Forest Biomass Change Detection Using Lidar in the Pacific Northwest
Master of GIS Capstone Proposal
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Background

At the 2005 United Nations meeting on the Framework Convention on Climate Change (UNFCCC), a program for Reducing Emissions from Deforestation and Forest Degradation (REDD) was instituted. The aim was for countries and participants to be rewarded for efforts to reduce greenhouse gas emissions associated with forest ecosystems. Refinements of the REDD concept in 2008 refer to the sustainable management of forests and the conservation and enhancement of forest carbon stocks (UNFCCC, 2008). In 2010, participating countries were requested to establish national forest monitoring systems (NFMS). Recommendations included approaches in which carbon stock measurements were made using a combination of remote sensing and ground based observations (UNFCCC, 2010).

The needs of the REDD program present a challenge to the remote sensing community to develop methods for characterizing initial carbon stocks, as well as changes in carbon stocks, over large domains. In order to measure the carbon contained in a forest, the above ground biomass (AGB) is estimated and multiplied by 0.5. This equation is standard in the forest industry (Blackard, 2008, Hoover, 2008). Traditional methods of estimating AGB include establishing a network of forest plots that, in theory, samples the spatial heterogeneity in forest condition and forest biomass over the domain of interest. Field data collection can incur substantial cost, so it is important to only obtain the number of samples needed to represent the mix of younger and older growth of the trees in the area of interest. Once the samples are taken, an average is calculated over the study area. A major challenge to this approach is obtaining the appropriate number of sample plots to ensure an accurate representation of the spatial heterogeneity of the full area. Large areas offer an even greater challenge in that even very comprehensive field measurement campaigns cover only small portions of any landscape. Understanding landscape-scale and larger patterns relies upon extending point-based field measurements, which can be accomplished by integrating and scaling them with remote sensing (Hoover, 2008 p.180).

In contrast to the traditional sampling approaches, remote sensing now offers the opportunity for continuous coverage over large domains, which can reduce the uncertainty with respect to sampling error caused from relying on field measurements alone (Hoover, 2008). Plot measurements are matched with the remote sensing data and averages can be interpolated across a grid, providing less room for error and more comprehensive results. Remote sensing has thus begun to be used in combination with plot scale measurements (Gibbs et al. 2007, Angelsen et. al., 2009, Asner et al., 2014).

Previous Research

Satellite data has been used in regional and national biomass models. Source platforms include the Shuttle Radar Topography Mission (SRTM) (Kellndorfer et al. 2000), Landsat (Powell et al. 2010) and the Moderate-resolution Imaging Spectrometer (MODIS) (Blackard et al. 2008). The resulting gridded biomass data sets have a spatial resolution ranging from 30 m to 1 km. While satellite imagery is economical in comparison to lidar (light detection and ranging), a 3D point cloud offers a better depiction of the canopy structure, enabling analysts to determine tree height and geometry.

A growing body of research shows that airborne lidar is one of the most promising methods for monitoring above ground forest carbon stocks for the REDD program (Mascaro et al., 2012). A regional approach for estimating aboveground biomass is to develop a generalized relationship between forest canopy characteristics from lidar and biomass from plot measurements (Lefsky et. al, 2005, Seidl et al., 2012). This method has led to efforts to detect the changes in biomass over an area, which is important for monitoring carbon stocks over time (Næsset et al., 2013).

In the absence of a reliable method to extract the number of stems in a forested area, lidar biomass studies often rely upon a plot level or "crown-distributed" approach, involving the creation of a grid similar to those used in satellite-based studies. In contrast, a tree level or "stem-localized" approach places biomass in space according to the x and y coordinates of the center of each stem, similar to a field inventory. Mapping biomass at tree-level is beginning to offer improved possibilities for more direct validation of biomass estimates from past studies, as individual tree metrics can significantly improve AGB estimation because they directly take into account stand density (Duncanson et al., 2015, Turner et al., 2016).

