THE INFLUENCE OF SILVICULTURAL MANAGEMENT ON FOREST STRUCTURE

A Dissertation in
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by
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Abstract

The loss of biodiversity and human-induced climate change are both contemporary global issues that are intimately linked to forest structure (Working Group III of the Intergovernmental Panel on Climate Change, 2007; Jenkins, 2003). This dissertation examines effects of land management on forest structure at both the stand and landscape scales. Specifically, it investigates the effect of five types of silvicultural cutting (clear-cut, improvement thinning, diameter-limited thinning from the top, diameter-limited thinning from below, and the initial cut of a shelterwood system) on forest structural diversity and carbon storage in mixed oak hardwood forests of Pennsylvania. Furthermore, it develops LiDAR (Light Detecting and Ranging) techniques to quantify forest structural diversity at a landscape level to examine forest structure, with comparisons between eco-provinces and management types.

At the stand scale, it was found that structural resilience to silvicultural disturbances was greater than compositional resilience, resulting in forests that appeared to recover quickly from disturbance but were compositionally altered. More intense disturbances caused greater changes in forest structure and composition, requiring longer to return to near pre-disturbance conditions; however, the forest strata disturbed also influenced the disturbance severity and therefore the forest’s response. This study demonstrated that silvicultural cutting may be used to increase structural diversity at the stand level (e.g., establishment cut of a shelterwood system); however, this comes at the cost of an increase in shade-tolerant regeneration to the detriment of economically and ecologically valuable mid-successional species. The long-term outcomes of partial cuts were complex and context specific, and this complexity may be useful for maintaining or increasing structural complexity at the landscape level. A variety of silvicultural techniques should be implemented to achieve management
objectives of increased forest structural diversity.

In terms of carbon storage at the stand scale, although the clearcutting treatment had the highest carbon periodic annual increment (cPAI) in the first 15 years post harvest, it was projected to store considerably less carbon in the long term (over 100-years) than the other treatments. The projected low carbon storage in this treatment is likely due to a shift in species composition to early successional species that store less carbon per tree. Amongst the partial cutting methods, the improvement thin was the best option with moderate timber harvest rates, moderately high cPAI in the first 15 years post-harvest and relatively high carbon storage in the long-term; however, refraining from cutting remains the best option for carbon storage if the forest is in the aggradation phase. Poor silvicultural decisions may lead to reduced carbon storage of forest stands in the long-term, reducing the effectiveness of these forest carbon sinks for climate change mitigation.

To explore forest structure at the landscape level, a method to map forest canopy structure over large areas was developed using low-density topographic Light Detection And Ranging (LiDAR) data and orthographic photography collected for Pennsylvania as part of PAMAP (Pennsylvania Map Program). K-means clustering of LiDAR statistics on a grid basis was used in conjunction with multinomial logistic regression to develop a LiDAR Canopy Structure Topology (LCST). The fourteen resulting LCST types reflect vegetation top height and canopy structural complexity with a correct classification rate of 96%. This LCST provides cost-effective forest structure information by relying on remote sensing data freely available for the entire state of Pennsylvania and that could be widely utilized for forest, wildlife and landscape planning. Furthermore, the methods developed here may be adapted to map forest structure in other contexts with different LiDAR data sets.

This LCST was then mapped over 20 large landscapes within Pennsylvania, and these contrasting landscapes analyzed to investigate the influence of both site and four differing land management types (non-government, Bureau of Forestry, Bureau of State Parks and Pennsylvania Game Commission) on forest structure. It was found that at the local scale both topography and land management type had significant influences over forest structure; however, combined they only explained 32% of the variation in forest structure. At the landscape scale, there were significant differences in forest landscape structure between both Bailey’s eco-provinces and management types. Specifically, non-government forests showed evidence of forest structure fragmentation. These non-government forested lands contained a higher proportion of short vegetation types, higher patch density, and greater heterogeneity of neighboring patches. This within-forest fragmentation is likely to have implications for both biodiversity and ecosystem services.

Together, the studies presented in this dissertation show that management has a great impact on forest structure and carbon storage at both the stand and landscape levels. Management modifies the underlying influence of the environment, resulting in the realized forest structure patterns on the landscape. Therefore managers need to consciously incorporate these considerations into their management decisions at both the stand and landscape levels.
Furthermore, this dissertation shows that despite its shortcomings, topographic LiDAR can be used for landscape scale vegetation studies in addition to topographic modeling.
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B.1 Description of the iterative LCST development.
I would like to thank my dissertation supervisor Dr Eric Zenner and advisory committee Drs Kim Steiner, Margot Kaye and Doug Miller. In addition, thanks go to Dr Jim Finley, Dr Stephen Jones, Joe Harding, John Portzline and Dave Henry for access to the silvicultural demonstration trials and historic data. Thanks also go to Dan Heggenstaller, the 2010 Oak-forest Regeneration Study in Pennsylvania (ORSPA) crew and Kristen Brubaker for assistance collecting field data, Scott Dane for assistance with the LiDAR data, and Dr Jeri Peck and the SFR GSO writing group members for their support and advice. I would also like to thank Chito Kendrick for his ongoing support, advice and field assistance.

Lastly, thank you to the editors and anonymous reviewers who provided feedback on the chapters which were individually submitted to journals as manuscripts.
The loss of biodiversity and human induced climate change are important contemporary global issues (Jenkins, 2003; Working Group III of the Intergovernmental Panel on Climate Change, 2007). Historically, forest management and silviculture have been focused on the production of timber (Puettmann et al., 2009); however, with the increasing constraints of multiple-use and environmental goals, biodiversity and carbon storage must now be taken into consideration (Working Group III of the Intergovernmental Panel on Climate Change, 2007; Puettmann et al., 2009). This may involve trade-offs among timber, biodiversity and carbon storage goals (Thornley and Cannell, 2000) and requires that forest managers understand the effects of various silvicultural activities on biodiversity and carbon in addition to timber production. In this context, the conceptual framework of Franklin (1995) (Figure 1.1), which highlights the complex interactions between site factors, natural disturbance and management to produce patterns of vegetative land cover, may be a useful paradigm for thinking about the relative influences of land management and the environment on vegetation, and therefore carbon storage and biodiversity. In terms of this framework, the present study is concerned with the effects anthropogenic disturbance and land use status have on the actual vegetation and land cover.

While biodiversity refers generally to variety of life (Oxford University Press, 2011), it can be interpreted to encompass species richness as well as within-species heterogeneity and
Figure 1.1. Conceptual framework of vegetative development adapted from Franklin, 1995. The present study is concerned with the influence anthropogenic disturbance (management) has on the actual vegetation and land cover (shaded).

population demographics (DeLong, 1996; McElhinny et al., 2005). Typically, high biodiversity is important for a variety of values including: aesthetics, social values, potential future economic values of new biological products, ecosystem resilience, and the provision of other ecosystem services such as clean air and water (Hooper et al., 2005; Young, 1999; Randall, 1991). Some view forest structural diversity as part of biodiversity (Crow et al., 1994; Helms, 1998), but more importantly, forest structural diversity has been linked to, and may be used as an indicator of, species richness (Crawford et al., 1981; Diaz et al., 2005; Barbier et al., 2008; Verschuyl et al., 2008). While forest structure is imprecisely defined (Crow et al., 1994;
Helms, 1998; Spies, 1998; McElhinny et al., 2005), it usually refers to the way biomass is ordered in space and associated attributes may include the abundance, size, shape, mass, type, texture, and horizontal and vertical spatial patterns of the foliage, tree crowns, bark, tree boles, woody tissues, standing dead, fallen trees, shrubs, herbs, mosses, forest floor, roots, soil structure and landscape patches (Helms, 1998; Spies, 1998; McElhinny et al., 2005).

Furthermore, forest structure and biomass are also intimately linked to carbon storage. Carbon storage in forests is widely accepted as an effective mitigation tool for human induced climate change (Working Group III of the Intergovernmental Panel on Climate Change, 2007). The anthropogenic release of greenhouse gases, such as carbon dioxide and methane, has been linked to elevated global temperatures (Working Group I of the Intergovernmental Panel on Climate Change, 2007). As individual plants grow, they absorb and assimilate carbon dioxide, sequestering carbon. In a forest, carbon is stored within the live biomass (above and below ground), soil, and decaying debris. Silvicultural techniques affect the amount of carbon stored in forests through the removal of biomass and manipulation of forest structure (Lal, 2005; Birdsey et al., 2006; Hoover and Stout, 2007; Rhemtulla et al., 2009; Nunery and Keeton, 2010).

Landscape-scale patterns of forest patches, as part of forest structure, influence ecological processes (Farina, 2006); however, historically the mapping of these patterns was an intensive process and therefore relatively little is known about vegetation patterns at the landscape level. The detailed mapping of forest structure will not only improve our understanding of the spatial patterns, but also provide new information for land management. While passive remote sensing methods with multi- and hyper-spectral sensors that utilize radiation normally reflected or emitted from the earth’s surface have allowed the mapping of many vegetation traits, they do not provide accurate information on the three-dimensional structure of the landscape and its vegetation (Campbell, 2007). Novel active remote sensing methods that record the reflection of actively emitted energy, such as Light Detection and Ranging (LiDAR), provide new opportunities for detailed three-dimensional landscape modelling and new data inputs for landscape ecology (Shan and Toth, 2008). A hypothesis that forest management focused on timber production may homogenize forest structure at the landscape level (Bobiec et al., 2000) by manipulating forest structure at the forest stand scale and primarily promoting structures with high economic values (generally uniform large straight tree boles with little branching) has been proposed. Different forest managers with varying objectives and management methods may have different impacts on forest structure.
at this larger scale (Spies et al., 1994). The general consensus is that the private forests of Pennsylvania are being degraded through a lack of management and high-grading (where all valuable timber is harvested); however, there is little quantitative information available.

This dissertation examines the relationship between forest management and forest structure at both the stand and landscape levels. Specifically, it investigates the effects of five common types of silvicultural cutting (clear-cut, improvement thinning, diameter limited thinning from the top, thinning from below, and the initial cut of a shelterwood system) on forest structure and carbon storage in mixed-oak hardwood forests of Pennsylvania. Furthermore, it develops LiDAR (Light Detecting and Ranging) techniques to examine forest structure at a landscape level, with comparisons between eco-provinces and management types.

1.1 Literature review

1.1.1 Forest stand structure, composition and silviculture

In order to implement sustainable forest management, information about forest structure and biodiversity are needed to estimate the effects of various management actions (Noss, 1999). Biodiversity is time-consuming and expensive to measure directly; however, forest structure has been linked to faunal diversity (Crawford et al., 1981; Ishii et al., 2004; Diaz et al., 2005; Verschuyl et al., 2008) and may be linked to vegetative species richness (Barbier et al., 2008). Measuring forest structure can be more cost-effective and may therefore be used as an indicator for biodiversity as a whole; however, the exact relationships between forest structure and species richness in specific regions have yet to be fully elucidated (Noss, 1999; Lindenmayer et al., 2000).

Silviculture is intimately related to structure, as various treatments specifically attempt to change the forest structure in order to better achieve specific management goals. These manipulations are disturbances to the ecosystem and both the severity and return time of disturbances are important to the response of biodiversity (Frelich and Reich, 1998; Seymour et al., 2002).

Generally, the forestry industry in Pennsylvania uses only two silvicultural systems, i.e. clear-cut with reserves (green tree retention) or shelterwood with reserves that both result in even-aged forests stands. Furthermore, in the central hardwoods region of the eastern
United States, much research has investigated the effects of both clearcut and shelterwood forest regeneration systems. Comparatively little research has looked at the range of other silvicultural cutting and thinning methods available. It has been shown that clearcutting of oak-mixed hardwood forests on mesic sites usually results in young stands dominated by yellow poplar (*Liriodendron tulipifera*), red maple (*Acer rubrum*) or sweet birch (*Betula lenta*) despite the presence of some advanced regeneration oak (Boring et al., 1981; Beck and Hooper, 1986; Groninger and Long, 2008), strongly altering the species composition of the stand. High densities of trees dominate these young stands with little variation in tree diameter or height and low levels of structural diversity. Of the oaks that do regenerate after a clearcut, a large proportion are from clumps of stump sprouts (Ross et al., 1986). Due to the problems presented by this change in composition with clearcutting, considerable research has looked at the use of shelterwood systems to promote oak regeneration. By thinning the stand from below in successive stages before the final overstory removal, a shelterwood system slowly opens up the canopy and gradually provides more light (Smith et al., 1997). This increase in light may allow intermediate shade-tolerant species such as oak (*Quercus* spp.) to regenerate and outcompete shade tolerant species such as sugar maple (*Acer saccharum*) without encouraging the growth of light-demanding species such as yellow poplar (Loftis, 1990b; Parker and Dey, 2008).

Diameter-limited thinning and selection cutting are often used as euphemisms for high-grading, although by their strict definitions they are somewhat different (Nyland, 2002). Generally, these terms are used to describe the harvesting of trees where only the largest and most valuable trees are removed. While these harvesting techniques are usually not recommended under best management practices, they are common on non-industrial private lands (Schuler, 2004) that make up 80% of the central Appalachian region (Fajvan, 2006). High-grading not only directly affects the forest structure by reducing the number of large trees, variation in tree size, and volume of specific species, but may also result in a loss of future desirable seed, timber supply, stand productivity, potential economic returns, biodiversity and ecological resilience, especially where repeated a number of times (Fajvan, 2006). Fajvan (2006) reviewed three studies in the Central Appalachians that suggested that the high-shade resulting from diameter-limited cutting may favor red maple and that smaller diameter limits that remove more volume may favor light-demanding species such as black cherry. However, Fajvan (2006) also found that the remaining residuals were patchy and may suppress the regeneration, therefore resulting in a heterogeneous (highly structural diverse)
forest stand. Similarly, Schuler (2004) found that repeated diameter limited cutting in the 
Fernow Experimental Forest resulted in an increase in red and sugar maple and a decrease 
in red and chestnut oak. Schuler (2004) also found that there was no decrease in species 
diversity over a 50 year period of repeated cutting.

Improvement thinning is where the trees selected to remain in the residual stand are 
based on species, form, vigor and spacing, leaving an economically more valuable stand 
that will grow into bigger size classes and increase in value (Nyland, 2002). In contrast, 
thinning from below is a diameter-limited cut that removes the smallest trees, leaving the 
largest trees to continue growing. While both of these techniques are known to directly 
manipulate the residual forest structure by removing small and suppressed trees, they have 
been rarely studied in the central hardwoods region of the United States and their longer-
term effects are unknown. There have also been few studies that have compared various 
harvesting and partial cutting techniques. Marquis and Ernst (1991) looked at a range of 
silvicultural cutting techniques, including thinning from below, above, middle, and combined 
thinning (which removes trees across all size classes) in a northern hardwood stand within 
Kane Experimental Forest. Marquis and Ernst (1991) found that while the thinning from 
below reduced the smallest size classes only, increasing the average tree size and reducing 
the amount of American beech and sugar maple. The stand grew little over the subsequent 
years in all of the size classes, resulting in an open understory in the forest stand with few 
suppressed trees. Conversely, the thinning from above removed the largest trees, reducing 
the amount of black cherry and decreasing average tree size, and grew large volumes over the 
subsequent years, mainly in the smaller size classes of shade-tolerant species. The combined 
thinning maintained stand composition and forest structure similar to the pre-treatment 
stand, while resulting in re-growth in most size classes.

There are no published medium- or long-term studies (more than six years) that directly 
contrast the effects of a range of partial-cutting silvicultural techniques on the forest structure 
and composition in Appalachian mixed-oak hardwoods.

1.1.2 Climate change, forest stand carbon storage and silviculture

Carbon dioxide levels in the earth’s atmosphere have been rising since records began in 1958 
(Keeling 1998 in Working Group I of the Intergovernmental Panel on Climate Change, 2007). 
On average, the surface temperature of the earth has also been rising since records began in
1867 and this change is unlikely to be explained by natural variation alone (Working Group I of the Intergovernmental Panel on Climate Change, 2007). It is likely that the anthropogenic release of greenhouse gasses has caused this change due to the effects of the earth’s greenhouse effect (Working Group I of the Intergovernmental Panel on Climate Change, 2007).

Forests have been estimated to account for up to 80% of the above-ground carbon storage and approximately 40% of the below-ground terrestrial carbon (Dixon et al., 1994). Forests may add to the amount of carbon in the atmosphere through fire, deforestation and decomposition; however, they may also decrease atmospheric carbon through increases in biomass (Birdsey, 1992). Forests in the United States currently sequester about 10% of the country’s emissions from burning fossil fuels (Birdsey et al., 2006). Recent data on the carbon balance of US forests conflicts as to whether forest carbon sequestration is declining (Myneni et al., 2001; Birdsey et al., 2006).

