CHAPTER 7

Conclusions

7.1. Conclusions

In this section I present a summary of the conclusions that can be drawn from this research. A comparison of the inventory methods is presented first followed by a discussion of the relevance of variable plot approaches to aerial inventory data and alternate approaches to the utilization of tree data derived from the LiDAR analysis. Further, commentary is made on the efficacy of the crown model employed. Future research directions are then identified and finally, a short summary places the results of the analysis in the context established in Chapter 1.

7.1.0.1. *Comparison of inventory methods.* The results of the analysis presented in the previous sections indicate that the methodology employed for detecting and delineating trees in dense, mixed-species stands on variable terrain tracks field based inventory methods for tree count and basal area estimation (see Tables 6.5 and 6.4). The method tested consistently results in fewer trees identified within the variable plot radius than produced from field survey. The small difference between average basal area estimated by the two methods indicates that though some trees are not identified using the LiDAR method, they tend to be smaller trees and contribute less to the aggregate statistics. Missing smaller trees is to be expected, as identification of individual trees is initiated using LM filtering. As a result, if the apex of a tree crown does not extend vertically above the surrounding canopy, it will not be detected. Approaches to resolving this are addressed in Section 7.3.

7.1.0.2. *Aerial data and variable plot methods.* This results indicate that the modified RANSAC approach is effective for use in replicating field-based variable plot inventory methods using aerial LiDAR if a regression derived from field data between tree height and DBH can be applied. Tree detection is accomplished without the use of regression models, and is based only on the distribution of points in three dimensional space.

However, to establish tree volumes using DBH, and to determine tree membership in variable plots, the regression relationship is needed. Individual tree detection and delineation was conducted for all trees in the study area from wall-to-wall coverage provided by the flight survey. The replication of a variable plot method was conducted in this research context so that the results could be compared with field methods. In practice, however, the use of variable radius plots with wall-to-wall survey data does not make sense when conduction a forest inventory using LiDAR. The variable plot method was devised to reduce the time required in the field to collect results within a tolerable error bound. Though variable plot methods increase the efficiency of field surveying compared with fixed plot approaches, as with all plot-based methods, total cost closely relates with total area surveyed. In contrast, the incremental cost of additional area surveyed with aerial LiDAR is small compared with the fixed costs associated with aircraft and equipment. Considering these factors, LiDAR inventory methods may be best suited where the amortization of the large fixed cost over the hectares surveyed in \$/ha is less than or equal to the \$/ha for field based methods.

7.1.0.3. *Crown model.* Critical to the adaptation of the RANSAC method to this research context are the modifications made to the shape model used for crown fitting. The equation used (5.4,5.5) enables rapid determination of a given points membership in a tree crown consensus set. The simplicity of the crown surface approach means that large amounts of data can be processed in a relatively short amount of time. The speed of processing indicates that this method shows promise for application to large scale forest inventory applications.

insert summary of processing time stats

7.2. Summary of Conclusions

This research gives insight into the problem of generating tree-based forest inventory from aerial LiDAR data across heterogeneous forest stands (management history, species mix, site characteristics). In this section, a summary of the contributions that this research makes to the body of research on the subject is presented.

7.2.0.4. *Modified RANSAC.* This study uses a modified RANSAC approach. Classical RANSAC selects randomly all points from the input data necessary to the solution of the model used for shape fitting. In the case of the equation used in this research, two points are required. The approach presented here deviates from the classical form by selecting one of the two necessary points based on LM filtering. Thus, processing time is reduced in testing unlikely models. Further, we found that the use of a pre-selected LMs avoids the difficulty of matching shapes below the canopy surface. Canonical RANSAC should function in this context without the pre-selection of model centroids as the approach will only pick the best models. However, test runs in which LM filtering is removed from the algorithm result in over estimation of tree counts. We surmise that the relative simplicity of the shape equation results in over identification of sub-dominant trees in the stand. Further, the wide error bound will inherently bias shape fitting toward zones of high point density, which are below the canopy surface. As discussed in Section 7.3, we are optimistic that refining the canopy shape model may result in the ability to more accurately identify sub-dominant trees and to eliminate LM filtering from the algorithm.