Tree level analysis is limited to lidar data sets that are rated QL1 (USGS, 2014) or better because the pulse density must be strong enough to detect individual tree tops, versus the canopy as a feature that cannot be further distinguishable (White Paper, 2013). It also requires a way to segment the lidar point cloud into individual trees. Automated methods to segment vegetation and delineate tree crowns from a lidar point cloud result in tree height and crown area (Gleason and Jungho, 2012, Li et al., 2012), which can be applied to a linear allometric equation to compare plot data, predicting the biomass contained in each tree (Bortolot & Wynne, 2005, Zhao, et al., 2012, Hailemariam et al., 2015).

Project Objectives

This study will test a method for measuring AGB at two points in time using airborne lidar collected in the Coast Range Mountains in western Oregon. Tree heights and crown areas will be determined through point cloud segmentation algorithms written by senior scientists at Quantum Spatial. Tree level biomass will then be calculated for a 2012 dataset with an equation derived by Andrew Gray of the US Forest Service using the Forest Inventory Analysis program data (Waddell and Hiserote, 2005). The model relies on allometric relationships in trees located in plots of similar forested areas in the region. Stand data from the US FIA program was used as ground truth. The methodology will then be repeated on a separate lidar data set collected over the same study area 6 years earlier. The two biomass measurements will be compared to determine the average biomass change per year over the study area.

The specific objectives are as follows:

- Develop and test a new method for estimating above ground biomass using LiDAR and FIA plot data.
- Detect the change in forest coverage and biomass over a 6 year period.
- Compare results to past studies that used other methods to estimate biomass: NBCD (Kellndorfer et. al., 2010), USFS (Blackard et. al., 2008) and Biome-BGC (Turner et al., 2011).

Study Area

The area of interest covers 52.76 km^2 of land located in northwest Oregon in Yamhill County, with small portions in Tillamook and Washington counties (Figure 1). It also includes the southern portion of Barney reservoir. The area is comprised of actively managed, temperate coniferous forest. It is classified as Coast Range in the Level III Ecoregions of the United States (Omernik, 1987). The Oregon Watershed Assessment Manual classifies the region as "Volcanics," with steep slopes of basalt composition. The area has heavy precipitation resulting from moist air masses moving off the Pacific Ocean on to land, but minimal snowfall. Large wildfires are not common in this ecoregion due to coastal fog influence and fire suppression techniques, resulting in high stand densities. Common tree species include hardwoods like red alder and conifers including: western hemlock, Sitka spruce, western red cedar, and Douglas fir. The land use in the study area is primarily forestry-related activities.

The study area was chosen in part because there are two lidar data sets covering the area, collected six years apart. This is a valuable data set because it allows for a change detection of biomass across the six-year period. It also adds value to the examination of the technique of estimating biomass on an individual tree level. Because the study area is an actively managed forest, the portions that were newly harvested and replanted during this timeframe offer a good opportunity to show growth. In contrast, a purely old growth forest may not necessarily show measurable change over six years. Past logging has had a greater influence on landscape above-ground biomass than past wildfires (Zald et al., 2016).

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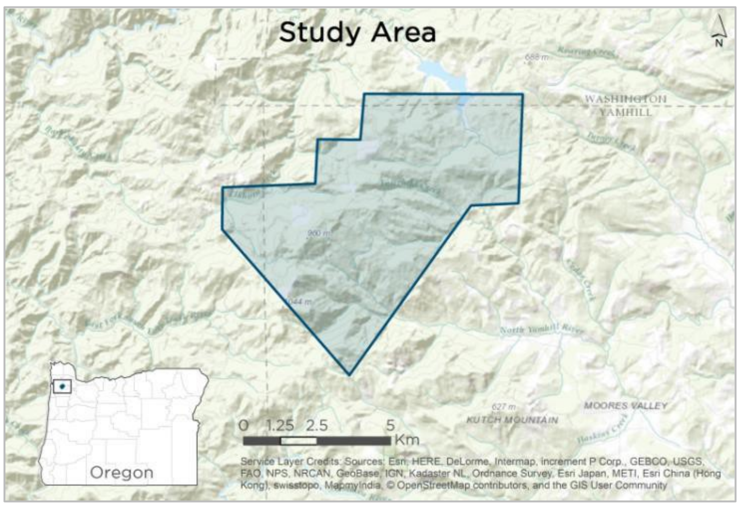