While carbon storage is strongly related to site characteristics and productivity (Kaczmarek et al., 1995), there is a potential for increasing the amount of carbon stored in forests through careful management (Lal, 2005; Birdsey et al., 2006; Rhemtulla et al., 2009; Nunery and Keeton, 2010). Hoover and Stout (2007) demonstrated that thinning from below resulted in higher production and carbon sequestration rates in the above-ground carbon pools in a cherry-maple Allegheny hardwood forest than thinning from above. Park et al. (2007a) simulated the growth of three Allegheny hardwood stands over 40 years after a 30% thinning, 50% thinning, 30% selection cut and 50% selection cut. Their results indicated that while the control maintained the highest carbon stock, the 30% selection cutting was the only treatment where carbon stock growth exceeded the carbon removed. In the mixed mesophytic forest of the Fernow Experimental forest, Davis et al. (2009) used a combination of field data and an ecosystem productivity model to examine carbon sequestration of four watersheds with different harvesting histories: no harvest, clearcutting, single tree selection, and a 43 cm diameter-limited cutting. They found that the clearcutting treatment had a sustained decline in plant carbon after 45 years; however, neither of the partial cutting methods exhibited these declines. As such, Davis et al. (2009) suggested that frequent but low intensity silvicultural systems may be a way to harvest timber and maintain carbon storage.

Importantly, carbon in forests is stored in four carbon pools: 1) overstory trees, 2) understory vegetation, 3) standing debris and debris on the forest floor, and 4) soils (Figure 1.2). While silvicultural cutting can alter carbon storage in live vegetation (decreasing it in the short term), it may increase carbon storage in other carbon pools, such as the detritus and
soils (Dixon, 1997; Colombo et al., 2005; Scott et al., 2004). Qinglin et al. (2007) examined the effects of both even and uneven aged harvesting after eight years on the carbon storage of upland oak forests in the Missouri Ozark Forest Ecosystem Project (MOFEP) in the overstory, coarse woody debris (CWD), forest litter, soil and live below-ground pools. They found that the higher intensity harvesting of the even aged management reduced the overstory carbon pool the most, but also increased the CWD carbon pool the most. They also found a small but significant increase in mineral soil carbon with harvesting. Surprisingly they found no significant effects of harvesting on below-ground live carbon, nor carbon stored in the forest litter layer.

There are no published medium or long-term studies that directly contrast the effects of a range of partial-cutting silvicultural techniques on the above-ground forest carbon stocks in Appalachian oak-mixed hardwoods.

1.1.3 Forest structure measures and indices

Forests have conventionally been evaluated using measures such as trees per acre (TPA), quadratic mean diameter (QMD), basal area (BA) and mean top height (MTH) with the focus on the useable timber volume (van Laar and Akca, 2007). While these measures are associated with forest structure, they focus on useable timber and do not measure the spatial distribution of biomass through the whole forest, nor do they directly reflect the aspects of
forest structure that are important for aesthetics, wildlife habitat and ecosystem functioning. With rising interest in forest structure, these measures have been adapted. For example, the standard deviation of tree diameter or tree height may be used as indicators of vertical complexity of the forest canopy (McElhinny et al., 2005). In forest research, graphical methods such as cross-sectional drawings of vertical forest structure along a transect or detailed mapping have also been used (Oldeman, 1990); however, these are difficult to produce and analyze.

Two dimensional spatial patterns of vegetation and spatial autocorrelation have also been analyzed and compared using spatial statistics such as Ripley's K and Moran's I; furthermore, these two dimensional methods have been expanded to three dimensions using marked point processes (Dale, 1999). Also, explicitly three-dimensional indices such as the Structural Complexity Index (SCI; Zenner and Hibbs, 2000) have been developed to simultaneously measure horizontal and vertical structural complexity using Triangular Irregular Networks (TIN). While these measures reflect the three-dimensional forest structures, they also require the spatial position of each tree. As such, they involve intensive data collection and can be difficult to implement.

Composite summary indices of forest structure that incorporate several measures into a single index have also been developed (McElhinny et al., 2005); however, these also tend to involve intensive data collection (e.g. Old Growth Index, Acker et al. 1998; and LLNS Diversity Index, Lähde et al. 1999). In addition, many composite summary indices are designed for specific research needs, focusing on particular aspects of forest structure, and may not be applicable to all circumstances (McElhinny et al., 2005).

With the increasing focus on structural diversity in forest management, there is a need for forest structure indices that can be efficiently measured over large forest areas. The current methods described above either inadequately describe forest structure as a whole or require expensive and intensive field measurements. As such, there is need to develop new approaches to measuring forest structure at the landscape scale.

1.1.4 Landscape structural diversity and forest management

Generally, landscapes can be viewed as a matrix of patches, each relatively homogenous within but differing from the next (Pickett and Cadenasso, 1995). Within forests specifically, this mosaic of patches has been referred to as the silvatic unit with each patch being an eco-
unit (Oldeman, 1990). Oldeman (1990) defined eco-units as a “... unit of vegetation which started its development at the same moment and on the same surface”; however, he also stated that “eco-units are not necessarily even-aged”. Oldeman (1990) also suggests than an eco-unit should be “small enough to fit into one unit of even a detailed map of soil, climate or a combination of both”. The smallest possible mosaic of eco-units that contains all of the locally possible eco-unit types is a silvatic unit (Oldeman, 1990). It is important to note that Oldeman recognizes delimiting eco-units as problematic and suggests using grid analysis as an alternative to assigning arbitrary “natural limits” perceived by the human eye.

Forest structure at larger scales may be important to aesthetics, ecosystem functioning and biodiversity (Farina, 2006). Patchiness has been linked to the diversity of bird species (Farina, 2006) and is likely to be linked to patterns of other fauna. In addition, this spatial heterogeneity may be linked to wildlife behavior and spatial density dependence where prey or vegetation has a patchy distribution that leads to concentrations of predators or herbivores (Farina, 2006). Movement of water, nutrients and propagules in a landscape is also affected by vegetation patterns (Farina, 2006). The size, shape, quantity, connectivity and spatial configuration of patches are all important to these ecological processes (Farina, 2006).

Fragmentation of forest (by non-forest land cover) has been widely researched; however, in this study we are interested in the landscape-scale structural diversity within forests. Spies et al. (1994) looked at the spatial patterns of two forest types across private and public forests in western Oregon and found that between 1972 and 1988 land under private management had larger reductions in conifer forest, greater increases in edges, and greater reductions in interior forest area. Furthermore, Bobiec et al. (2000) examined the landscape-scale structure of protected and commercial forests in Poland and found that forest management for timber reduced patch type richness and increased average patch size, homogenizing forest structure. Geomorphology and natural disturbance patterns may also be important factors in landscape-level forest structure (Forcier, 1975; Turner and Romme, 1994; Gauthier et al., 1996; Sprugel et al., 2009) through influencing nutrient, water and temperature regimes, and patch size and age.

To specifically study forest fragmentation in Pennsylvania, detailed land cover maps are required. Small-scale maps of Pennsylvania’s land cover in broad classes (PSU, 2007) and spatial habitat models of Pennsylvania (Myers et al., 2010) have been developed from a variety of data sources. However, the resolution of these maps are inappropriate for studies of within-forest spatial patterns. As such, little is known about the spatial patterns of
Pennsylvania’s forests that influence aesthetics, ecosystem functioning and biodiversity. Furthermore, detailed mapping of Pennsylvania’s forests may assist forest and wildlife managers and planners by allowing for greater understanding of the distribution of resources.

### 1.1.5 LiDAR and forestry

Light detection and ranging (LiDAR) is a suite of active remote sensing techniques using a laser which emits pulses of light and determines the distance to a target by precisely measuring the time delay between the pulses emission and detection of its reflection (Shan and Toth, 2008). This technology has been implemented for numerous applications with a wide variety of specific technological parameters including building and infrastructure management, laser rangefinders, topographic modeling, atmospheric and environmental monitoring (Shan and Toth, 2008), and computer generated imagery. LiDAR may utilize terrestrial, airborne (Figure 1.3) or space platforms depending on the specific objectives. It is also possible to record the whole reflected laser pulse as a full waveform (Lefsky et al., 2002) or just the peaks in the reflected laser pulse, known as discrete returns (Figure 1.4). Discrete return LiDAR produces a three-dimensional cloud of points representing known locations of mass and groups of these points together render the surface of the ground, buildings or vegetation (Hyypaa et al., 2008). The focus of this literature review is discrete-return LiDAR from aerial platforms used for vegetation studies.

There is increasing interest in using LiDAR techniques to study vegetation (Vierling et al., 2011b). As LiDAR directly records the three-dimensional location of biomass in a forest, it provides an opportunity to directly quantify forest structure in a way that was previously impractical (Gatziolis and Andersen, 2008; Dubayah and Drake, 2000; Hyypaa et al., 2008). Many algorithms have been developed to estimate forest structure measures from LiDAR point-cloud statistics or canopy surface models (CSM, or Canopy Height Model, CHM) including tree density (Barilotti and Sepic, 2010), species composition (Brandtberg et al., 2003; Liang et al., 2007), species richness (Lucas et al., 2010), above-ground carbon stock (Patenau de et al., 2004; Beets et al., 2011; Mascaro et al., 2011), tree height (Means et al., 2000), Lorey’s height (Lim et al., 2003a), vertical vegetation profiles (Goodwin et al., 2006; Andersen, 2003; Coops et al., 2007), crown diameter (Popescu et al., 2003), basal area (Popescu et al., 2004), stocking (Pehuskurinen et al., 2011), stand development stages (Falkowski et al., 2009; Kane et al., 2010b; van Ewijk et al., 2011), leaf area index (Peng
and Chen, 2008), crown fuel weight and bulk density (Skowronski et al., 2010), wood volume (Andersen et al., 2005b) and quality (van Leeuwen et al., 2011), live and dead biomass (Kim et al., 2009c), vertical and angular canopy cover (Korhonen et al., 2011), and canopy gaps (Andersen, 2003; Koukoulas and Blackburn, 2004; Vehmas et al., 2011). However, these algorithms tend to be site- and LiDAR system-specific (Junttila et al., 2010).

The primary advantages of using LiDAR for forest surveys are reduced costs for large areas and the ability to undertake wall-to-wall mapping of forest structural measures to within-stand resolutions. While the initial cost of LiDAR data collection is large, the accuracy and cost of flying large forested areas is similar to traditional stand exams with the additional benefit of collecting data for digital elevation, wildlife habitat and hydrological modelling (Tilley et al., 2004; Hummel et al., 2011). As the area surveyed increases, the cost per hectare may be further reduced. Asner et al. (2011) created a map of Hawaii’s vegetative carbon stock from LiDAR and multi-spectral remote sensing data at a cost of US$0.16 per
Figure 1.4. LiDAR systems may record either the full waveform of the laser backscatter or just the peaks, called discrete returns (from Lim et al., 2003b).
ha, compared to US$1500 per ha for field measurements on 39 ha.

LiDAR also has advantages over other remote sensing tools. Specifically, passive remote sensing tools such as multi-spectral and hyper-spectral sensors are unable to measure canopy height and LiDAR was found to be more accurate for estimating biophysical parameters (Naesset et al., 2004; Clark et al., 2011). LiDAR is also able to provide more comprehensive detailed information regarding three-dimensional forest structure than other active remote sensing techniques such as InSAR (Andersen et al., 2004; Breidenbach et al., 2008).

Generally, most work using LiDAR for forestry has been in coniferous forests or deciduous forests during the summer months (“leaf-on” conditions). Consequently, until recently the developed techniques used characteristics of the canopy surface only (e.g. Parker and Russ, 2004). Research looking at the full canopy structure, including the suppressed trees, is relatively new (Hyyppä et al., 2008). Both Korpela et al. (2011) and Maltamo et al. (2005) had limited success detecting and identifying the understory of conifer-dominated stands using leaf-on data; however, there has been promising research indicating that LiDAR carried out over the winter months in deciduous forests (“leaf-off”) may give more accurate profiles of forest structure (Brandtberg et al., 2003; Liang et al., 2007). Furthermore, in leaf-off conditions the laser is able to penetrate further into the canopy and is more likely to reflect the full structure of both the forest understory and the canopy. Collecting LiDAR in the leaf-off condition generally results in more accurate modeling of the terrain surface, and it is therefore common to carry out data collection after leaf-fall, during the winter months (Shan and Toth, 2008).

In addition to time of data collection, some parameters of the LiDAR system itself are influential on forest inventory accuracy (Naesset, 2009). These parameters include scanning frequency, scanning pattern, beam divergence, scanning angle, footprint diameter, pulse length, number of returns, footprint spacing, flying height, and discretization settings; all of which influence pulse density, return density and return intensity (Hopkinson, 2007; Gatzioulis and Andersen, 2008; Morsdorf et al., 2008). In addition, LiDAR system parameters might interact with canopy shape to produce different accuracies for different structural parameters. For example, scan angle was influential on tree height estimation errors in tall slender coniferous trees (Holmgren et al., 2003), but no such result was found in the normalized canopy height profiles of eucalyptus forests (Goodwin et al., 2006), suggesting that canopy shape influences canopy height errors. Furthermore, point cloud densities as low as 0.5 points per square meter may be sufficient for plot and stand modeling but not individual
Models to estimate forest structural measures from LiDAR may also include either statistics characterizing the elevation of returns, the intensity or both; however, the majority of studies to date have utilized LiDAR return height only. While Bater et al. (2011) found that LiDAR return elevation statistics are consistent between passes of the same equipment on the same day, intensity data need to be normalized. Further, normalized intensity data may also be beneficial for species identification (Yoon et al., 2008; Kim et al., 2009a,b). Rather than utilizing the intensity data from LiDAR, many studies incorporate spectral data from other remote sensing techniques including aerial photography (Stephens et al., 2008; Bertoldi et al., 2011), multi-spectral (Popescu et al., 2004; Hill and Thomson, 2005; Garcia et al., 2011) and hyper-spectral sensors (Forzieri et al., 2008; Asner et al., 2011; Chen et al., 2011).

There are three approaches to modelling forest structural measures from LiDAR data: individual tree, object-oriented or area-wise. The individual tree approach attempts to identify individual tree crowns first and then applies allometric equations to estimate the size of each tree (such as tree height, crown-area and diameter at breast height) (Farid et al., 2006; Barilotti and Sepic, 2010; Gatziolis et al., 2010). Stand level estimates may then be calculated from the individual tree estimates. This approach has been commonly used in coniferous forests where the conical crowns are easily delineated (Andersen, 2009; Dalponte et al., 2011; Edson, 2011). An object-oriented approach first delineates areas (“objects”) of a canopy height model derived from the LiDAR point cloud based on the surface traits, and then characterizes the object based on field data (van Aardt et al., 2006). The area-wise approach characterizes the upper surface of an area, whether a plot, stand or cell within a grid, without identifying individual trees (Andersen et al., 2005a). While some information may be lost, this approach is useful for mapping forest structure over large areas where individual tree crowns are indistinct (Angelo et al., 2010), data was collected leaf-off (Hawbaker et al., 2010), or LiDAR point density is low (Coops et al., 2007). Peuhkurinen et al. (2011) compared the individual tree and area-wise approaches in a Scots pine forest, and concluded that the area-wise approach had better accuracies and fewer biases when predicting biophysical measures of forests. Furthermore, Tuominen and Haapanen (2011) found that despite the theoretical advantages of the object-oriented approach, a gridded area-wise approach was superior as the former approach did not delineate segments optimally for stand variable estimation.

A wide variety of specific statistical methods have been used to model forest structural
measures from LiDAR point clouds. While multiple linear regression has been commonly used in the published literature (Andersen et al., 2005a; Ioki et al., 2010; Jenkins, 2011; Beets et al., 2011), it has been shown to underestimate at high parameter values (Hudak et al., 2008; Goerndt et al., 2011). As LiDAR point clouds tend to be multimodal (rather than unimodal), Jaskierniak et al. (2011) implemented mixture models to estimate basal area and volume with higher accuracy. Other studies have found that imputation methods may be superior to regression methods by achieving similarly high coefficient of determination values without bias (Hudak et al., 2008; Garcia-Gutierrez et al., 2010, 2011), with the Random Forest regression tree-based classifier proving to be more robust than other imputation methods (Hudak et al., 2008; Latifi et al., 2010; Korpela et al., 2010; Latifi and Koch, 2011).

Rather than estimating individual forest structural measures, several studies have attempted to classify the vegetation by pre-defined land-cover, habitat or forest types that encompass the forest structure as a whole (Antonarakis et al., 2008; Falkowski et al., 2009; Kane et al., 2010b,a; van Ewijk et al., 2011). Both van Ewijk et al. (2011), and Kane et al. (2010a) concluded that forest structure does not develop linearly in discrete stages, and that ecologists should measure forest structure rather than using stand developmental models.

Furthermore, a handful of studies forwent the modeling of species habitat in favor of modeling the presence of the focal species directly from the LiDAR statistics (Graf et al., 2009; Vierling et al., 2011a). While this approach is direct and therefore reduces the loss of information, it is species-specific and may not provide general information on the landscape as a whole.