7.2.0.5. *Theoretical surface fitting.* We present a novel approach to geometric shape fitting to identify trees within LiDAR data. Previous work using geometric models to identify trees has focused upon fitting geometric shapes to gridded surfaces. Extensive work has been conducted deriving geometric shapes point clouds representing solid surfaces (walls, sculpture, etc.) using RANSAC. Tree crowns do not conform to the characteristics ascribed to a surface. However, the maximal horizontal extent of branches radiating from the bole can be used as reference points for the creation of a theoretical crown surface. The methodology presented here extends approaches used in recreating physical surfaces from point clouds to the delineation of a theoretical surface representing the extent of the canopy of individual trees.

7.2.0.6. *Propagation of error.* Previously used methods using LiDAR data emphasize the conversion of point data into gridded surfaces and the application of algorithmic tools widely used for terrain surface analysis to identify and delineate individual trees. While these methods have been shown to be effective under a range of circumstances (see Chapter 3), the conversion to gridded data followed by watershed, valley-following or other such methods have the potential to introduce error from both steps. Surface interpolation from non-uniform point data is non-trivial, requiring arbitrary (albeit logically defensible) decisions about cell size and interpolation strategy. Equally, strategies for delineating individual trees from gridded data are subject to error resulting from application of algorithms designed to function on terrain surfaces to idiosyncratic forest canopy surfaces [1]. As these steps are sequential, errors from the first step can be compounded in the second. To reduce the impact of such errors, methods are often parameterized by field data (species, canopy height, etc.) and as a result can be quite accurate in tree detection and delineation. While this solves a problem of accuracy in the results, it overlooks the problem of efficiency. If extensive field data collection is required to parameterize the algorithm, the efficiency of the inventory effort is compromised. To be sure, the methodology employed here depends upon field data to parameterize the height/dbh regression. However, this approach avoids compounding error described above by performing all of the analysis steps directly on the point data. Further, the approach to tree detection is capable of identifying the location, height, and crown area of all trees within the scene without parameterization from field data. The current crown model equation is tailored to the range of tree crown shapes found in the study area, thus using location specific information as inputs to the method. As described in Section 7.3, improvements to the shape equation may result in an approach that is parameterized for the complete range of potential crown shapes for any tree such that customization of the crown from equation to specific conditions is not necessary. Derivation of tree bole parameters commonly used to derive biomass volume (i.e. DBH) remains a theoretical and practical problem. The difficulty on extracting bole measures from LiDAR identified by Rahman et al. (2009) and others results in the need to impute bole measures using allometric relationships. Work by Hyyppä et al. (2001) combining height and crown area derived from LiDAR to estimate total biomass may provide theoretical framework for abandoning the historical imperative for using DBH in biomass calculations from aerial data. The widely cited database of biomass allometric relationships by Jenkins et al. (2003) provides a model for such work but is notably lacking in allometric equations useful to aerial, i.e. those which relate height and crown area to biomass.

[1] Watershed delineation requires establishing a "pour point" above which all terrain can be considered to be within a watershed. Identifying the "pour point" for the delineation of individual trees can result in over or under counting depending on the surface interpolation method used and filtering or smoothing methods applied to the interpolated surface

7.2.0.7. *Wall to wall inventory.* Aerially acquired data is continuous across the study area in contrast with traditional field methods which are often stratified and extrapolated due to the logistics of collecting field data. As described above many previous efforts to use aerial data to conduct inventory require substantial field data collection to parameterize the approaches to detection and delineation of trees. Notably, though this method does require limited field data to determine bole attributes (via regression from LiDAR-derived height), the method used in this work for tree detection and partial delineation (presence, location, height) does not require parameterization based upon field data.

7.3. Future research

While the methodology tested here shows promising results, further work is needed to refine aspects of the approach which will increase accuracy and reduce the need for field data collection. As well, metrics must be generated for integration with LCA frameworks such as outlined in Chapter 1.