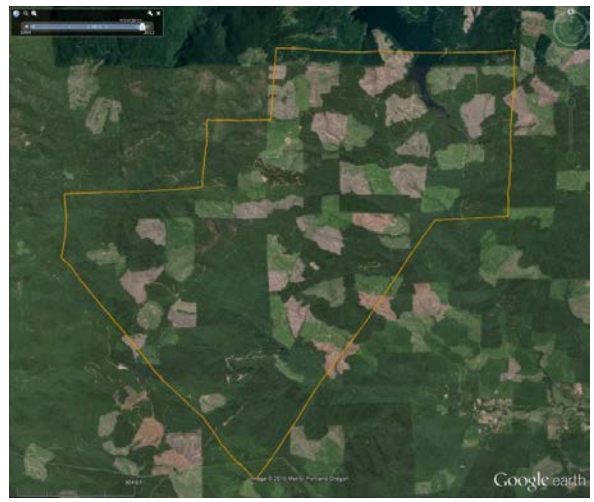

Figure 1. Study Area terrain and imagery from 2012

Data and Methods

Lidar data from 2006 and 2012 will be used in the biomass change detection analysis. The metadata corresponding to each original data set is provided in Table 1.

T*able 1. Lidar data sets to be used in the biomass change detection analysis.*

Data Set:	**2006 Lidar**	**2012 Lidar**
Acquisition Date:	Feb. 6, 2006 – Feb. 7, 2006	Sept. 23, 2012 – Oct. 4, 2012
Sensor:	Optech ALTM 3100	Leica ALS60
Platform:	Cessna Caravan 208	Cessna Caravan 208
Coordinate System:	UTM10, Meters	UTM10, Meters
Target Density:	8 pulses/m^2	8 pulses/m^2
LiDAR Accuracy:	0.03 m RMSEz	0.04 m RMSEz
File Format:	LAS 1.2	LAS 1.2
Provider:	Watershed Sciences, Inc.	Watershed Sciences, Inc.

The analysis will be performed using airborne lidar data collected in 2006 and 2012, covering an approximately 53 square kilometer portion of the Coast Range Mountains in western Oregon. For this study, tree heights and crown areas of each individual tree will be determined through point cloud segmentation algorithms. In addition, tree-level biomass will be calculated using an equation derived from allometric relationships in trees located in plots of similar forested areas in the region.

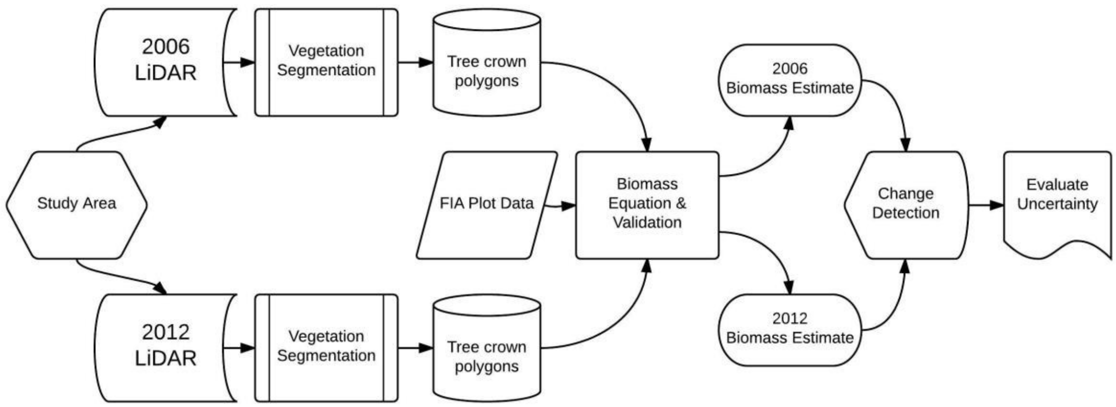

Figure 2. Workflow Diagram

Step 1: Prepare lidar point cloud
At the time of collection, the lidar data sets underwent calibration techniques using aircraft-based kinematic GPS and static ground GPS to ensure seamless alignment of the flightlines. For this study, vegetation will be classified at or above 2m from the ground.