The studies discussed above use a priori forest structure measures, which are then estimated utilising LiDAR data; however, this approach may lead to the problems suggested by van Ewijk et al. (2011) and Kane et al. (2010a), detailed above. Furthermore, the inadequacy of many of these traditional measures of forest structure have already been discussed. Rather than pre-defining forest structure categories, Pasher and King (2010) used unsupervised multivariate statistics to classify areas with similar passive remote sensing data and then described the vegetation traits of these classes. This approach of a posteriori definition of classes allows for the objective delineation of forest structure classes based on the patterns present in the remotely sensed data.

The majority of published studies utilizing LiDAR to estimate forest structure measures utilize specifically collected data sets. Increasingly, LiDAR datasets collected for topographic modeling are becoming publicly available (USGS, 2011); however, few studies have attempted
to utilize these datasets that are collected leaf-off with relatively low point densities and wide scan angles. The availability of such a dataset for the whole of Pennsylvania (PAMAP, 2006-8) provides an opportunity to create detailed maps of the three-dimensional forest structure over the whole landscape; however, new techniques for analyzing and interpreting the raw data need to be developed.

1.1.6 Pennsylvania’s forests

Estimates indicate that prior to settlement by Europeans up to 90% of Pennsylvania was forested (Stevens, 1956). Extensive logging and land clearance in 18th and 19th centuries (Stevens, 1956; Klein and Hoogenboom, 1973) have left few small old-growth remnants (Davis, 1993, 1996). Much of the cleared forest area has regenerated and by 2004 approximately 58% of Pennsylvania’s total land area was again forested (McWilliams et al., 2007). Recent forest monitoring by the USDA Forest Services Forest Inventory and Analysis Program indicates that in the medium term the area of poor and moderately stocked forests in Pennsylvania has increased and the area of full and overstocked forests has declined; particularly on private forest land (McWilliams et al., 2007).

Pennsylvania’s humid continental climate has large annual temperature variations with a seasonally even distribution of the 104 cm mean precipitation; however, it is strongly influenced by the Great Lakes, Atlantic Ocean and physiography (Waltman et al., 1997; Shultz, 1999). As a result of interactions between bedrock, tectonic movement and weathering (particularly glaciation in northeast and northwest), three physiographic provinces dominate Pennsylvania’s landscape: the Appalachian Plateaus Province and the Piedmont Province, bisected by the Ridge and Valley Province (Figure 1.5; Shultz, 1999). The climate and physiography of Pennsylvania strongly influence its forests. Pennsylvania lies at the intersection of Mixed Mesophytic, Mixed-oak and Northern Hardwoods forest regions (Barrett, 1980; Barnes et al., 1998). The northern hardwoods tend to be dominated by beech, birch and maple species in a self perpetuating shifting-mosaic steady state (Bormann and Likens, 1979; Walker, 1999). In contrast, the disturbance regimes of the mixed-oak forests have historically been fire dominated (Barrett, 1980; Abrams, 1992). Invasive pests and changes in disturbance regimes have led to a decline of many tree species, such as the oaks, American chestnut and eastern hemlock (Ellison et al., 2005; McWilliams et al., 2007; Fei et al., 2011), and compositional mesophication (Abrams and Downs, 1990; Abrams et al., 1995; Abrams,
The availability of LiDAR data for all of Pennsylvania through the PAMAP program, as described earlier, may allow detailed mapping of forest structure over the whole state. In addition, the environmental gradients (described above) and complex forest management patterns (described below) of Pennsylvania provide an opportunity study the influence of both environmental and management on landscape forest structure patterns.

1.1.6.1 Private forestland

Seventy one percent of Pennsylvania’s forest lands are in private ownership (McWilliams et al., 2007; Gruver, 2010). The forest management objectives of these private landowners
are as varied as the owners themselves and it is difficult to characterize the management of these lands as a whole. However, forest practices on private forest land have led to increases of poor and moderately stocked forests and decline of full and overstocked forests in Pennsylvania that are particularly pronounced (McWilliams et al., 2007).

Pennsylvania’s private forests are characterized by many small landholdings. Private forest landowner surveys in Pennsylvania indicate that 63% of landowners own less than 4 hectares with most living within a mile of the forest area, but 11% living further than 160 kilometers from their forest area (Metcalf, 2010). Furthermore, 19% visited their forest land less than several times per year and the majority of private forest landowners own land for recreation, solitude and hunting (Metcalf, 2010). While 46% of private forest landowners have harvested timber in the last 10 years, much of the harvested wood was for private use (Metcalf, 2010). Of the 20% of private forest landowners who have harvested for commercial timber, most managed the activities themselves and many were direct sales to loggers or timber companies, few consulted a forester and many described their harvesting as “cutting of few select large trees” (Metcalf, 2010). Furthermore, McWilliams et al. (2007) estimate that only 2% of private landowners have a formal forest management plan and only 8% have sought professional advice.

The parcelization of private forest lands is also a concern in Pennsylvania. Nine percent of private forest landowners plan to subdivide and sell their land, while a further 52% plan to leave their land to multiple heirs (Gruver, 2010). This further division of already small landholdings leads to the proliferation of very small forest parcels that are difficult to manage and may be associated with the physical fragmentation of forests.

While studies from the social science perspective have been undertaken on Pennsylvania’s private forest owners (Metcalf, 2010; Gruver, 2010; Hill, 2011), little is known about the ecological status of the private forest estate. It is generally thought that these forests are being degraded through poor forest management, and while data collected under FIA (McWilliams et al., 2007) do support this, the resolution of the data is poor and only general conclusions can be reached. There is a need to understand the health and physical status of these forests for planning and policy makers, without impinging on landowner and privacy rights.
1.1.6.2 Pennsylvania’s public forests

Public landownership encompasses 29% of Pennsylvania’s forest land (McWilliams et al., 2007) and includes state parks, state forests, state gamelands, local publicly owned parks (county parks etc), national parks and the Allegheny National Forest. Federal and local publicly owned forest land account for just 6% of Pennsylvania’s forests (McWilliams et al., 2007), with the remainder of the public lands managed by the state. The objectives of the various public land managers varies greatly and so do the management actions taken on these lands to fulfill these varied objectives.

1.1.6.3 Pennsylvania Bureau of State Parks

Pennsylvania’s state parks are managed by the Department of Conservation and Natural Resources (DCNR) Bureau of State Parks (BoSP). Pennsylvania’s first state park was established in 1893 at Valley Forge; however, the Bureau of State Parks was not established until 1929 (BoSP, 2010). The total area of state parks in Pennsylvania has increased since the establishment of the Bureau to 117 state parks, encompassing 119,400 hectares by 2011 (Figure 1.6; BoSP, 2010).

The purpose of the Bureau of State Parks is to “provide opportunities for enjoying healthful outdoor recreation and serve as outdoor classrooms for environmental education” (BoSP, 2010) through the conservation of natural, scenic, aesthetic and historical values. Each park is managed under an individual master plan tailored to its specific conservation, education and recreational resources. While revenues from harvesting of Pennsylvania’s state forests contribute to the operating budget of the state parks, there is generally no harvesting of forests from the state’s parks.

1.1.6.4 Pennsylvania Bureau of Forestry

Pennsylvania’s state forests are managed by DCNR Bureau of Forestry (BoF) whose mission is “to ensure the long-term health, viability and productivity of the Commonwealth’s forests and to conserve native wild plants” (BoF, 2010). In particular, BoF objectives are to conserve the state’s forests while utilizing the resources they provide, and to manage “... State Forests under sound ecosystem management, to retain their wild character and maintain biological diversity while providing pure water, opportunities for low density recreation, habitats for forest plants and animals, sustained yields of quality timber, and environmentally sound
utilization of mineral resources.” (BoF, 2010).

Of the 8,498 square kilometers of state forest (Figure 1.6), 1,198,600 ha form the commercial forest land base that is managed to provide a sustained yield of timber through the use of a timber harvest allocation model (BoF, 2003). The timber harvest allocation model attempts to maximize the net present value (NPV) of the forest estate within policy and resource limitation constraints. The BoF aims to promote balance of age and size class distributions, native forest communities, patch sizes and forest successional stages to mimic natural patterns and manage landscape-level concerns (BoF, 2003). The current age class distribution of the state’s forests is skewed with much “late successional” forest (defined as 60-100 years old by the BoF) and little young and old growth forest (BoF, 2003).

Figure 1.6. Map of land managed by Pennsylvania’s Bureau of State Parks, Bureau of Forestry and Game Commission.
To mitigate the impacts of harvesting, the state forest resource management plan stipulates that green tree retention must be undertaken in harvested stands (for both even or uneven-aged treatments and salvage logging where applicable) of “an average basal area between 10-20 square feet over the entire treatment area and a minimum of 5 trees per acre in the dominant, codominant and/or intermediate class on each acre” based on genetic diversity, species diversity, structural diversity, live crown ratio and tree vigor (BoF, 2003). Furthermore, the plan protects federal or state listed fauna or flora species, or habitat critical to their survival, either presently known or subsequently identified, and archaeological sites (BoF, 2003).

In 1998, the state forests of Pennsylvania were certified under the forest management principles of the Forest Stewardship Council (FSC) (BoF, 2003).

1.1.6.5 Pennsylvania Game Commission

The purpose of the state gamelands managed by the Pennsylvania Game Commission (PGC) is specifically to “protect, propagate, manage and preserve the game or wildlife of this Commonwealth” (The Game and Wildlife Code Title 34 Chapter 3b Sec. 322). The PGC is in the process of writing management plans for each State Gameland (Figure 1.6) that will be individually tailored to the specific resources and goals for that gameland (Anon., 2009). The PGC use timber harvesting and other silvicultural techniques to enhance wildlife habitat. Strategic Objective 4.7 of the PGC 2009-2014 Strategic Plan is to “Enhance wildlife habitat on State Game Lands through the recovery of natural resources”, specifically to “Utilize a full spectrum forest habitat management program to diversify forest structure and composition” (Anon., 2009). Furthermore, the value of early-successional habitats, as a result of timber harvesting, in addition to mature and old growth forests is recognised in PGC planning documents (Anon., 2005). Pennsylvania’s comprehensive wildlife conservation strategy (Anon., 2005) stresses the importance of maintaining mid- and late-successional forest, ensuring long-term species composition and structural diversity, limiting forest fragmentation, and designating high-priority sites and conservation areas.

1.2 Objectives and Hypotheses

The literature review above highlights the need for further research examining the relationship between forest management and forest structure at both the stand and landscape levels.
The specific objectives and hypotheses of this dissertation are discussed further below.

1.2.1 Objective 1

To investigate the effect of clear-cutting, improvement thinning, diameter-limited thinning from the top, diameter-limited thinning from below and the initial shelterwood cut on the forest structure and carbon stock in mixed oak-hardwood forest stands.

While the use of partial cutting silvicultural techniques is being promoted as a way to increase forest structural diversity as desired, there have been no studies to date in mixed oak-hardwood forest types comparing and contrasting a range of partial cutting techniques in terms of forest structure and carbon storage in the long-term. Chapter Two contrasts the effects of four partial cutting techniques against both control and clearcut treatments (as forest disturbances) over approximately fifteen years after the harvest. In addition, it investigates the relationship between disturbance characteristics (i.e., cutting technique) and forest resilience, and contrasts forest resilience in terms of forest structure and composition. Furthermore, Chapter Three looks at the effects of these treatments on above-ground carbon stock over an approximately fifteen-year field trial and models the effect of these treatments over a further 100 years.

1.2.1.1 Hypothesis 1.1

Both disturbance intensity and the forest canopy strata disturbed influence the forest’s response to partial cutting and resilience. In addition, both the number and stature of remnant trees after a partial cut influence the physical environment and therefore will influence the presence and composition of regeneration.

1.2.1.2 Hypothesis 1.2

In the short-term, partial cutting increases structural diversity at the stand level by retaining some trees while simultaneously releasing resources, creating a heterogenous growing environment for regeneration and in-growth whereas clear-cutting will decrease structural diversity by removing all trees and homogenizing the physical environment. As time since cutting increases, structural diversity will return to the untreated condition through regeneration and in-growth.
1.2.1.3 Hypothesis 1.3

All cutting will reduce the carbon stock (as biomass is removed), but the level of reduction will depend on the severity and type of cutting. Carbon sequestration will increase after cutting due to regeneration and ingrowth that will replace the reduced carbon stock, but the level and rate of increase will depend on the severity and type of cutting. High intensity disturbances (e.g. clear-cutting) will have a more pronounced reduction and longer-lasting effects than low intensity disturbances (e.g. diameter-limited thinning from below) due to changes in forest composition due to species differences in stature and wood-density.

1.2.1.4 Hypothesis 1.4

The untreated controls will change over time in terms of both forest structure and composition because these forests are still undergoing succession; however, these changes will be relatively small when compared to the treated plots as the sites are fully stocked and mortality due to senescence or competition for resources must occur for further structural development.

1.2.2 Objective 2

To develop LiDAR methods to quantify forest structural diversity over landscape scales (approximately ten thousand hectares).

The public availability of a topographic LiDAR dataset for Pennsylvania provides an opportunity to create detailed maps of forest structure at the landscape scale; however, methods for utilizing leaf-off LiDAR data with low return densities and wide scanning angles to describe forest structure as a whole are lacking. Chapter Four develops a LiDAR Canopy Structure Topology (LCST) for mapping Pennsylvania’s Forest Structure utilizing this dataset.

1.2.3 Objective 3

To examine the pattern of forest structural diversity across the landscape, and examine the relationship between forest management type and landscape-level structural diversity.

The landscape-level structure of Pennsylvania’s forests influence and reflect management; however, landscape ecology studies have been historically limited to studying the patterns
of forest versus non-forest land-uses. Furthermore, there is little knowledge of the status of forests on private lands. There is need to understand the pattern of within-forest mosaics in Pennsylvania and how management influences these patterns. Chapter Five utilizes the LCST developed in Chapter Four to investigate the relationship between forest structure and topography and to compare the landscape forest structure across eco-provinces. Furthermore, contrasts between lands managed by private forest owners, the Bureau of Forestry, the Bureau of State Parks and the Pennsylvania Game Commission are made in order to better understand the relationships between these managements and forest structure.

1.2.3.1 Hypothesis 3.1

Different forest management types will result in different landscape-level structural diversity patterns as different forest management methods are employed to achieve these varied objectives. Forest management types with comprehensive planning and philosophies and objectives that do not preclude timber harvesting (i.e. Pennsylvania’s State Forests) will have reduced patch richness with a low level of tall, structurally complex forest structures. Furthermore, they will have an increased average patch size due to homogenous silvicultural prescriptions applied over large areas. In contrast, due to the haphazard nature of private forest management, structural diversity at the landscape scale will be greater than that of public land, but may have a prevalence of low structural complexity patches due to forestry practices such as high-grading and complete clearcutting that are unavailable to public forest managers. Forests managed by the Bureau of State Parks will have the greatest amount of tall, structurally complex forest structures due to low amounts of anthropogenic disturbance.

1.2.3.2 Hypothesis 3.2

Topography (slope, aspect and elevation) is associated with landscape-scale structural diversity patterns because of inter-relationships between topography, edaphic factors, climatic factors, disturbance regimes, site productivity, species composition and silvicultural techniques. Specifically, forest structures on sites with extreme environments (e.g., dry ridge tops, and low-lying wetlands) will have a short stature with low canopy cover. In contrast, mesic sites with moderate environments will have tall dense forest structures due to high site productivity.
1.2.3.3 Hypothesis 3.4

Different eco-provinces will have different landscape-level structural diversity patterns due to differences in geologic, topographic, climatic and ecological histories and processes. Specifically, the Laurentian Mixed Forest will have forest structure patterns consistent with gap-phase dynamics and the presence of shade-tolerant species, i.e., small patches of short forest structure present within a matrix of tall forest structures with high structural complexity.
Compositional and structural resilience to a gradient in intensity and strata of disturbance in mixed central Appalachian Hardwoods

2.1 Abstract

The shift towards more complex silvicultural systems requires a greater understanding of ecological responses to partial disturbances and cutting. Characteristics of the disturbance itself are likely to be important when predicting responses to differing disturbances. In this study, we examined the effects of six cutting methods on forest composition, structure and advanced regeneration across a forest management gradient of disturbance severity and forest strata disturbed. The treatments (patch clearcut, diameter-limited thinning from the top, diameter-limited thinning from below, improvement thinning, the establishment cut of a shelterwood system and an uncut control) were applied to adjacent 0.8 hectare blocks in central Appalachian hardwood forests at three sites approximately 15 years ago. We compared compositional and structural development and regeneration over time using both field-based and aerial laser scanning data.

In these forest stands, structural resilience to silvicultural disturbances was greater than
compositional resilience, resulting in forests that appeared to recover quickly from disturbance but with compositional changes. Our results indicate that both disturbance intensity and the strata disturbed influence the response of a forest to partial disturbances. While more intense disturbances caused greater changes in forest structure and composition, requiring longer to return to near pre-disturbance conditions, the forest strata disturbed modified the disturbance severity and therefore the forest’s response. While specific types of silvicultural cutting may be used to increase structural diversity at the stand level (e.g., establishment cut of a shelterwood system), this comes at the cost of an increase in shade-tolerant regeneration to the detriment of economically- and ecologically-valuable mid-successional species. The long-term outcomes of partial cuts are complex and context-specific, and this complexity may be useful for maintaining or increasing structural complexity at the landscape level, particularly where a variety of silvicultural techniques are implemented.

