tr>
<td></td>
<td>L3</td>
<td>0.25</td>
<td>1449.4</td>
<td>5.2</td>
</tr>
<tr>
<td></td>
<td>L4</td>
<td>0.46</td>
<td>1481.6</td>
<td>4.7</td>
</tr>
<tr>
<td></td>
<td>L5</td>
<td>0.44</td>
<td>1695.5</td>
<td>15.6</td>
</tr>
<tr>
<td></td>
<td>L6</td>
<td>0.47</td>
<td>1577.1</td>
<td>17.5</td>
</tr>
<tr>
<td></td>
<td>L7</td>
<td>0.45</td>
<td>1719.3</td>
<td>27.9</td>
</tr>
<tr>
<td></td>
<td>L8</td>
<td>0.36</td>
<td>2104.3</td>
<td>11.6</td>
</tr>
<tr>
<td>Sugar Pine</td>
<td>S1</td>
<td>0.25</td>
<td>983.8</td>
<td>11.4</td>
</tr>
<tr>
<td></td>
<td>S2</td>
<td>0.23</td>
<td>1237.3</td>
<td>12.3</td>
</tr>
<tr>
<td></td>
<td>S3</td>
<td>0.31</td>
<td>1327.4</td>
<td>22.3</td>
</tr>
<tr>
<td></td>
<td>S4</td>
<td>0.35</td>
<td>1721.9</td>
<td>25.6</td>
</tr>
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<td></td>
<td>S5</td>
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<td>17.2</td>
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<tr>
<td></td>
<td>S6</td>
<td>0.55</td>
<td>1639.0</td>
<td>13.1</td>
</tr>
<tr>
<td></td>
<td>S7</td>
<td>0.54</td>
<td>2020.3</td>
<td>19.7</td>
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<tr>
<td></td>
<td>S8</td>
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<td>2218.8</td>
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<tr>
<td></td>
<td>S9</td>
<td>0.51</td>
<td>2451.3</td>
<td>17.5</td>
</tr>
</tbody>
</table>

* MHW, PPN, WFR, RFR and SMC represent Montane Hardwood, ponderosa pine (Pinus ponderosa) forest, white fir (Abies concolor) forest, red fir (Pseudotsuga menziesii) forest, Sierra Mixed Conifer.

Table A2 A summary of the topographic information (including the mean, minimum and maximum values of elevation, slope and TWI) of field measurements.

<table>
<thead>
<tr>
<th>Study area</th>
<th>Plot number</th>
<th>Elevation, m</th>
<th>Slope, degree</th>
<th>TWI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>min</td>
<td>mean</td>
<td>max</td>
</tr>
<tr>
<td>Last Chance</td>
<td>35</td>
<td>1430.</td>
<td>1654.</td>
<td>2088.</td>
</tr>
<tr>
<td>Sugar Pine</td>
<td>26</td>
<td>973.6</td>
<td>1616.</td>
<td>2071.</td>
</tr>
</tbody>
</table>

* MHW, PPN, WFR, RFR and SMC represent Montane Hardwood, ponderosa pine (Pinus ponderosa) forest, white fir (Abies concolor) forest, red fir (Pseudotsuga menziesii) forest, Sierra Mixed Conifer.
Table A3 A summary of the vegetation conditions (including the mean, minimum and maximum values of canopy cover, tree height and tree number by species) of field measurements.

<table>
<thead>
<tr>
<th>Study area</th>
<th>Plot number</th>
<th>Canopy cover, %</th>
<th>Tree height, m</th>
<th>Tree number by species</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>mi</td>
<td>mea</td>
<td>ma</td>
</tr>
<tr>
<td>Last Chance</td>
<td>35</td>
<td>41</td>
<td>67</td>
<td>83</td>
</tr>
<tr>
<td>Sugar Pine</td>
<td>26</td>
<td>43</td>
<td>64</td>
<td>81</td>
</tr>
</tbody>
</table>

Appendix B

Tree Height Growth
**Figure B1** The summary of adjusted $R^2$ of multi-variable linear regression models for individual tree growth in height, crown area, crown volume. The model was generated from all combination of dependent variables from original tree sizes ($H_1$, $A_1$, and $V_1$), competition indices ($CC$, $CC66$, and $CCH_T$), forest density ($NNI$), and terrain conditions ($DEM$, $Slope$, $GI$, and $TWI$). The adjusted $R^2$ are generated from the “leaps” package in R language.

**Appendix C**

**Akaike's An Information Criterion (AIC) model selection**

The AIC was used to assist the selection of multi-variable linear regression models for individual tree growth in height, crown area, crown volume. We used the stepAIC function in the “MASS” R package to revise the initial model in “both” direction. Results indicated all the 12 variables should include in the growth model for tree height, only $CCH_T$, $CCH_T$ and $TN$ should be excluded from the growth models for crown area and volume, respectively. This analysis provides a reference for model selection, the final models were generated mainly based on the adjusted $R^2$ and conciseness of the model.

Initial tree height growth model (fitH1):
- AIC: 167581.8;
- $dH \sim H_1 + A_1 + V_1 + CC + CC66 + CCH_T + TN + NNI + Slope + DEM + GI + TWI$

Final tree height growth model (fitH2):
- AIC: 167581.8;
- $dH \sim H_1 + A_1 + V_1 + CC + CC66 + CCH_T + TN + NNI + Slope + DEM + GI + TWI$

Initial crown area growth model (fitA1):
- AIC: 167581.8;
- $dA \sim H_1 + A_1 + V_1 + CC + CC66 + CCH_T + TN + NNI + Slope + DEM + GI + TWI$

Final crown area growth model (fitA2):
- AIC: 167581.2;
- $dA \sim H_1 + A_1 + V_1 + CC + CC66 + TN + NNI + Slope + DEM + GI + TWI$

Initial crown volume growth model (fitV1):
- AIC: 138600.1;
- $dV \sim H_1 + A_1 + V_1 + CC + CC66 + CCH_T + TN + NNI + Slope + DEM + GI + TWI$

Final crown volume growth model (fitV2):
- AIC: 138598.3;
- $dA \sim H_1 + A_1 + V_1 + CC + CC66 + NNI + Slope + DEM + GI + TWI$