Step 2: Vegetation Segmentation: Segmentation will be applied to the classified lidar data sets using automated tree segmentation tools written by senior scientists at Quantum Spatial, Inc. The tools apply point cloud geometry, spatial distribution patterns, and neighborhood analysis to delineate and attribute individual trees. The algorithms take advantage of the relative spacing between trees; specifically the fact that the horizontal spacing between trees is larger at the top and smaller at the bottom (Li et. al., 2012).

Every estimated tree is assigned a unique ID, crown area, treetop height and coordinates. The analysis will include data within 30 m outside of the study area to ensure periphery vegetation is fully accounted for. Estimated tree crowns smaller than $1m^2$ will be excluded from the analysis, as they most often represent small shrubs or grasses.

Step 3: Allometric equation for AGB
The AGB will be calculated by reference to data from the U.S. Forest Service's Forest Inventory and Analysis (FIA) Program. Andrew Gray, a Research Ecologist and FIA analyst for the Forest Service, designed a model to estimate live tree biomass at the tree level, based on tree height and crown area (Gray, 2015). Tree-level observations from FIA Program plot data was drawn from plots in the EPA level III Coast Range ecoregion (Omernik 1987) in Oregon, north of Douglas County. The allometric biomass equation was developed by Gray through a stepwise regression on simple and quadratic terms, and provided specifically for this study via personal communication. The steps were as follows:

Data compilation

1. Selected FIA plots in the EPA level III Coast Range ecoregion that were north of Douglas County.
2. Only used forested conditions that covered at least 75% of the plot area and were either in a conifer forest type or classified as nonstocked (<10% stocking in tally trees and seedlings). N=506 plots.
3. Calculated above-ground biomass for live trees which included all above-ground wood plus foliage. N=14,709 trees.
4. Calculated crown area for each live tree using equations in the Forest Vegetation Simulator (FVS) that estimate crown diameter from DBH (and other variables, depending on the equation) and assuming a circular crown.
5. Calculated per- and crown area using the trees-per hectare values of biomass -hectare (TPH) expansion for each tree's plot size and the proportion of the plot in the condition and summed them to the condition. Used the FVS assumption for random crown overlap to adjust canopy cover (unadjusted percent cover ranges up to 350%).
6. Calculated mean tree height for dominant and co-dominant trees on each condition, weighted by TPH.

Equation development

1. Scatter-plot of tree biomass with height and crown area indicated some curvature to the relationship (Fig 3).
2. Started with stepwise regression of biomass on simple and quadratic terms. All terms were significant, R^2=0.96, and the Mallow's Cp criteria indicated using all 4 terms was fine. Equation was run without an intercept term (i.e., intercept =0). The final equation was:

$$\textbf{AGB (kg/m}^2\textbf{) =} (-55.53 * H) + (2.386 * H^2) + (5.062 * SqM) + (0.4238 * SqM^2)$$

AGB = Above Ground Biomass
H = Tree Height (feet)
SqM = Crown Area (square meters)

Step 4: Application

The AGB equation will be applied to the lidar-derived trees (i.e. to the height and crown area of estimated trees) delineated from the lidar data sets, and the total biomass for the study area will be determined for each year. The amount of above ground carbon will then be estimated by multiplying the biomass by 0.5. This biomass to carbon relationship is standard in the forest industry, as described in Blackard et al. (2008).

Step 4: Evaluate Uncertainty

The accuracy of each lidar data set was measured against the GPS benchmarks and real-time kinematic ground control points that were collected during data acquisition. Vertical error of the point clouds were measured at 0.03m RMSE for the 2006 data set and 0.04m RMSE for the 2012 data set.

To assess the accuracy of vegetation segmentation results, it is ideal to have field measurements to use as ground truth. However, the tree or plot locations would need to be very well rectified, usually requiring manual adjustment to the locations regardless of the GPS used to locate them, as satellite masking from the canopy is too significant to locate any one tree with GPS alone. Past projects at Quantum Spatial have yielded R-squared values of ~0.80 when predicting biomass using this method. In the absence of XY locations of the FIA data, this study will rely on a visual comparison to aerial photography.