2.2 Introduction

Forestry has seen a shift in focus away from simple silvicultural prescriptions to more complex ones that attempt to mimic natural disturbances. Partial cutting has been advocated as one approach (Gillis, 1990; Franklin et al., 1997; Palik et al., 2002), yet the ecological consequences of partial disturbances, including partial cutting, are still poorly understood. Furthermore, few studies have directly compared the effects of different forms of partial cuttings on forest structure and composition in contrast to no-cutting and clearcutting (but see Marquis and Ernst, 1991; Qinglin et al., 2007; Belote et al., 2009). However, to make informed management decisions, forest managers need to be able to predict the ecological outcomes of different silvicultural prescription (Smith et al., 1997).

Successional theory suggests that the development over time of primary vegetation follows general patterns of increasing stature and biomass (Clements, 1916, 1936). While these ideas have been expanded and modified over time (Lewontin, 1969; Loucks, 1970; Cattelino et al., 1979; Bormann and Likens, 1979) they still form the basis for the generalized model of vegetation development after clearcutting (Oliver, 1980) in which forests develop through four stages after a major disturbance: stand initiation, stem exclusion, understory re-initiation and old growth. In the North American central hardwood forests, an extensive literature of applied silvicultural research supports Oliver’s (1980) generalized model of forest development after a major disturbance (Leopold and Parker, 1985; Ross et al., 1986; Gilliam
et al., 1995). The intense disturbance of clearcutting such stands initially results in young forest stands with many small trees and simple forest structures, dominated by fast-growing species such as yellow poplar (*Liriodendron tulipifera*), red maple (*Acer rubrum*) or sweet birch (*Betula lenta*) despite the presence of some small advanced oak (*Quercus* spp.) regeneration (Beck and Hooper, 1986; Elliott and Swank, 1994; Arthur et al., 1997; Groninger and Long, 2008). Furthermore, with an aim to minimize erosion and enhance aesthetics and oak regeneration, considerable research has also investigated shelterwood systems (Loftis, 1990a; Schlesinger et al., 1993); however, much of this research has focused solely on the promotion of oak advanced regeneration, overlooking the development of the vegetation as a whole (Clark and Watt, 1971; Johnson et al., 1989; Loftis, 1990a; Schlesinger et al., 1993; Dey and Parker, 1996).

In contrast to succession after major disturbances, forest development and resilience after partial disturbance is less well understood. In the context of this paper, resilience is operationally defined as “the ability of the system to maintain its identity in the face of internal change and external shocks and disturbances” (Cumming et al., 2005), in which the identity of a system can be measured in terms of both forest structure and/or species composition. Resilience is a measure of the forest’s ability to return to pre-disturbance conditions through successional processes, and characteristics of the disturbance are likely to influence forest resilience; for example, disturbance intensity has a strong influence on compositional resilience (Halpern, 1988). Oliver and Larson (1990, p. 157) presented a brief model of succession following a partial disturbance, where either a single cohort stand is maintained or a multi-cohort stand is created depending on the intensity of the disturbance (*sensu* Sousa, 1984) and the vigor of the remaining trees. Specifically, if the trees remaining after a partial disturbance are healthy and numerous, they will quickly close the gaps in the canopy and suppress new regeneration. However, if the remaining trees are sparse or have poor vigor and do not quickly close the canopy gaps, a new cohort of regeneration may grow under the canopy gaps. We hypothesize that both disturbance intensity (as suggested by Oliver and Larson, 1990) and the forest strata disturbed will influence succession after a partial disturbance. Furthermore, we hypothesize that disturbances of similar intensities affecting different forest strata will have differing severity (*sensu* Chapin et al., 2002) and therefore differing effects on forest resilience in terms of both forest structure and composition.

Partial cutting silvicultural techniques such as thinning may be applied to harvest some timber while only partially disturbing the forest stand. These thinning techniques differ
in the amount of biomass cut and the forest strata that they target. In contrast to the abundance of published literature investigating forest succession after major disturbances in the central hardwood forests, relatively little research has investigated these partial cutting methods. Increases in structural diversity with partial cutting have been discussed in relation to other forest types by O’Hara (1998), Bauhus et al. (2009), Zenner (2000) and Gronewold et al. (2010).

Of the research that has investigated partial cutting in the central hardwoods, diameter-limited thinning from the top, or “high-grading” has been the most researched. This technique removes all trees larger than a threshold, however, it is now commonly accepted as a poor forest management practice in the central hardwoods (Smith et al., 1997). Fajvan (2006) undertook two studies of high-grading in the Central Appalachians and suggested that the cumulative effect of residual stocking may reduce the amount of regeneration as a whole and result in patchy regeneration. In addition, diameter-limited cutting with a large size limit may produce high shade and have a positive effect on shade-tolerant species such as red maple. Trimble (1971) and Schuler (2004) found that repeated diameter-limited cutting resulted in increased amount of shade-tolerant species such as sugar maple (Acer saccharum) and red maple and reduced growth of the residual trees.

Other partial cutting techniques such as diameter-limited thinning from below (which removes all trees smaller than a threshold) and improvement thinning (which removes trees across all size classes) (Smith et al., 1997; Nyland, 2002), are poorly understood in central hardwood forests of North America.

The objectives of this study were: a) to evaluate the relationship between disturbance characteristics and forest resilience by directly contrasting a range of silvicultural cutting techniques; b) to contrast forest resilience in terms of forest structure and composition; and c) to investigate the compositional and structural effects of a diameter-limited thinning from below and an improvement thinning, and directly contrast these with silvicultural techniques that are more comprehensively understood. In addition, both traditional field measures and Light Detection and Ranging (LiDAR, a novel remote sensing technique) were used to measure forest structure.
2.3 Material and methods

2.3.1 Study sites

The three sites used in this study (Table 2.1) are oak-mixed hardwood forest stands located on publicly accessible lands in central Pennsylvania. Prior to treatment, these forest stands were full stocked (McGill et al., 1999), over 70 years old, and in the understory reinitiation stage of Oliver’s (1980) stand development model.
Table 2.1. Study site description prior to treatment

<table>
<thead>
<tr>
<th>Site</th>
<th>Latitude and Longitude</th>
<th>Aspect</th>
<th>Slope (%)</th>
<th>Elevation (m)</th>
<th>Soil Type (Anon., 2008)</th>
<th>Forest Type (Fike, 1999)</th>
<th>Upland Oak Site Index (McGill et al., 1999)</th>
<th>Stocking (%) of Oak Basal Area (%)</th>
<th>Proportion of Oak Basal Area (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>State Game-lands 211 (site 1)</td>
<td>40°23’54&quot;N 76°51’29&quot;W</td>
<td>S-SE</td>
<td>5-12</td>
<td>160</td>
<td>Calvin very stony silt loam</td>
<td>Mixed red oak-hardwood</td>
<td>56</td>
<td>65-91</td>
<td>21-78</td>
</tr>
<tr>
<td>Stone Valley Forest (site 2)</td>
<td>40°39’23&quot;N 77°53’7&quot;W</td>
<td>W</td>
<td>5-12</td>
<td>320</td>
<td>Blairton and Binkerton silt loams</td>
<td>Mixed red oak-hardwood</td>
<td>49</td>
<td>63-96</td>
<td>21-50</td>
</tr>
<tr>
<td>Tiadaghton State Forest (site 3)</td>
<td>41°27’29&quot;N 76°59’1&quot;W</td>
<td>NE-E</td>
<td>20-70</td>
<td>310</td>
<td>Oyuaga and Lordstown very stony loams</td>
<td>Transitional between mixed red oak-hardwood and northern hardwood</td>
<td>82</td>
<td>88-92</td>
<td>5-11</td>
</tr>
</tbody>
</table>
2.3.2 Silvicultural treatments

Six cutting treatments across a forest management gradient of disturbance intensities and forest strata disturbed (Figure 2.1) were applied to adjacent 0.8 ha (2 acre) blocks between 1993 and 1995. These treatments included: 1) a control with no cutting (Control); 2) a patch clearcut where all trees were removed (Clearcut); 3) a diameter-limited thinning from the top where a diameter threshold was applied removing 40% of the relative density focusing on the largest trees (Top); 4) a diameter-limited thinning from below with a threshold removing 40% of the relative density focusing on the smallest trees (Below); 5) an improvement thinning where 40% of the relative density was removed, 2/3 from below the median diameter and 1/3 from above, based on the spacing and log quality of remaining trees (2/3 Below); and 6) the establishment cut of a shelterwood system which consisted of a low-thinning where suppressed and intermediate trees were cut (Establishment). The Control and Clearcut treatments are the two extremes of the forest management gradient, with the Clearcut having the most intense disturbance (with the greatest relative density reduction). The remaining partial cutting treatments all have intermediate treatment intensities, with the Top and Establishment treatment being somewhat more intense than the Below and 2/3 Below treatments. The Below treatment focused solely on the lower strata of the forest (smallest trees), while the Establishment and 2/3 Below disturbed a greater size range of trees. The Top treatment focused on the largest trees and therefore the upper forest strata (the canopy). The Establishment treatment was only applied at sites 1 and 2. At the time of treatment, a small number of trees at site 2 suffered from Oak Wilt; however, these trees were among those that were cut.

While the interpretation of this study is constrained by the relatively small treatment plot size (0.8 ha) and few replicates within each treatment (one per site), it does allow the direct comparison of a number of treatments over relatively homogenous forest areas within each site.

2.3.3 Aerial laser scanning data

Light Detection and Ranging (LiDAR) is a new remote sensing technique that is increasingly being utilized for vegetation studies (Hyyppa et al., 2008; Hummel et al., 2011). LiDAR uses laser pulses to model the surface of the earth and produces a three-dimensional cloud of point locations where vegetation covers the earth’s surface. This point cloud of known tree
locations can be used to model the canopy of a forest, providing measures of forest structure and structural diversity (Kane et al., 2010b; Jenkins, 2011).

Between 2006 and 2008, Pennsylvania’s Department of Conservation and Natural Resources (DCNR) collected leaf-off low-density LiDAR data for all of Pennsylvania under the PAMAP program. The discrete return LiDAR data was collected and processed by numerous contractors with a 1.4 m average point spacing (2 m maximum), approximately 50 cm diameter footprint, minimum of 2 returns, 30% sidelap, 43° field of view (full angle) and laser pulse rate of 40.6 kHz, resulting in a bare earth vertical accuracy of 18.5 cm RMSE. These data were collected and processed under the US Department of Homeland Security Federal Emergency Management Agency’s (FEMA) Guidelines and Specifications for Flood Hazard Mapping Partners. The LiDAR point clouds, break-lines and LiDAR derived digital elevation model (DEM) are publically available in 9.29 km² (10000 × 10000 ft) tiles (all remote sensing data are available from http://www.pasda.psu.edu/).

Differentially corrected GPS positional data were used to clip the LiDAR point cloud for each treatment plot from the state-wide dataset using FUSION (McGaughey, 2010). All returns within 30.5 cm (1 ft) of the DEM were discarded as potential ground returns. The 95th percentile of return height was calculated and a canopy rumple index (Figure 2.2, the ratio of the canopy surface area to the planar surface area) was computed utilizing the CANOPYMODEL algorithm in FUSION (McGaughey, 2010) with 3.05 m (10 ft) cell size, and a 8 × 8 cell neighborhood size. This rumple index is an indicator of the of forest structural diversity and high values are associated with high complexity.

2.3.4 Field data

All stems over 2.5 cm (1 inch) diameter at breast height (DBH) within the interior 0.2 ha (0.6 acres) of each plot were inventoried prior to the cutting, within a year after the treatment, and in 2009 (14-16 years later). This left a 20.1 m (one chain) buffer zone of treated forest around the measured plot. Differentially corrected GPS (Global Positioning System) was used to record the precise location of each plot corner (excluding the buffer zone). In addition, within a year of cutting and again in 2009, woody vegetation between 30.5 cm (1 ft) tall and 2.5 cm (1 inch) DBH was inventoried in eighteen 4.04 m² (milacre) subplots within each treatment area laid out on a grid. Due to the great inter-annual variability in small advance regeneration (Sander, 1972; Loftis, 1990b; Norden et al., 2007; Steiner et al., 2008), seedlings
less than 30.5 cm tall were not included in this study.

### 2.3.5 Data analysis

Forest structure was characterized in this study by basal area (BA, m$^2$/ha), stems per hectare (SPH), quadratic mean of the diameter at breast height (QMD, cm), and the coefficient of variation of the diameter at breast height (CVDBH, cm). In addition, overstory species richness and Shannon’s diversity index were calculated (Barnes et al., 1998, p. 586). These forest structure and biodiversity variables were contrasted among treatment types and sites at each of three points in time (pre-treatment, post-treatment and 2009) using the Kruskal-Wallis rank sum test in R v. 2.11.1 (R Development Core Team, 2009). The overstory composition of the plots at each of the sites was characterized by non-metric multidimensional scaling (NMS) of the species’ basal area relativized by species maximum based on the Sørensen distance measure in PC-ORD v. 5 (McCune and Mefford, 2006). Scree plots of the final stress indicated that it was most appropriate to use two dimensions for all three of the NMS ordinations.

The LiDAR statistics were centered to the Control plot values (i.e., the difference between the control and treated plot at each site) and statistically tested using ANOVA with follow-up 95% confidence intervals for each treatment.

Changes in the advance regeneration (between 30.5 cm tall and 2.5 cm DBH) by shade tolerance were also plotted over time. Species were assigned to one of three shade tolerance classes (light demanding, LD; intermediate, I; or shade tolerant, ST) based on Burns and Honkala (1990a and b).

### 2.4 Results

#### 2.4.1 Overstory structure

Between 10 and 100% of the relative density (McGill et al., 1999) was removed by the cutting treatments (Figure 2.1). Both the Establishment and Top treatments removed approximately 40% of the pre-treatment relative density (45 and 36%, respectively), while the Below and 2/3 Below treatments removed less than 40% (24.1 and 27.4%, respectively).

Prior to treatment there were no significant differences among the treatment plots in terms of BA, SPH, QMD or CVDBH (all $P \geq 0.2$). Likewise, there was no significant
difference among the sites in BA (P = 0.18); however, there were significant site differences in SPH, QMD and CVDBH (P = 0.0022, 0.046 and 0.0078 respectively). As expected, within a year of treatment there were significant differences among the treatments in terms of all structural measures (P = 0.015, 0.013, 0.014, 0.048 for BA, SPH, QMD and CVDBH respectively). There were no longer significant differences among sites (all P ≥ 0.2); however, in 2009, some structural differences among the treatments still existed. Both the BA (P = 0.026) and QMD (P = 0.040) showed significant differences among treatments, whereas the SPH and CVDBH were no longer significantly different (P = 0.069 and 0.096, respectively). Despite the various treatments received, the plots exhibited stocking values between 65 and 109% by 2009 and were considered to be adequately stocked.

Over time, the BA and QMD of the Control plots both slightly increased, while the CVDBH trended downwards and the SPH was relatively stable (Table 2.2). In all of the cut plots, the BA and SPH were initially reduced by the harvest and increased over time to approximately pre-harvest levels in most treatments. In Clearcut plots, where the most BA and SPH were removed, BA was still only approximately half of the pre-treatment level after 15 years. Not surprisingly, the SPH in the Clearcut plots increased post-treatment, and were about four times higher in 2009 than before the cut. The CVDBH and QMD were both still significantly reduced in 2009, reflecting the current dominance by numerous, small, even-sized trees.

The Top treatment, which had the next largest proportion of BA removed during treatment, returned to almost pre-treatment levels by 2009. The small reduction in SPH in the Top plots following treatment reversed over time, returning to pre-treatment levels. The QMD and CVDBH, however, had not recovered by 2009. The Below, 2/3 Below and Establishment treatments, which all lost approximately similar amounts of basal area during treatment, had all recovered most of the basal area after 15 years. While the Below treatment lost the second most SPH during the harvest, this has increased slowly in the intervening years. The Below, 2/3 Below, and Establishment treatments also all recovered the majority of the SPH that was lost during treatment. Because the smallest diameter trees were removed during the treatment, the QMD of the Below and Establishment treatments initially increased post-treatment; however, this was quickly reversed as advanced regeneration grew into these small tree size classes. The CVDBH of the shelter treatment remained close to the control in the first year after treatment; however, it significantly increased over time as small trees grew to form a secondary canopy below the residual canopy. The QMD and CVDBH of
Table 2.2. Measures of forest structure pre-treatment (1993), post-treatment (1996) and 2009 including basal area (BA, m²/ha), density (SPH, stems per hectare), quadratic mean diameter (QMD, cm) and coefficient of variation of the overstory diameter at breast height (CVDBH, cm) (>2.5 cm DBH) by treatment with standard deviations in parentheses.