7.3.0.8. *Crown shape.* The crown shape outlined in Section 5.5.2.1 is employed based upon a compromise between the relative ease with which a points membership in a given canopy model can be determined and the range of possible shapes that can be used. As stated before, the further parameterization of the shape equation may result in a more refined model which can be used with a reduced error tolerance, thus more precisely representing the tree surface. This approach may be able to extract a greater range of tree and stand characteristics including crown area, canopy cover, and species. An improved shape may be used in a modified algorithm which would not need to be initialized by a local maxima search. By increasing the number of parameters in the surface equation, the computational time to determine membership will be increased. However, a more fully parameterized crown equation may enable the detection and delineation of sub-dominant trees and herbaceous shrubs whose canopies do not reach above the canopy surface but from whose canopies, laser returns could be used for detection and delineation. Though the vast majority of the biomass comprising forest stands is in trees comprising the larger DBH percentiles, sub-dominant trees and shrubs are important in (a) determining the risk and potential impacts of wildfire, (b) determining the volume of biomass available for electricity, heat, liquid fuel, or other markets, (c) habitat characterization, and (d) stand health (suppression, etc.).

7.3.0.9. *Crown metrics.* In this research, the utility of the geometric crown model in *StarSac* is to determine the validity of the LM as an actual tree crown apex. Though the current approach does measure crown radius we were not able to test the accuracy of the estimate due to the lack of spatially explicit field data for individual trees. However, the consensus set of points determined to be representative of a tree canopy can provide several additional metrics which may further reduce the need for field data collection. Previous work has established the utility of allometric equations used to derive total biomass from aerially acquired tree height and crown radius metrics for a limited number of species found in Scandinavia (Laasasenaho 1982). The further development of allometric equations correlating tree height and crown radius with bole biomass may increase the efficiency of aerial inventory. While allometric equations relating crown radius and height to DBH are of use, as DBH is used as an intermediate measure to derive bole volume, such relationships are susceptible to compounding error problems. Further, if the crown surface and area can be accurately established, a range of structural measures relating to habitat, fire behavior, and forest health can the be determined.

7.3.0.10. *Integration with Life Cycle Analysis.* A comprehensive assessment of existing forest conditions is critical in predicting the impact of forest management strategies on system level GHG balance. Accurate, spatially dis-aggregated forest data is the basis for assessing wildfire and disease risk, growth, as well as the value and likely industrial utilization pathways for harvested biomass. The novel methods for forests resource assessment presented here in combination with a framework for risk-aware life-cycle analysis of forest management strategies outlined in Chapter 1 present two significant yet disparate pieces of a complex model framework for predicting impacts of interacting social, economic, and ecological forces at work in forest management decision making. To integrate inventory data generated from the methods presented here into the larger LCA framework, the inventory must be extended in the following ways: (a) assess vegetative carbon pools not addressed here including DWD and understory biomass, (b) generate relevant fire behavior metrics for vegetation (CBH,CBD, and fine fuels) as well as terrain characteristics such as slope and aspect, (c) resulting inventory data must be linked with growth models, preliminary work has been conducted building linkages to the Forest Vegetation Simulator (FVS)[2] (d) establishing harvest systems for likely management scenarios so that inventory data can be linked with industrial product supply chain models such as the Geospatial Bioenergy System Model (GBSM) (Tittmann, Parker, Hart & Jenkins 2010, Parker, Tittmann, Hart, Nelson, Skog, Schmidt, Gray, & Jenkins 2010).

7.4. Summary

The use of aerial platforms for forest assessment has expanded rapidly in recent years. The increasing precision and diminishing cost of such data will result in the continuing improvement in the ability to rapidly and efficiently conduct forest assessments. Its is logical to assume that the need for extensive field based inventory campaigns will be replaced with more limited and specific field data collection with the objective of parameterizing methods applied to remotely acquired data. While variable plot methods increase the efficiency of field inventory in comparison with fixed plot methods, the underlying assumption of both methods is that stratification (i.e. sampling and extrapolation) can provide a sufficient level of accuracy. While this is true in many cases for singular metrics such as basal area, as the dimensionality of the inventory increases, the ability to stratify and maintain accuracy rapidly diminishes. As outlined in Chapter 1, forest, climate, and energy policies as well as markets energy feedstocks are increasingly focused on forest management strategies to achieve an expanding array of objectives. To address the increasing complexity of forest management decision making, the need for greater dimensionality and precision in forest assessment will surely increase. The wall-to-wall nature of data collected from aerial and satellite platforms has significant advantages over field based methods in this regard if it can be demonstrated that metrics derived from these data are accurate and cost effective. This research presents a small but significant step forward in achieving that goal.

[2] A description of the FVS can be found here