The accuracy of the biomass equation was tested using Statistical Analysis System (SAS). Improvement in the regression model results in proportional increases in R-squared. Adjusted R-squared incorporates the model's degrees in freedom for equations that have more than one predictor. It increases as predictors are added, if the increase in model fit is worthwhile. The adjusted R-squared is interpreted as the proportion of total variance that is explained by the model. The biomass equation resulted in an adjusted R-squared value of 0.9556.

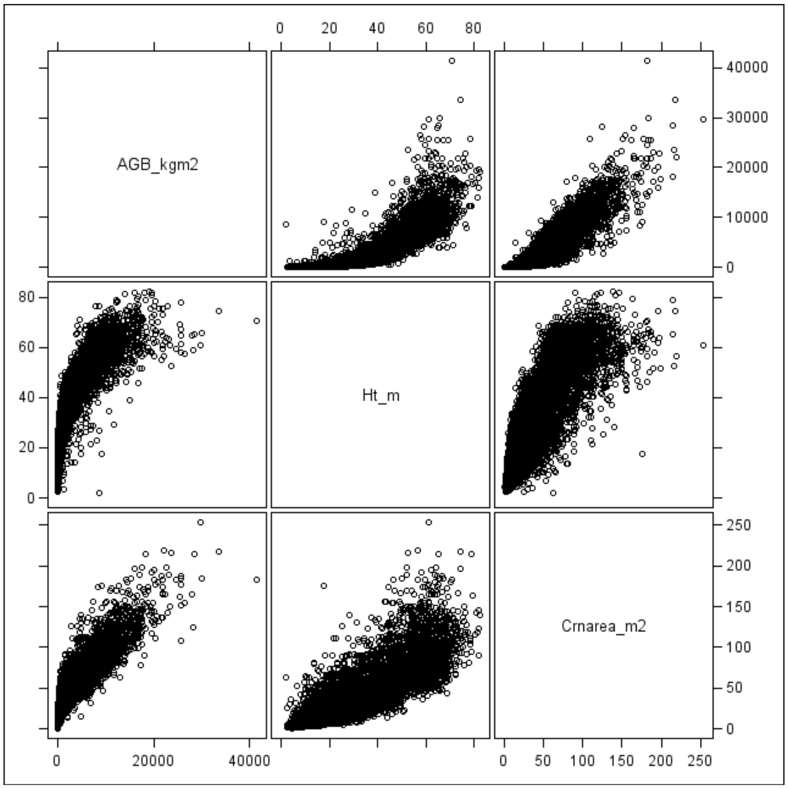

Figure 3. Tree scatter-plot of biomass with height and crown area.

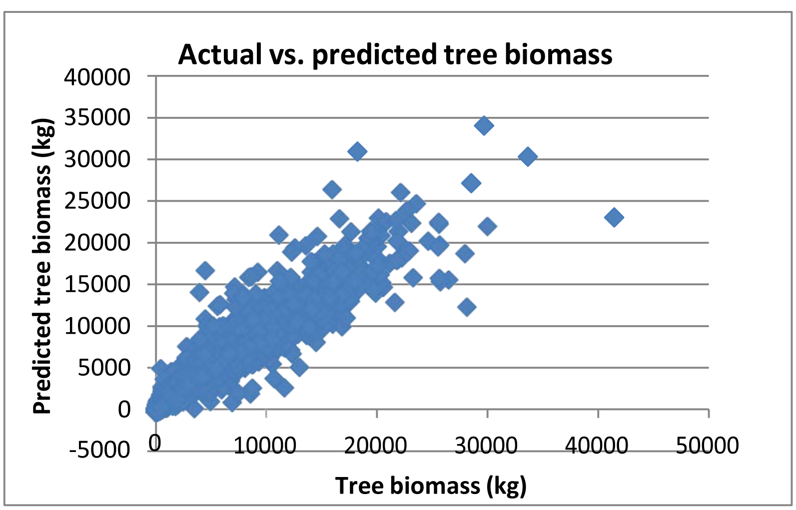

Figure 4. Actual vs. Predicted tree biomass for FIA data.