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Year</th>
<th>BA</th>
<th>SPH</th>
<th>QMD</th>
<th>CVDBH</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control</td>
<td>1993</td>
<td>31.86</td>
<td>(5.08)</td>
<td>702</td>
<td>(252)</td>
</tr>
<tr>
<td></td>
<td>1996</td>
<td>33.65</td>
<td>(5.73)</td>
<td>762</td>
<td>(186)</td>
</tr>
<tr>
<td></td>
<td>2009</td>
<td>37.98</td>
<td>(4.46)</td>
<td>685</td>
<td>(163)</td>
</tr>
<tr>
<td>Below</td>
<td>1993</td>
<td>29.20</td>
<td>(4.70)</td>
<td>754</td>
<td>(208)</td>
</tr>
<tr>
<td></td>
<td>1996</td>
<td>22.10</td>
<td>(6.52)</td>
<td>295</td>
<td>(58)</td>
</tr>
<tr>
<td></td>
<td>2009</td>
<td>27.26</td>
<td>(3.56)</td>
<td>491</td>
<td>(252)</td>
</tr>
<tr>
<td>Establishment</td>
<td>1993</td>
<td>30.53</td>
<td>(1.58)</td>
<td>556</td>
<td>(23)</td>
</tr>
<tr>
<td></td>
<td>1996</td>
<td>18.62</td>
<td>(5.29)</td>
<td>229</td>
<td>(44)</td>
</tr>
<tr>
<td></td>
<td>2009</td>
<td>28.43</td>
<td>(6.44)</td>
<td>669</td>
<td>(44)</td>
</tr>
<tr>
<td>2/3 Below</td>
<td>1993</td>
<td>29.99</td>
<td>(2.04)</td>
<td>674</td>
<td>(199)</td>
</tr>
<tr>
<td></td>
<td>1996</td>
<td>22.91</td>
<td>(2.88)</td>
<td>475</td>
<td>(68)</td>
</tr>
<tr>
<td></td>
<td>2009</td>
<td>28.70</td>
<td>(3.57)</td>
<td>571</td>
<td>(131)</td>
</tr>
<tr>
<td>Top</td>
<td>1993</td>
<td>25.54</td>
<td>(7.78)</td>
<td>739</td>
<td>(270)</td>
</tr>
<tr>
<td></td>
<td>1996</td>
<td>14.07</td>
<td>(3.86)</td>
<td>567</td>
<td>(77)</td>
</tr>
<tr>
<td></td>
<td>2009</td>
<td>23.32</td>
<td>(2.90)</td>
<td>787</td>
<td>(111)</td>
</tr>
<tr>
<td>Clearcut</td>
<td>1993</td>
<td>30.06</td>
<td>(6.68)</td>
<td>751</td>
<td>(106)</td>
</tr>
<tr>
<td></td>
<td>1996</td>
<td>0</td>
<td>(0)</td>
<td>0</td>
<td>(0)</td>
</tr>
<tr>
<td></td>
<td>2009</td>
<td>16.93</td>
<td>(5.48)</td>
<td>22.34</td>
<td>(1.75)</td>
</tr>
</tbody>
</table>

the 2/3 Below treatment both remained similar to the control immediately post-treatment, and were still so in 2009.

The LiDAR based canopy rumple index exhibited no significant difference among sites (P = 0.17), but there was a significant difference among treatments (P = 0.0017). Ninety-five percent confidence intervals of the rumple index values centered on the Control plot values indicate that the Clearcut treatment had a significantly smoother canopy surface model than all other treatments. The Establishment treatment had a significantly rougher canopy surface model than the control, but was not significantly different from the remaining
Table 2.3. LiDAR (2006-8) forest structure indices by treatment.

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Mean Rumpel Index</th>
<th>95% Confidence intervals of Centered Rumpel Index</th>
<th>Mean 95th Percentile of Return Height (m)</th>
<th>95% Confidence intervals of Centered 95th Percentile of Return Height (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Control</td>
<td>1.91</td>
<td>NA</td>
<td>25.8</td>
<td>NA</td>
</tr>
<tr>
<td>Below</td>
<td>4.50</td>
<td>-0.87 - 1.13</td>
<td>23.9</td>
<td>-4.4 - -2.0</td>
</tr>
<tr>
<td>Establishment</td>
<td>5.35</td>
<td>0.35 - 1.13</td>
<td>23.7</td>
<td>-5.2 - -2.5</td>
</tr>
<tr>
<td>2/3 Below</td>
<td>4.42</td>
<td>-1.21 - 0.86</td>
<td>23.2</td>
<td>-3.5 - -1.7</td>
</tr>
<tr>
<td>Top</td>
<td>3.85</td>
<td>-1.82 - 0.34</td>
<td>18.4</td>
<td>-8.0 - -6.7</td>
</tr>
<tr>
<td>Clearcut</td>
<td>4.59</td>
<td>-3.53 - -1.85</td>
<td>8.3</td>
<td>-18.1 - -16.9</td>
</tr>
</tbody>
</table>

treatments (Table 2.3). There was no significant difference among the 95th percentile LiDAR return height of sites (P = 0.918), but was a significant difference among treatments (P << 0.0001) (Figure 2.3). Analysis of the 95th percentile of return height indicated that all treatments had a significantly shorter canopy than the Control, that the Top treatment was significantly shorter than the other partial cutting treatments and that the Clearcut treatment was significantly shorter than all other treatments (Table 2.3).

2.4.2 Overstory composition

Prior to treatment, there were no differences in species richness and diversity among the treatments (P = 0.68 and 0.97, respectively), but there were significant differences among the sites (P = 0.032 and 0.0018, respectively). Post-treatment (1996), there were significant differences in species richness among treatments (P = 0.087), but not among sites (P = 0.14); however, the opposite was true for diversity (P = 0.17 and 0.041, respectively). Only the Clearcut treatment lost richness following treatment (Figure 2.4). These same patterns of species richness and diversity in respect to treatment and site remained in 2009. All of the treatment types lost some richness following the cut, but by 2009 richness equalled or exceeded pre-treatment levels with no significant differences among sites (P = 0.42), but significant differences among treatments (P = 0.014). By 2009, all of the treatments, including the Clearcut, had Shannon’s diversity index values close to their pre-treatment levels (Figure 2.4) with no significant differences among treatments (P = 0.89), but significant
differences among sites ($P = 0.0050$).

The NMS ordinations of the BA by species for each site resulted in final stress values between 6 and 13 (Figures 2.5, 2.6 and 2.7). As expected, the Control plots at each of the sites exhibited the smallest amount of change. Changes in the species composition reflected the growth of existing trees into larger size classes, particularly of the dominant or co-dominant trees. At site 1, the trajectory of the Control was most influenced by the increased basal area of American beech and northern red oak (Figure 2.5). In contrast, at site 2 the increase in the basal area of large yellow poplars and black oaks was most influential (Figure 2.6). Increased growth in large yellow poplars and medium-sized sugar maples influenced the trajectory of the control plot at site 3 (Figure 2.7).

In contrast to the Control plots, the Clearcut plots at all three sites exhibited the longest vectors and therefore the greatest amount of compositional change. Following the clearcut, light-demanding pioneering species, primarily yellow poplar and sweet birch, increased dominance at all three sites (as exhibited by the Clearcut trajectories in Figures 2.5, 2.6 and 2.7). The majority of the partial cutting treatments exhibited acute angles in the vectors connecting points over time, indicating a change in trajectory from pre-treatment to immediately post-treatment and from post-treatment to 2009. The direction and length of the treatment vectors varied among treatments.

### 2.4.3 Advance regeneration

The quantity and composition of the advance regeneration also exhibited changes among treatments in 2009 (Figure 2.8). Many of the treatments, including the Control, exhibited increases in advance regeneration (between 30.5 cm and 2.5 cm DBH). Total advance regeneration increased differentially among treatments from immediately post-harvest to 15 years post-harvest ($P = 0.0064$). This difference was primarily due to increases in shade-tolerant advance regeneration ($P = 0.014$), rather than changes in light-demanding or intermediately shade-tolerant advanced regeneration ($P = 0.22$ and 0.26, respectively). The Establishment treatment resulted in a substantial increase in shade-tolerant advance regeneration, whereas the Clearcut treatment lost the majority of its advance regeneration due to growth into the next size class.

2.5 Discussion and conclusions

The outcomes of this study suggest that both disturbance intensity and the strata disturbed influence the forest’s response to partial disturbances. Specifically, the forest structure data demonstrated that the low intensity partial disturbances (Below and 2/3 Below) maintained a single cohort structure, and one of the higher intensity partial disturbances (Establishment) developed a multi-cohort structure as predicted by the model of Oliver and Larson (1990). The influence of disturbance intensity on forest resilience also confirms the findings of investigations in Douglas-fir stands of the Pacific Northwest (Halpern, 1988). However, the other higher intensity partial disturbance (Top) did not develop a multi-cohort structure. This suggests that disturbance intensity is not the only influential factor for a forest’s response to a partial disturbance. While the Top and Establishment treatments were of similar intensity, they focused on different forest strata, indicating that the forest strata disturbed may also be an influential factor. The Top treatment removed the canopy while leaving sub-canopy trees intact, whereas the Establishment treatment cut trees both within and below the canopy. The severity (sensu Chapin et al., 2002) of the treatments would therefore be different, with the Establishment treatment causing greater changes in the understory environment by removing both canopy and sub-canopy trees.

Results indicate that mixed-oak hardwood forests are more resilient structurally than compositionally. While the ongoing changes within the control plots at all three sites indicate that structural development is progressing within these stands even without disturbance, the field-measured structural characteristics of the partial cutting treatment blocks after 15 years are similar to pre-treatment levels. As would be expected, this return to a structure similar to pre-treatment condition has been quicker for the partial cutting treatments than the Clearcut treatment. In terms of remotely-sensed canopy measures, the structural characteristics of the partial cutting treatments after 15 years remain different from the Control plots. All of the treated plots had a shorter 95th percentile of return height, which is an indicator of a shorter canopy. In addition, the Clearcut treatment rumple index was significantly smaller than the Control, indicating a simpler canopy structure, and the Establishment treatment rumple index was significantly higher than the Control, indicating a more complex canopy structure; changes to the structural complexity of the forest canopy thus remain. However, remotely-sensed measurements only offer a snapshot in time of the forest canopy and we can not be sure of the direction or rate of change which these stands may undergo in the
future. It is possible that these differences between the treatments and the Control may be decreasing over time as existing and regenerating trees grow and change the canopy structure (Belote et al., 2009).

In contrast to forest structure, the composition of some of the treated plots changed and seem unlikely to quickly return to pre-treatment conditions due to accompanying compositional changes in the advanced regeneration. After partial cutting, the environment is strongly influenced by remnant structures (Holbo et al., 1985; Deluca et al., 2009), producing a physical growing environment different from that when the stand was first initiated after the last major disturbance. While environment may determine which species may survive on a site, stochastic processes such as propagule dispersal also have a strong influence on regeneration composition (Egler, 1954; Halpern, 1988). Also, species composition in these stands differed by forest strata; therefore, partial cutting directed at specific strata removed a greater proportion of some species compared to others. All three of these processes influence the compositional response of the stand after a partial disturbance. In contrast, forest structure is an emergent property of individual tree architecture (West et al., 2009) and many tree species have similar architectures (Tomlinson, 1983). This functional redundancy may lead to forest structure to be more structurally than compositionally resilient. This difference between structural and compositional resilience leads to situations where a forest may, to the casual observer, appear to recover from forest disturbance when in fact their composition remains altered. This phenomenon may be problematic when trying to promote sustainable forestry practices as the ecological implications of compositional changes are not always obvious.

In terms of the trajectories of the treatments in compositional ordination space, there remain large differences between the pre-treatment and 2009 compositions of the Top treatment, particularly when compared to the small differences in the Below and Establishment treatment trajectories. In terms of only the “return” trajectories (post-treatment to 2009), the angle of the trajectory of the Top treatment at each site mimics the Clearcut treatment, indicating that basal area growth since treatment within these plots is similar to the growth in the Clearcut treatments. These acute angles of the partial cutting treatment vectors indicate that these forests are somewhat resilient to these disturbances with their compositions returning toward pre-treatment conditions. However, the partial cutting treatments rarely resulted in a precise return to pre-treatment composition. Generally, intense disturbances and disturbances higher in the canopy had greater overstory compositional differences be-
 tween pre-treatment and 15 years post-treatment condition. In this study, the Clearcut and Top treatments demonstrated greater changes in composition than the 2/3 Below, Establishment and Below treatments. This confirms the results of other studies that suggest that the greater the intensity of a disturbance, the greater the shift in forest composition and the longer the recovery time (Halpern, 1988; Rydgren et al., 2004; Belote et al., 2009). Furthermore, while the response to severe disturbances is relatively predictable (following models of succession), the responses to partial disturbances are complex and context specific. In this study, the Clearcut treatment at all three sites lead to a forest composition dominated by pioneering species such as yellow poplar and sweet birch. In contrast, the compositional changes following the partial cutting treatments were more variable and unpredictable.

The diameter-limited thinning from below (Below) and improvement thinning (2/3 Below) have been rarely studied in the Central Hardwoods forests. In terms of overstory compositions, these two techniques had relatively little effect compared to the diameter-limited thinning from the top (Top) or patch clearcut (Clearcut). In terms of overstory structure these treatments were also relatively resilient, resulting in structures similar to the control after 15 years. While both the Below and 2/3 Below treatments had relatively benign effects on forest structure and composition, they both allowed removal of some biomass, although the biomass removed was limited to generally low quality and small trees.

In contrast to the Below and 2/3 Below treatments, the slow growth of the QMD and CVDBH following the Top treatment suggests that trees remaining in these stands after the Top cut are only growing slowly. In addition, the remotely-sensed canopy measures indicate that the canopy of the Top treatment remains significantly shorter than the other partial cutting treatments 15 years after treatment. These results confirm the conclusions of Fajvan (2006) and Schuler (2004), who suggest that diameter-limited thinning from the top results in stands that have a lower capacity to grow as they release trees that have been suppressed for long-periods of time, perhaps due to poor genetic quality.

While the establishment cut of a shelterwood system (Establishment) is also a thin from below, it resulted in increases in shade-tolerant advanced regeneration unlike either the diameter-limited thin from below or the improvement thinning. This increase in shade-tolerant regeneration is probably due to the greater intensity of disturbance, with greater basal area cut. It must be cautioned that the Establishment treatment in this study was only a single cut and that when this treatment is included in a typical shelterwood system, further cuttings would modify the overstory sooner than 15 years post-treatment. As such,
this treatment indicates what would happen if a shelterwood system is not completed and
the overstory is not further disturbed after the establishment cut.

As demonstrated by the Establishment treatment in this study, structural diversity (as
measured by the coefficient of variation of tree DBH, and LiDAR rumple index) at the stand
level can also increase with partial cutting. This increase in structural diversity with partial
cutting generally agrees with published literature focusing on other forest types (O’Hara,
1998; Zenner, 2000; Bauhus et al., 2009; Gronewold et al., 2010). The results of this study also
reinforce the results of other studies that suggest that species richness of a site may increase
after a disturbance, with severe disturbances inducing greater increases in species richness
than light disturbances (Belote et al., 2009). However, caution must be exercised as this
increase in structural and compositional diversity at the stand level with the Establishment
treatment comes at the cost of the increased shade-tolerance of the regeneration. There
has been much concern regarding the lack of regeneration of economically- and ecologically-
valuable mid-successional oak species in the eastern hardwood forests (Loftis and McGee,
1992; Brose et al., 2008; Steiner et al., 2008) and the results of the current study indicate that
the Establishment treatment without the final overstory removal promotes shade-tolerant
regeneration to the detriment of these more light-demanding species.

When considering the results of this study it must be remembered that none of the plots
were fenced and therefore grazing pressure may have played a role in the response of the
vegetation to treatment. However, all of the treatments on each site were directly adjacent
and cut at the same time and therefore would have been exposed to similar grazing pressure.
In addition, small plots in the buffer zone of each treatment were fenced (data not reported),
and visual comparisons between the fenced and unfenced areas suggest that grazing pressure
was not severe.

The complex and context-specific response of forest stands to partial cutting could be
used to increase structural and compositional diversity at a landscape level, particularly if
a greater range of silvicultural techniques were utilized. Where maintenance of biodiversity
is a priority, the use of silvicultural cutting may be a useful technique for increasing and
managing species richness and structural diversity at a stand level, and compositional and
structural diversity at a landscape level.
Figure 2.1. At top, the box and whisker graphs show percent of the initial relative density cut in each of the treatment plots (Control, A; Below, B; Establishment, C; 2/3 Below, D; Top, E; Clearcut, F.) at each site, as calculated using the stocking equations of McGill et al. (1999). At bottom, an example of strata removed by the treatments in a forest stand with a negative exponential distribution of tree diameter at breast height (DBH on the y-axis and frequency on the x-axis).
Figure 2.2. Canopy height models for 24.4 × 24.4 m² forest plots with high (a) and low (b) canopy rumple indices respectively.
Figure 2.3. Canopy height model (m) for site 3, with boundaries of treatment plots in red: 1) 2/3 Below 2) Below 3) Control 4) Thin from the middle (not included in this study) 5) Clearcut 6) Top.
Figure 2.4. Synoptic measures of forest overstory composition (stems >2.5 cm DBH) pre-treatment (1993), post-treatment (1996) and 2009 including (a) species richness (per plot), (b) shannon diversity index by treatment (solid heavy line, control; dot-dash, Below; fine line, Establishment; short dash, 2/3 Below; dot-dot-dash, Top; long dash, Clearcut). Error bars represent +/- 1 standard error.
Figure 2.5. NMS ordination of the overstory species composition by basal area relativized by species maximum for site 1. The ordination has been rotated to align the successional trajectory of the Control plot with Axis 1. The axes are scaled proportionally to facilitate comparison with Figures 2.6 and 2.7. YP = Yellow Poplar (Liriodendron tulipifera), DOG = Dogwood (Cornus florida), H = Hickory (Carya spp.), SAS = Sassafras (Sassafras albidum), RM = Red Maple (Acer rubrum), BL = Black Locust (Robinia pseudoacacia), BAS = American Basswood (Tilia americana), AB = American Beech (Fagus grandifolia), OST = Ostrya virginiana, A = White Ash (Fraxinus americana), RO = Red Oak (Quercus rubra), WO = White Oak (Quercus alba), SO = Scarlet Oak (Quercus coccinea), BG = Black Gum (Nyssa sylvatica), SB = Sweet Birch (Betula lenta), BC = Black Cherry (Prunus serotina).
Figure 2.6. NMS ordination of the overstory species composition by basal area relativized by species maximum for site 2. The ordination has been rotated to align the successional trajectory of the Control plot with Axis 1. The axes are scaled proportionally to facilitate comparison with Figures 2.5 and 2.7. BO = Black Oak (*Quercus velutina*), AUO = Autumn Olive (*Elaeagnus umbellata*), WHL = Witch Hazel (*Hamamelis virginiana*), AE = American Elm (*Ulmus americana*), YP = Yellow Poplar (*Liriodendron tulipifera*), SAS = Sassafras (*Sassafras albidum*), AIL = Ailanthus altissima, ASP = Aspen (*Populus* spp.), SUM = Sumac (*Rhus* spp.), BL = Black Locust (*Robinia pseudoacacia*), CUC = Cucumber Magnolia (*Magnolia acuminata*), WP = Eastern White Pine (*Pinus strobus*), BAS = American Basswood (*Tilia americana*).
Figure 2.7. NMS ordination of the overstory species composition by basal area relativized by species maximum for site 3. The ordination has been rotated to align the successional trajectory of the Control plot with Axis 1. The axes are scaled proportionally to facilitate comparison with Figures 2.6 and 2.5. SB = Sweet Birch (*Betula lenta*), PC = Pin Cherry (*Prunus pensylvanica*), SUM = Sumac (*Rhus* spp.), EB = Elderberry (*Sambucus* spp.), SM = Sugar Maple (*Acer saccharum*), A = White Ash (*Fraxinus americana*), ASP = Aspen, CUC = Cucumber Magnolia (*Magnolia acuminata*), RO = Red Oak (*Quercus rubra*), BC = Black Cherry (*Prunus serotina*), YP = Yellow Poplar (*Liriodendron tulipifera*).
Figure 2.8. Mean density (per hectare) of the advanced regeneration (30.5 cm tall to 2.5 cm DBH) for each treatment immediately post-treatment and in 2009. Light-demanding (white), intermediate (grey) or shade-tolerant (black) classification was based on Burns and Honkala (1990b) and Burns and Honkala (1990a)
Chapter 3

Effect of Silviculture on Carbon Storage in Oak Mixed Hardwood Forests

3.1 Abstract

The storage of carbon in forests is a potential strategy to mitigate the effects of climate change. Partial cutting techniques have been suggested as a way of balancing carbon storage and wood production values in forests. This study evaluates the effects of six silvicultural cutting strategies on long-term above-ground carbon storage of mixed-oak hardwood forest stands using field data spanning 15 years from four sites and 100 years of FFE-FVS model simulations. The control treatment with no cutting stored the most carbon on-site both in the medium and long term, with increases in carbon suggesting that these forest stands are still sequestering carbon. While the clearcutting treatment had the highest carbon periodic annual increment (cPAI) in the first 15 years post harvest, it stored considerably less carbon in the medium and long-term than the other treatments. The projected low carbon storage in this treatment is likely due to a shift in species composition to early successional species, which store less carbon per tree. Amongst the partial cutting methods, the improvement thin was the best option in terms of carbon storage with moderate timber harvest rates, moderately high cPAI in the first 15 years post-harvest and relatively high carbon storage in
the long-term; however, refraining from cutting remains the best option for carbon storage if the forest is in the aggradation phase. Poor silvicultural decisions may lead to reduced carbon storage of forest stands in the long-term.

3.2 Introduction

The storage of carbon in forests is a potential strategy to reduce the level of carbon dioxide in the atmosphere and therefore mitigate the effects of climate change (Dyson, 1977; Schroeder, 1991; Thornley and Cannell, 2000; Hoover and Heath, 2011). Various governmental policies, taxes, landuse regulations and “cap and trade” schemes have been established to provide incentives to increase carbon storage in forests (e.g., Joint Initiative and Clean Development Mechanism of Kyoto Protocol, California’s Global Warming Solutions Act of 2006, and the United States Regional Greenhouse Gas Initiative and Western Climate Initiative). Most forests are not at maximum carbon storage due to disturbances and management (Lorenz and Lal, 2009). To maximize forest carbon storage, land managers and policy makers must understand the implications of various forest management actions on carbon storage.

Carbon storage and sequestration following major disturbances have been comprehensively studied and are well understood in a variety of vegetation types (Oliver, 1980; Elliott et al., 2002; Smith et al., 2006). After major forest disturbances or harvesting operations, the live above-ground biomass is greatly reduced; however, over time regeneration occurs and the live biomass of the site increases to near pre-disturbance levels generally defined as the aggradation phase (Bormann and Likens, 1979). The time taken for this biomass to recover is dependent on the post-disturbance site conditions and propagule dispersal, but may be reduced through silvicultural techniques.

Several studies have suggested that partial cutting techniques that mimic minor disturbances may have advantages over even-aged silvicultural systems in terms of balancing carbon storage, carbon sequestration and wood production (Thornley and Cannell, 2000; Lorenz and Lal, 2009; Davis et al., 2009). These cutting methods would maintain a relatively high biomass on the site while increasing carbon sequestration rates (compared to the undisturbed condition) and allowing for the harvest of trees; however, little work has contrasted different partial cutting techniques (Lorenz and Lal, 2009). The published literature looking at biomass responses to partial cutting and minor disturbances have generally focused on the growth of timber volumes in a stand (Miller and Smith, 1991; Schuler, 2004),
neglecting the changes that occur in the other carbon pools. Neither live tree biomass nor timber volumes directly correspond to carbon storage as carbon is also stored in the soil, coarse woody debris, forest litter and understory herbs and shrubs (Litton et al., 2007). Furthermore, the species composition (and therefore growth form, carbon density and growth rate), retention of live biomass post-disturbance, amount of remnant woody debris and decay rates all play a role in estimating carbon storage responses to disturbance.

Efforts have been made to understand carbon storage in the forest as a whole, rather than just in terms of timber volumes and live biomass (Litton et al., 2007); however, the variety of techniques and parameters used has limited our ability to compare and contrast results even within a single forest type. Studies of carbon storage response to disturbance may: use empirical (e.g. Hoover and Stout, 2007) or modelled data (e.g. Schroeder, 1991); examine carbon stocks and/or fluxes (e.g. Chiang et al., 2008); look at short term responses (e.g. Qinglin et al., 2007) or attempt to model equilibrium levels over long time frames (e.g. Thornley and Cannell, 2000); measure all (e.g. Qinglin et al., 2007) or a subset of the various carbon pools (e.g. Park et al., 2007b and Huntington et al., 1988); and either include or exclude carbon storage in wood products ex-situ (e.g. Nunery and Keeton, 2010). Furthermore, the definition of each carbon pool may be inconsistent between studies. The disturbances applied themselves may also vary greatly in terms of the type, intensity and return interval.

The response of carbon storage to silviculture in the mixed-oak hardwood forests of the eastern United States has been studied in terms of both general forest management approaches and cutting intensity, but not specific cutting treatments. Specifically, studies of even- and uneven-aged silvicultural systems in the Missouri Ozark Experimental Forest showed that while both uneven- and even-aged silvicultural systems reduced the aboveground live biomass carbon storage and increased the level of carbon storage in coarse woody debris, even-aged management had a more pronounced impact (Qinglin et al., 2007). In addition, studies have been undertaken in the Fernow Experimental Forest using a calibrated ecosystem process model with field measurements of four watersheds to reconstruct their carbon storage and fluxes of the live biomass and soil over approximately 50 years (Davis et al., 2009). Each watershed had a different management history including a no-harvest control, clearcut, selection system and diameter-limited thin from above treatments. The treatments were applied multiple times. While the clearcut watershed (an even-aged silvicultural system) was found to have reduced the mean monthly carbon stored in live vegetation
for approximately 20 years post-treatment, the partial cutting treatments (selection and
diameter limited thinning) maintained similar levels of carbon storage to the control water-
shed. Furthermore, the net ecosystem productivity (NEP) was enhanced in all of the treated
watersheds in contrast with the control.

Cutting intensity is an important factor in terms of the response of carbon storage to
silvicultural treatments. Two empirical studies summarized by Hoover (2010) examined the
effect of thinning intensity on carbon storage in the above-ground live trees of mixed-oak
(Vinton Furnace, Ohio) and northern hardwood (Bartlett Experimental forest, New Hamp-
shire) forests. A range of thinning intensities was applied at both sites and the response
of carbon storage in the live trees above-ground measured several times over approximately
30 years. Both studies found that more intense thinning treatments resulted in greater re-
ductions of post-treatment carbon storage in the live trees above-ground. The disparity
between carbon stocks across the gradient of thinning intensity remained statistically signif-
icant after 30 years, despite higher post-harvest periodic annual increments of carbon in the
above-ground live trees in the more intense treatments.

In the northern hardwoods, Hoover and Stout (2007) undertook one of the few studies
that examined the effect of thinning approach on above-ground live tree carbon storage and
concluded that the resulting forest structure after a thinning is a significant factor. This post-
hoc study of a thinning trial estimated the carbon stock of three thinning approaches with
similar intensities and a no-harvest control over approximately 80 years, with the treatments
applied twice in this time. Ten years after the second treatment, the thin from below and
control both had increased live above-ground carbon since the pre-treatment measurement,
while the thin from above and thin from the middle saw a decrease. These studies were
post-hoc and did not attempt to quantify carbon stocks in other forest carbon pools. The
results from their study on northern hardwood stands may not be applicable to other forest
types. Furthermore, by focusing on the above-ground live tree carbon pool to the neglect of
the other carbon pools, the results of their study may not reflect the effects of this thinning
approach on overall forest carbon storage.

The objective of the current study is to investigate the influence of a variety of cutting
methods (no-harvest control, patch clearcut, diameter-limited thin from below, diameter-
limited thin from the top, improvement thin and establishment cut of a shelterwood) on
medium- (15 years) and long-term (100 years) forest carbon storage in the overstory, under-
story, coarse woody debris and forest litter. We hypothesized that (a) both the even-aged
Figure 3.1. Carbon storage of individual trees in central Pennsylvania estimated using allometric equations of Jenkins et al. (2003a). BO = black oak (*Quercus velutina*), CO = chestnut oak (*Quercus montana*), WO = white oak (*Quercus alba*), SO = scarlet oak (*Quercus coccinea*), RO = red oak (*Quercus rubra*), SB = sweet birch (*Betula lenta*), YP = yellow poplar (*Liriodendron tulipifera*), SM = sugar maple (*Acer saccharum*), RM = red maple (*Acer rubra*), ASP = aspen spp. (*Populus* spp.).

and partial cutting methods would stimulate carbon sequestration rates in the medium-term with longer-lasting effects of partial cutting methods on above-ground carbon storage, and (b) there would be long-term differences in the live-overstory forest carbon storage among the cutting methods due to their effects on the composition of tree species that strongly differ in their capacity to store carbon as a function of their physical form and wood density (Figure 3.1).
3.3 Material and methods

3.3.1 Study sites

The four sites in this study (Table 3.1) are central Appalachian mixed-oak hardwood forest stands located in central Pennsylvania. The forest of each site was fully stocked (McGill et al., 1999), over 70 years old and at the understory reinitation stage of Oliver’s (1980) stand development model prior to treatment.

Prior to treatment, the State Gameland 211 (SGL211) site held many large dominant yellow poplars (*Liriodendron tulipifera*), with co-dominant northern red oak (*Quercus rubra*), black oak (*Q. velutina*), scarlet oak (*Q. coccinea*) and white oak (*Q. alba*). Red maple (*Acer rubrum*) was also present as subdominant trees. Similarly, the overstory found at the Stone Valley Forest (SVF) site was a mixture of black oak, white oak, northern red oak, yellow poplar with a few eastern white pine (*Pinus strobus*). Red maple and sweet birch (*Betula lenta*) dominated the understory. The Bald Eagle State Forest (BE) site contained large black, scarlet, white, chestnut (*Q. montana*) and northern red oaks with a complement of eastern white pine, and pole sized red maple and eastern hemlocks (*Tsuga canadensis*). Similar to the other three sites, the Tiadaghton State Forest (TIAD) site contained large yellow poplars with northern red oak and white oak co-dominants, and sweet birch and red maple subdominants; however, the pole size class was dominated by northern hardwoods species such as sugar maple (*A. saccharum*) and American basswood (*Tilia americana*).
Table 3.1. Characteristics of the study sites including their location, aspect, slope, elevation, soil type (Anon., 2008), forest type (Fike, 1999), upland oak site index (Carmean et al., 1989), pre-treatment stocking (McGill et al., 1999) and pre-treatment proportion of oak basal area.

<table>
<thead>
<tr>
<th>Site</th>
<th>Latitude and Longitude</th>
<th>Aspect</th>
<th>Slope (%)</th>
<th>Elevation (m)</th>
<th>Soil Type</th>
<th>Forest Type</th>
<th>Upland Oak Site Index</th>
<th>Stocking (%)</th>
<th>Proportion of Oak Basal Area (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>State Game-lands 211 (SGL211)</td>
<td>40°23'54&quot;N 76°51'29&quot;W</td>
<td>S-SE</td>
<td>5-12</td>
<td>160</td>
<td>Calvin very stony silt loam</td>
<td>Mixed red oak-hardwood</td>
<td>56</td>
<td>65-91</td>
<td>21-78</td>
</tr>
<tr>
<td>Stone Valley Forest (SVF)</td>
<td>40°39'23&quot;N 77°53'7&quot;W</td>
<td>W</td>
<td>5-12</td>
<td>320</td>
<td>Blairton and Binkerton silt loams</td>
<td>Mixed red oak-hardwood</td>
<td>49</td>
<td>63-96</td>
<td>21-50</td>
</tr>
<tr>
<td>Bald Eagle State Forest (BE)</td>
<td>40°54'31&quot;N 77°12'39&quot;W</td>
<td>SE</td>
<td>2-10</td>
<td>280</td>
<td>Buchanan gravelly loam and very stony loam</td>
<td>Mixed red oak-hardwood</td>
<td>75</td>
<td>66-97</td>
<td>71-94</td>
</tr>
<tr>
<td>Tiadaghton State Forest (TIAD)</td>
<td>41°27'29&quot;N 76°59'1&quot;W</td>
<td>NE-E</td>
<td>20-70</td>
<td>310</td>
<td>Oyuaga and Lordstown very stony loams</td>
<td>Transitional between mixed red oak-hardwood and northern hardwood</td>
<td>82</td>
<td>88-92</td>
<td>5-11</td>
</tr>
</tbody>
</table>
3.3.2 Field methods

Six silvicultural cutting treatments were applied at the four sites between 1993 and 1997. Each treatment was applied to 0.8 ha (2 acres) adjacent blocks, ensuring that the entire study area at each site was relatively homogeneous prior to treatment. The control treatment (Control) did not receive any cutting; in contrast, all trees in the clearcut (Clearcut) were cut. The remaining four partial cutting treatments included: 1) a diameter-limited thinning from the top where a diameter threshold was applied aiming to remove 40% of the relative density focusing on the largest trees (Top); 2) a diameter-limited thinning from below with a threshold aiming to remove 40% of the relative density focusing on the smallest trees (Below); 3) an improvement thinning where the goal was to remove 40% of the relative density, 2/3 from below the median diameter and 1/3 from above, based on the spacing and log quality of remaining trees (Improve); and 4) an establishment cut of a shelterwood system which consisted of a low-thinning (Shelter) where suppressed and intermediate trees were cut (Figure 3.2). The Shelter treatment was not followed by the overstory removal that would normally complete a shelterwood silvicultural system. The replication of these treatments across the four sites was uneven, with no Shelter treatment applied to the TIAD or BE sites and the Below treatment at the BE site undergoing overstory removal before the final re-measurement in 2009.