Preliminary Results

Initial results indicate that in 2012 the area of interest contained 32.59 kg/m^2 of above ground biomass (ABG) in approximately 800,000 trees. The mean tree height was 25.9 m, mean crown area was 38.4 m^2 and mean biomass per tree was 2,142 kg.

Table 2. Biomass, tree height and crown area in 2012.

	Tree Height (meters)	Crown Area (square meters)	Biomass (kg)
Mean	25.9	38.4	2,142.4
Total	20,813,978	30,839,145	1,682,410,981

Table 3. Results of current study compared to previous studies using other methods.

Study	Source Data / Year	Biomass	Carbon
Lidar Analysis (Current Study)	High resolution LiDAR (2012)	32.59 kg/m^2	16.3 kgC/m^{-2}
NBCD (Kellndorfer, 2010)	Landsat (1999-2001), NLCD (2001), SRTM Radar (2000), med res LiDAR (2003), FIA	31.2 kg/m^2	15.6 kgC/m^{-2}
USFS (Blackard, 2008)	MODIS 250m (2001), NCLD (2001), FIA	25.2 kg/m^2	12.6 kgC/m^{-2}
Biome-BGC (Turner, 2011)	Landsat (1985-2010), NCLD (2001), FIA	32.4 kg/m^2	16.2 kgC/m^{-2}

In an actively managed forest in the Pacific Northwest, average biomass is expected to remain steady over time. This assumption relies on the idea that certain plots are harvested while others are replanted and allowed to grow. Judging by imagery analysis alone, vegetation coverage appears higher in 2000, which was when the satellite data for the NBCD and USFS studies was acquired. In addition, Global Forest Watch reports that more forest area was lost than gained in this region between 2001 and 2014 (Global, 2015). However, when focusing on non-harvested areas it is likely that biomass was gained due to normal growth. A lidar-based study in conifer forests of the Northern Rocky Mountains detected an average biomass increase over 6 years of 0.24 kgC m^{-2} yr^{-1} for a non-harvested area (Spangler and Vierling, 2011).

Assuming that there was less biomass each year when averaged over the study area, the current study using 2012 data should have resulted in a lower average biomass than the previous studies. However, it resulted in the highest average out of all the studies. This may indicate that the biomass calculation or the vegetation segmentation algorithms could benefit from further refinement. Another possible explanation is that since the previous studies used lower resolution data they captured a lower amount of ABG than actually existed at the time. Repeating the analysis with the 2006 lidar data should provide further insight into these possibilities.

Timeline

After presenting the proposal to the Penn State World Campus Department of GIS, the analysis will be run on the 2006 lidar data set and the change in biomass will be detected. The write-up for submission to a technical journal will occur during the fall of 2016.

Table 4. Planed timeline for study completion.

Capstone Timeline	**Apr-16**	**May-16**	**Jun-16**	**Jul-16**	**Aug-16**	**Sep-16**	**Oct-16**	**Nov-16**
Run biomass analysis on 2012 lidar								
Proposal write up and presentation								
Run biomass analysis on 2006 lidar								
Change detection								
Accuracy reporting								
Write-up for journal submission								
Submit to journal								
Conference presentation								

Summary

The method used in this study takes advantage of previously collected forest inventory plot data and remote sensing data. The preliminary results demonstrate that 8ppsm LiDAR paired with FIA plot data can support biomass measurements at the individual tree level. The preliminary results also fall in line with other studies covering the same area. One challenge to wide application of this method is the cost and limited availability of high-resolution lidar. However, several states have publicly available lidar data covering large areas that can be downloaded at no cost from a web portal, such as the Oregon Lidar Consortium and the Puget Sound Lidar Consortium.

Customers or end users of this analysis may include forestry companies, urban planning (e.g. Tree City USA), government agencies and environmental organizations such as the UN-REDD program. The main benefit of using the technique in this study is that it requires few inputs and delivers results with high spatial resolution. Access to accurate biomass measurements are critical components in quantifying carbon stocks and sequestration rates, assessing potential impacts due to climate change, locating bio-energy processing plants, and mapping and planning fuel treatments (Hailemariam et al., 2015).

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