A buffer zone at least 20.1 m (one chain) wide was treated but not measured to avoid any edge effects. Prior to treatment, all live stems over 2.5 cm (1 inch) diameter at breast height (DBH) within a 0.24 ha (0.6 ac) plot were inventoried by their DBH and species. Within a year of treatment, a follow up inventory of all trees within the plot was undertaken.

A second follow up inventory was undertaken during the summer months of 2009 and 2010. At this time both live and dead standing trees were included, as well as measures of coarse woody debris (CWD), the understory and forest litter following Pearson et al. (2006). In addition to measuring the DBH, dead standing trees were assigned to one of three decay classes: 1) recently dead with leaves and small twigs intact, 2) stem, large branches and bark intact, but leaves and twigs lost, or 3) leaves, twigs, bark, small and large branches lost, leaving just the wood of the trunk.

Within up to three 0.04 ha (one square chain) subplots per treatment, the dimensions of all CWD greater than 5 cm on the small end diameter (SED), including stumps, were measured. For branches and logs, two end diameters and a length were recorded. For stumps, the cut surface diameter and the height above-ground level were recorded. Decay
classes similar to that for the dead standing trees were also recorded, with the addition of one further class: 4) CWD not integrated into the soil or litter but falls apart easily when force is applied. In addition, 30 samples of CWD across the range of decay classes and sites were collected. Each sample was at least 5 cm SED and approximately 25 cm long.

Within each treatment plot, eighteen 4.04 m² (one milacre) subplots located on a grid were established and the basal diameter and height of all stems between 30 cm (1 ft) tall and 2.5 cm (1 inch) DBH were measured. The herbaceous layer (herbaceous vegetation and all
woody vegetation less than 0.30 m tall) and forest litter layer (including fine woody debris up to 5 cm large end diameter, LED) within a 0.25 m quadrat were clipped and collected.

Because some of the inventories undertaken at the BE site used a different protocol to the other sites, pre- and post-treatment data can be used to demonstrate the relative intensity of the treatments but they cannot be used to estimate the carbon storage in the live overstory on this site prior to, and immediately post, harvest. These data are also adequate to ensure that the site was relatively homogeneous prior to treatment, the treatments at this site were compatible with the other three sites and to give an indication of the volume and composition of the pre-treatment forest. The 2009/2010 data were collected using a consistent protocol throughout all four sites.

### 3.3.3 Data analysis

Allometric equations from Telfer (1969), Brown (1976), Roussopoulos and Loomis (1979), Young et al. (1980), Smith and Brand (1983), Williams and McClenahen (1984), Wagner and Ter-Mikaelian (1999), Jenkins et al. (2003a) and Dickinson and Zenner (2010) (Appendix A) were used to estimate the above-ground oven-dry biomass of both shrubs and overstory trees from either DBH or stem basal diameter. The specific equations were chosen based on species, the size range of the original sample, sampling location, the number of samples, and the fit of the equation to the original sample data. Where a species did not have an appropriate equation, the equation for a congener or a general (multi-species) equation was used. The allometric equations were only used for stems within the size range of the original sample data. Fewer equations exist for shrubs and where an appropriate equation for a particular species could not be found, an allometric equation for a species with a similar growth form and wood density was used. The estimated oven-dry biomass for live trees and shrubs was then summed by plot and averaged on a per hectare basis.

Because no allometric equations for estimating the oven-dry biomass of dead standing trees have been developed, estimations were made based on reductions to the live standing biomass estimations following the methods of Smith et al. (2002) and Jenkins et al. (2003b). The following reductions were made to the live tree biomass based on the decay class: 1) reduced to 90% of the whole live tree; 2) reduced to 90% of stem and bark biomass, 77% of branch biomass and no leaf biomass; 3) reduced to 90% of biomass in the stem with no biomass in the bark, branches and leaves. Similarly, no allometric equations have been
developed for dead standing shrubs less than 2.5 cm (one inch) DBH. Estimated live shrub biomass was reduced to 70% to account for the loss of leaves and minor twigs. This level of reduction was chosen based on the average ratio of foliage to woody biomass in the allometric equations of a range of species (Telfer, 1969). The estimated oven-dry biomass for dead standing trees and shrubs was then summed by plot and averaged on a per hectare basis.

The collected samples of the herbaceous layer and forest litter were oven-dried to a constant weight. The oven-dry biomass of the herbaceous layer and forest litter was then estimated on an average per hectare basis.

The oven-dry specific density of the thirty samples of CWD was estimated using the Archimedes principle for sample volumes (i.e., using water displacement), followed by oven-drying and weighing the sample (Pearson et al., 2006). The average specific density of each of the decay classes was then estimated. The volume of each piece of CWD measured in the field was estimated using Smalian’s formula (van Laar and Akca, 2007) for branches and logs, and a cylinder for stumps. This volume and the average specific density of each decay class were then used to estimate the oven-dry biomass (Pearson et al., 2006). The estimated oven-dry biomass for CWD was then summed by plot and averaged on a per hectare basis.

The carbon stock of each carbon pool was estimated from the oven-dried biomass using a conversion rate of 0.5 (Lamlom and Savidge, 2003; Coile, 1937). The overall carbon stock, the carbon stock in each pool and the proportion of the overall carbon stock in each pool were analysed using a Kruskal-Wallis rank sum test by both site and treatment. Similarly, the carbon stock in the pre-harvest and post-harvest overstory live carbon pool at SVF, SGL211 and TIAD was also analysed using a Kruskal-Wallis rank sum test. In addition the carbon periodic annual increment (cPAI) in the live overstory between post-harvest and the 2009/10 inventories were also calculated and tested using Kruskal-Wallis rank sum tests. Where the Kruskal-Wallis rank sum tests were significant a series of Holm adjusted pairwise Wilcoxon rank sum tests were also undertaken. All statistical analyses were performed in R 2.11.1 (R Development Core Team, 2009).

To examine long-term carbon storage in the live overstory pool, storage was modeled for each treatment plot over 100 years (in 10 year cycles) using the 2009/2010 field data and the northeastern variant of the Forest Vegetation Simulator Forest Fuels Extension, FFE-FVS (Reinhardt and Crookston, 2003). FFE-FVS uses algorithms based on the FVS volume equations and does not include carbon stored in the bark.
3.4 Results

While the clearcut plots lost all of their standing basal area (BA) during treatment, the control plots increased their BA on average 2% between the pre- and immediately post-treatment inventories. The Below, Improve, Shelter and Top treatments lost on average 17%, 27%, 43% and 54% of their standing BA, respectively, following harvest. By 2009/10 all of the stands had returned to fully stocked (McGill et al., 1999).

The species composition of the treatment plots also changed between the pre-treatment and 2009/2010 inventories. While these changes were relatively small in the control plots, the composition of the Clearcut treatment plots changed substantially with large reductions in the proportion of mid-successional species such as oak (between 58 and 98% reduction in oak BA at all sites) and sugar maple (91% reduction in sugar maple BA at TIAD site) and increases in early successional species such as sweet birch and yellow poplar. The FVS model predicts that these changes in composition will remain in the long-term with oak species making up just 2.5% of the BA on average in the Clearcut treatments by 2110. In contrast, the partial cutting treatments and the controls were predicted to maintain 29.0% and 38.6% oak BA on average. The FVS model predicted that all of the stands will remain fully or overstocked by 2110.

3.4.1 Overstory

The live overstory carbon pool constituted a large portion of the total above-ground carbon pool, accounting for 16% to 89% of the total above-ground carbon (Table 3.2). Dead standing snags accounted for 0.1-8.9% of the total above-ground carbon in 2009/10 (Table 3.2).
Table 3.2. Mean carbon storage in each plot in 2009/10 by pool (tC ha\(^{-1}\)) and standard deviations in parentheses where applicable.

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Site</th>
<th>Live</th>
<th>Dead</th>
<th>Herbaceous Litter</th>
<th>Dead Shrub</th>
<th>Live Shrub</th>
<th>CWD</th>
<th>Total Above-Ground Carbon</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Over-</td>
<td>Standing</td>
<td>Snags</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Top</td>
<td>BE</td>
<td>39.4</td>
<td>3.1</td>
<td>0.1 (0.3)</td>
<td>6.0 (3.5)</td>
<td>0.1 (0.1)</td>
<td>3.6 (3.0)</td>
<td>63.6 (NA)</td>
</tr>
<tr>
<td></td>
<td>SGL211</td>
<td>92.7</td>
<td>4.0</td>
<td>0.1 (0.0)</td>
<td>5.1 (2.2)</td>
<td>0.0 (0.0)</td>
<td>1.3 (1.8)</td>
<td>32.2 (11.8)</td>
</tr>
<tr>
<td></td>
<td>SVF</td>
<td>59.6</td>
<td>1.4</td>
<td>0.1 (0.1)</td>
<td>4.8 (1.3)</td>
<td>0.0 (0.1)</td>
<td>0.9 (1.0)</td>
<td>12.0 (0.9)</td>
</tr>
<tr>
<td></td>
<td>TIAD</td>
<td>76.6</td>
<td>2.7</td>
<td>0.3 (0.3)</td>
<td>4.6 (2.9)</td>
<td>0.0 (0.1)</td>
<td>0.4 (0.7)</td>
<td>11.1 (4.1)</td>
</tr>
<tr>
<td>Below</td>
<td>SGL211</td>
<td>100.3</td>
<td>1.4</td>
<td>0.1 (0.1)</td>
<td>4.7 (2.6)</td>
<td>0.0 (0.0)</td>
<td>2.0 (4.4)</td>
<td>68.1 (68.9)</td>
</tr>
<tr>
<td></td>
<td>SVF</td>
<td>85.9</td>
<td>0.5</td>
<td>0.3 (1.1)</td>
<td>7.4 (3.4)</td>
<td>0.1 (0.2)</td>
<td>1.6 (1.7)</td>
<td>28.7 (17.3)</td>
</tr>
<tr>
<td></td>
<td>TIAD</td>
<td>119.0</td>
<td>0.5</td>
<td>0.8 (1.3)</td>
<td>4.0 (2.2)</td>
<td>0.0 (0.0)</td>
<td>0.1 (0.3)</td>
<td>14.8 (1.0)</td>
</tr>
<tr>
<td>Clearcut</td>
<td>BE</td>
<td>26.1</td>
<td>0.6</td>
<td>0.1 (0.2)</td>
<td>6.8 (6.2)</td>
<td>0.1 (0.3)</td>
<td>1.6 (2.5)</td>
<td>121.3 (83.2)</td>
</tr>
<tr>
<td></td>
<td>SGL211</td>
<td>39.1</td>
<td>6.3</td>
<td>0.1 (0.0)</td>
<td>6.3 (1.8)</td>
<td>0.1 (0.1)</td>
<td>0.3 (0.7)</td>
<td>18.9 (3.0)</td>
</tr>
<tr>
<td></td>
<td>SVF</td>
<td>43.2</td>
<td>0.4</td>
<td>0.5 (1.7)</td>
<td>6.0 (3.2)</td>
<td>0.2 (0.4)</td>
<td>0.4 (0.7)</td>
<td>11.4 (4.4)</td>
</tr>
<tr>
<td></td>
<td>TIAD</td>
<td>23.1</td>
<td>1.0</td>
<td>0.6 (0.7)</td>
<td>4.5 (2.7)</td>
<td>0.3 (0.7)</td>
<td>2.0 (3.4)</td>
<td>58.8 (50.7)</td>
</tr>
<tr>
<td>Control</td>
<td>BE</td>
<td>127.6</td>
<td>1.4</td>
<td>0.1 (0.1)</td>
<td>5.9 (2.7)</td>
<td>0.0 (0.0)</td>
<td>0.5 (0.7)</td>
<td>9.8 (4.1)</td>
</tr>
<tr>
<td></td>
<td>SGL211</td>
<td>147.8</td>
<td>16.0</td>
<td>0.1 (0.0)</td>
<td>6.4 (3.1)</td>
<td>0.0 (0.0)</td>
<td>0.2 (0.6)</td>
<td>22.5 (23.5)</td>
</tr>
<tr>
<td></td>
<td>SVF</td>
<td>121.4</td>
<td>1.4</td>
<td>0.2 (0.1)</td>
<td>4.6 (2.2)</td>
<td>0.0 (0.0)</td>
<td>1.6 (1.7)</td>
<td>6.7 (3.2)</td>
</tr>
<tr>
<td></td>
<td>TIAD</td>
<td>122.1</td>
<td>7.9</td>
<td>0.2 (0.2)</td>
<td>5.8 (3.8)</td>
<td>0.0 (0.0)</td>
<td>0.2 (0.4)</td>
<td>36.6 (17.5)</td>
</tr>
<tr>
<td>Improve</td>
<td>BE</td>
<td>90.5</td>
<td>0.6</td>
<td>0.0 (0.0)</td>
<td>5.3 (1.5)</td>
<td>0.0 (0.0)</td>
<td>0.2 (0.3)</td>
<td>20.9 (14.5)</td>
</tr>
<tr>
<td></td>
<td>SGL211</td>
<td>111.9</td>
<td>0.7</td>
<td>0.1 (0.0)</td>
<td>6.5 (3.4)</td>
<td>0.0 (0.1)</td>
<td>1.6 (2.2)</td>
<td>16.2 (4.5)</td>
</tr>
<tr>
<td></td>
<td>SVF</td>
<td>116.7</td>
<td>3.1</td>
<td>0.3 (0.2)</td>
<td>7.7 (3.7)</td>
<td>0.0 (0.0)</td>
<td>0.5 (0.5)</td>
<td>12.3 (10.0)</td>
</tr>
<tr>
<td></td>
<td>TIAD</td>
<td>85.4</td>
<td>2.8</td>
<td>0.5 (0.5)</td>
<td>4.4 (1.7)</td>
<td>0.0 (0.0)</td>
<td>0.1 (0.2)</td>
<td>30.3 (23.1)</td>
</tr>
<tr>
<td>Shelter</td>
<td>SGL211</td>
<td>130.4</td>
<td>1.4</td>
<td>0.1 (0.0)</td>
<td>5.5 (1.4)</td>
<td>0.3 (0.5)</td>
<td>1.3 (1.8)</td>
<td>26.7 (5.6)</td>
</tr>
<tr>
<td></td>
<td>SVF</td>
<td>86.9</td>
<td>0.1</td>
<td>0.3 (0.9)</td>
<td>5.7 (2.2)</td>
<td>0.0 (0.1)</td>
<td>2.4 (3.3)</td>
<td>25.6 (15.4)</td>
</tr>
</tbody>
</table>
Prior to treatment, there were no statistically significant differences in the carbon storage of the live overstory among the treatments at SGL211, SVF and TIAD (P = 0.79; Figure 3.3). There were significant differences in the carbon storage among the sites (P = 0.017), with SVF having lower carbon stocks than TIAD (P = 0.013). The live overstory carbon stock at SGL211 was intermediate between these two sites, but not significantly different from either site (P = 0.082 and 0.33 respectively). While the pre-harvest data collected at BE does not permit estimation of the carbon stock of the live overstory, the BA was similar among all of the treatments with a mean of 29.0 m²ha⁻¹ (126.5 ft²ac⁻¹) and standard deviation of 3.6 m²ha⁻¹(15.9 ft²ac⁻¹); therefore, it is likely that the carbon storage between the treatments at BE were not significantly different pre-treatment.

Post-treatment, there were significant differences in live above-ground overstory carbon storage among the treatments (P = 0.018; Figure 3.3), but not among sites (P = 0.72). While the Control plots exhibited little change in carbon stock, the Clearcut plots no longer stored any carbon in the live overstory carbon pool. The Top treatment lost more than the Improve and Shelter treatments, which also lost more carbon stock than the Below treatment. The post-harvest data collected at BE does not permit estimation of carbon stock of the live overstory; however, the reductions in BA in each of the treatments reflect the trends in the loss of carbon stock at the other sites. The Clearcut treatment at the BE site lost all of the live overstory BA, while the Top treatment lost the most of all the partial cutting treatments, and the Improve had a small reduction in its BA.

In 2009/2010, there were still significant differences among the treatments in live overstory carbon (P <0.001; Figure 3.3), but no significant differences among sites (P = 0.090). The Clearcut treatment carbon stock had increased since the post-treatment inventory; but still stored less carbon than pre-treatment levels. The Top treatment also stored less carbon than before treatment. The Below, Improve and Shelter treatments returned to close to pre-treatment levels of carbon storage in the live overstory; however, they still stored less carbon than the control plots, which increased their storage over time.
Figure 3.3. Box-plots (median, upper- and lower-quartiles, maximum, and minimum) of pre-harvest, post-harvest and 2009/10 live overstory carbon stock by treatment.
Growth in carbon storage (cPAI) was not statistically significantly different among the treatments at SVF, SGL211 and TIAD ($P = 0.11$; Figure 3.4), nor among sites ($P = 0.24$). The Control and Below had the smallest cPAI with slow growth in carbon storage; however the Top, Clearcut and Shelter treatments had similarly high cPAIs. The Improve treatment had a cPAI intermediate between these two groups. There were no significant differences among treatments nor sites in carbon storage in dead standing snags ($P = 0.11$ and 0.29, respectively) in 2009/10.

Although, the FFE-FVS uses different methods from the allometric methods described above to estimate the live overstory above-ground carbon stock, the 2010 estimates of carbon in the overstory using the FFE-FVS model were generally similar to those estimated from the 2009/10 field measurements (Figure 3.5 and Table 3.2). Whereas carbon storage of the Control, Shelter, Improve and Below was somewhat underestimated in the FFE-FVS model compared to the allometric equation methods, the relative carbon storage of all treatments is consistent with the allometric equation estimations. The FFE-FVS simulation shows that
the live above-ground overstory carbon stock of the Control plots continued to increase to an approximate equilibrium in 2070 (Figure 3.5). Similarly, each of the treatment plots reached an approximate equilibrium by 2090; however all of the treated plots stored less carbon than the Control. While the Shelter treatment had the highest carbon storage of all of the partial treatments in 2010, its projected rate of increase was lower than the other partial cutting methods, resulting in a lower live above-ground carbon stock in the long term. The Improve, Top and Below cutting treatments all reached an approximate equilibrium, which was intermediate between the Control and the Shelter treatments. In the long term, the Clearcut treatment stored considerably less carbon than any of the other treatments.
3.4.2 Understory

In 2009/2010 the live shrub and herbaceous layer carbon pools accounted for 0.1-3.1% and 0.1-0.8% of the total above-ground carbon, respectively. There were no significant differences among the treatments in carbon storage in the herbaceous layer (P = 0.82) nor for live shrubs (P = 0.70, Table 3.2). There were differences among sites in the herbaceous layer carbon stock (P = 0.0015), with SGL211 storing significantly less carbon compared to both the TIAD and SVF site (P = 0.022 and 0.013, respectively). There was no difference among the sites in the carbon stock of live shrubs (P = 0.33).

While dead standing shrubs accounted for a very small proportion of carbon storage, there were significant differences among the treatments (P = 0.015), with the greatest carbon storage in the Clearcut treatments. There were no significant differences among sites in dead standing shrub carbon stock (P = 0.74).

3.4.3 Coarse woody debris and litter

In 2009/10 the litter and CWD carbon pools accounted for 2.7-8.9% and 4.9-77.5% of the total above-ground carbon, respectively. There were significant differences of the estimated wood density among the three decay classes sampled (P <0.0001; Figure 3.6); but no significant differences among the sites in estimated density of the CWD samples (P = 0.32). The mean estimated density of these three decay classes was 374, 416 and 211 kg m⁻³, respectively.

There were no significant differences among treatments or sites in carbon storage in CWD (Table 3.2, P = 0.80 and 0.31, respectively), nor were there significant differences among treatments or sites in terms of carbon storage in forest litter (P = 0.86 and 0.057, respectively).

3.4.4 Total above ground carbon stock

When summed, these pools of carbon storage give an estimate of the above-ground carbon storage of the forest stand as a whole. In 2009/10 there were no significant differences among sites (P = 0.40) in total above-ground carbon stock. Differences among treatments were only weakly significant (P = 0.077; Figure 3.7). The Clearcut and Top treatments stored approximately the same amount of carbon above-ground 15 years after treatment, but less than the Below, Improve and Shelter, which were similar to the Control.
Figure 3.6. Estimated density of coarse woody debris (CWD) samples by decay class (2-4) by site. BE = open circle, SGL211 = open triangle, SVF = plus, and TIAD = open diamond.

3.5 Discussion

The total above-ground carbon storage estimated for these forest stands is generally consistent with other estimates of carbon storage for the mixed red oak-hardwood forest type in Pennsylvania. Smith et al. (2006) estimated that 75-115 year old northeastern oak-hickory stands regenerated after clearcutting store between 170.6-226.5 tCha$^{-1}$ in the live trees (above- and below-ground), 4.9-5.2 tCha$^{-1}$ in dead standing, 1.8-1.7 tCha$^{-1}$ in the understory, 11.8-15.5 tCha$^{-1}$ in CWD, and 8.9-115 tCha$^{-1}$ on the forest floor. In contrast, the storage of above-ground carbon of the control plots studied here is somewhat lower, ranging between 135 and 195 tCha$^{-1}$ (excluding soil), with 121-147 tCha$^{-1}$ in the live trees. Simi-
Figure 3.7. 2009/10 total above-ground carbon stock by treatment

Larly, Smith et al. (2006) estimated that 15 year old regenerating northeastern oak-hickory stands regenerated after clearcutting store 69.1 tCha\(^{-1}\) in all non-soil carbon pools. The difference between their estimates and those estimated in this study may be accounted for by the exclusion of below ground live carbon (roots), which are generally estimated at 26% of above-ground live carbon stock (Cairns et al., 1997). The 2009 USDA Forest Inventory and Analysis (Anon., 2010) estimated that stands between 0-19 years old store on average 16.39 tCha\(^{-1}\) in live trees and stands over 80 years old store 87.1 tCha\(^{-1}\). These values are comparable but somewhat lower than the estimates found in this study (averaging 32.8 tCha\(^{-1}\) for 15 year old clearcuts and 129.7 tCha\(^{-1}\) for the control plots). However, the FIA means include a greater range of site qualities and sites in this study were generally of good quality.
with moderate to high site indices, which likely explains their higher carbon stocks.

We hypothesized that while all cutting methods would increase carbon sequestration rates in the medium term, the Clearcut would have a greater reduction in above-ground carbon storage and longer-lasting effects. The results of this study confirm that the Clearcut had the greatest and longest reduction in above-ground carbon storage compared to the other treatments. In contrast, the live overstory carbon storage of the control plots increased over 15 years post-treatment, indicating that these forest stands continued to develop and grow during that time and were in the aggradation phase as described by Bormann and Likens (1979). However, in comparison to the post-treatment increment in the Top, Clearcut, Improve and Shelter plots, the increase in carbon storage was small. The results of this study show that the cPAI increased in four of the five treatments. The Below cPAI post-treatment was similar to the Control, suggesting that unlike the other cutting treatments, the Below treatment does not induce an increase in carbon sequestration immediately post-treatment.

The Top, Below and Shelter treatments lost between 17 and 43% of their BA during treatment, but after 15 years stored similar amounts of overall carbon and were only a little lower than the Control. While the Top treatment lost only a little more BA than the Shelter treatment during treatment, 15 years post-treatment it still stored less carbon with similar carbon storage to the Clearcut treatment. This indicates that cutting intensity alone does not dictate medium-term carbon stock and that, similar to the findings of Hoover and Stout (2007), the forest structure remaining after treatment and the treatment type are influential.

As hypothesized, there were long-term carbon-storage differences among the treatments due to changes in species composition. The FFE-FVS model suggests that the Clearcut treatment is unlikely to return to the same carbon storage level as the partial cutting and control plots, even over a long time frame. This is due to the loss of mid-successional species such as oaks, which store more carbon per tree than early successional species such as yellow poplar and sweet birch (Figure 3.1). FVS is an individual-tree distance-independent growth and yield model. Therefore, projections based on the current composition and advanced regeneration are possible; but the introduction of new species cannot be predicted. The loss of oak composition is probably due to oak species having lower growth rates than both yellow poplar and sweet birch, that often out-compete oak species. This reduction in long-term carbon stock after disturbance due to changes in species composition runs counter to Lorenz and Lal (2009), who suggest that forest net C storage may approximate zero in the
long term despite compositional changes. Furthermore, this reduction in carbon storage due to compositional changes has important implications for the management of mixed-oak hardwood forests, particularly as widespread declines and regeneration failures of oak species have been recorded (Loftis and McGee, 1992; McWilliams et al., 2007; Fei et al., 2011). The most favorable treatment was the Control, followed by the Improve, Top and Below treatments. While this model suggests that the Top treatment stores similar levels of carbon as the Improve and Below in the long term, these results should be viewed with caution; FFE-FVS does not account for depressed growth rates that may occur after a diameter-limited thinning from the top due to the release of trees that have been suppressed for a long time, nor for the degradation of population genetics that is likely to occur when harvesting all of the large trees in a stand (Trimble, 1971; Hawley et al., 2006; Fajvan, 2006).

It is also important to note that the relative difference of carbon stock among the treatments in the long-term projections (100 years) differ from those after 15 years. While the shelter treatment would appear to be the best option in terms of carbon storage in the live above-ground overstory 15 years after treatment, it is one of the worst options after approximately 80 years (2075). Further, this treatment is an incomplete shelterwood system with no final overstory removal cut; therefore, these results do not apply to complete shelterwood systems that are implemented to regenerate oak stands in the central hardwoods.

The greater reduction in the above-ground live carbon storage in the even-aged management treatment (Clearcut) than in the partial cutting treatments (Top, Below, Improve and Shelter) seen in this study agree with results reported by Qinglin et al. (2007). However, the estimated carbon storage of CWD was more variable in this study. Our results that the annual increment of carbon for approximately the first decade post-harvest is much higher for the clearcut than for the control and the majority of the partial cutting treatments also agree with Davis et al. (2009); however, the Shelter and Top treatments in this study demonstrated a comparable cPAI to the Clearcut. Based on these results, forest management for the sole objective of medium-term carbon sequestration (as opposed to storage) would be most successful implementing a Shelter, Top or Clearcut treatment.

Similar to both the Vinton Furnace, Ohio and Bartlett Experimental Forest, New Hampshire studies summarized in Hoover (2010), this study found that generally the greater the thinning intensity the greater the annual increment of carbon post-treatment; however, the variation between partial cutting treatments of similar intensity in this study indicates that this is not a simple relationship. For example, the Below treatment had a more intense cut.
than the Control (that had none); however the cPAI post-harvest was similar. Furthermore, the Shelter, Top and Clearcut all demonstrated similar cPAI post-harvest, but were treated with greatly varying intensities. In addition, the Shelter treatment was less intense than the Top (43 and 54% of the BA removed, respectively), but had a somewhat higher 15-year post-harvest cPAI. These results suggest that the forest structure left behind after thinning as well as the thinning intensity had an effect on the post-harvest carbon sequestration in the live above-ground carbon pool.

Hoover and Stout (2007) compared carbon storage among different thinning approaches in an Allegheny hardwood forest. Similar to their work, this study found that there was increased carbon storage over time in the controls and that there were differences among the thinning approaches; however, the specific differences among the thinning approaches differ between the two studies. The Improve and Shelter treatment in this study are most similar to the thin from the middle in Hoover and Stout (2007). They found that 10-years after the harvest, the thin from below and control both had increased live above-ground carbon, but the thin from above and the middle saw a decrease. The study presented here found that the Below, Improve and Shelter were similar to each other, and after 15 years returned to close to precut carbon storage levels in the above-ground live carbon pool, but stored less than the Control; the Top was intermediate between these cuts and the Clearcut treatment. The differences between these two studies may be attributed to the compositional differences between these two forest types. The prevalence of shade-tolerant species, such as American beech (*Fagus grandifolia*), sugar maple and red maple in the mid- and understory of the Allegheny hardwood forests may allow for greater growth in overtopped trees with limited canopy disturbance. This would account for the greater response (similar to the control) in the diameter-limited thin from below seen in Hoover and Stout (2007).

The mean estimated density of the three decay classes utilized in this study were consistent with the five decay classes of Harmon et al. (2008). While CWD is a major pool of carbon storage, there were no significant differences among sites or treatments in the 2009/10 CWD carbon stock. Carbon storage in CWD should be accounted for; however, it cannot be relied upon as a large, consistent or long-term form of carbon storage. Carbon storage in CWD is likely to be dependent on a number of factors including the average piece size of the stand, the machinery and techniques used to harvest the stand, and the markets available for biomass.

The objective of this study was to investigate the implications of various cutting practices
on within-forest carbon storage; however, carbon that is cut may also be stored in derived products (e.g., timber). The inclusion of these wood products in long-term models of carbon storage may give results that differ from the current study, particularly as large high-quality logs from Clearcut and Top treatments may produce veneer and sawtimber, which will store carbon for longer periods than wood products derived from small-dimension low-quality logs. However, modeling of carbon storage within-forest and wood-products in northern hardwood-conifer forests using FIA data has shown results that are consistent with the current study (Nunery and Keeton, 2010). Furthermore, many governmental policies, taxes, landuse regulations and “cap and trade” schemes assume instant devolution of carbon (e.g., New Zealand’s Permanent Forest Sink’s Initiative) when the forest is harvested due to the complexities of modeling carbon storage in wood products. As such, the current study addresses the storage of carbon in forests only, and does not attempt to quantify the carbon storage in wood products.

This study demonstrated that silviculture has long-term impacts on carbon stock. Silvicultural activities that alter the species composition of the stand will lead to reduced long-term carbon storage in forest stands. Furthermore, the effect of various cutting techniques in terms of relative carbon storage in the medium term (15 years) is not indicative of long-term (100 years) carbon storage projected by the FFE-FVS model. Overall, if a forest stand is in the aggradation phase, the optimum option for carbon storage is to not cut. Clearcuts may recover quickly initially with a high cPAI in the medium term, but may be slow to recover the full amount of carbon lost due to species compositional changes. The Top was only somewhat better than the clearcut in the in medium term; however, modelling suggests that it may be similar to other partial cutting methods in the long term, with only somewhat less carbon stock than the no-cut control. The Top results should be viewed with caution as FFE-FVS does not take into account the slower growth rates of trees that have been supressed for a long time, nor the poorer genetics left behind by high-grading. The Below treatment was slow to recover in the medium term, but over the long term increased carbon storage to levels similar to those in the Controls. The Shelter was the worst of all the partial cuts in the long term, despite showing a good cPAI and good recovery in medium term. Overall the Improve treatment was the best, with a moderately high cPAI and recovery in the medium term. In addition, the Improve treatment returned to control levels of live above-ground carbon storage in the long term. Furthermore, improvement thinning is compatible with the longer rotation lengths that have been suggested by others as another
technique to increase forest carbon storage (Lorenz and Lal, 2009).
Chapter 4

Mapping forest canopy structure using topographic LiDAR

4.1 Abstract

A method to map forest canopy structure over large areas was developed using low-density topographic Light Detection And Ranging (LiDAR) data and orthographic photography collected for Pennsylvania as part of the USGS National Map program. The LiDAR point cloud and orthographic photographs at four sites were divided into a grid of square 0.06 ha cells. K-means clustering of the cells was used in conjunction with multinomial logistic regression to develop a LiDAR Canopy Structure Topology (LCST), which was then applied to a further twenty large landscapes for validation. The fourteen resulting LCST types reflect vegetation top height and canopy structural complexity with a correct classification rate of 96%. The resulting LCST provides cost-effective information for forestry, wildlife management, and landscape ecology by relying on data already available for the entire commonwealth of Pennsylvania. Furthermore, this method could be applied in other regions to map forest canopy structure using low-density topographic LiDAR.
4.2 Introduction

Forest and wildlife ecosystem management increasingly relies on spatially explicit information about forest structure over large areas. Although the value of high-density LiDAR for estimating traditional forest structure measures has been demonstrated for a wide range of forest types and scales (e.g. Lefsky et al., 1999; Andersen et al., 2005b; Means et al., 2000; Thomas et al., 2006; Kane et al., 2010a; Jenkins, 2011; Zhao et al., 2011), the collection of these data can be prohibitively expensive (Tilley et al., 2004). Further, many of these measures of forest structure (diameter at breast height, stem density, biomass) best estimate forest productivity and only indirectly assess forest canopy structure. In contrast, low-density discrete return LiDAR data have already been collected over large areas for the development of digital elevation models (DEM) and flood risk mapping in many regions (USGS, 2011), making it a cost-effective data source. Although data collected with wide return spacing and wide scan angles may not be ideal for studies of vegetation (Holmgren et al., 2003; Morsdorf et al., 2008), using the entire LiDAR point cloud may adequately represent the biophysical structure of the forest canopy (position of branches, stems and leaves), permitting direct estimates of canopy height and structural complexity.

Forest canopy structure is often treated as a discrete condition identified within predetermined classes with arbitrary divisions (e.g. Falkowski et al., 2009; Kane et al., 2010a; van Ewijk et al., 2011). For example, the successional stages of Oliver and Larson (1990) have been used as forest structure classes (Kane et al., 2010a; van Ewijk et al., 2011). However, forest structure is a multi-dimensional non-linear continuous phenomena. Numerous attributes contribute to forest structure, of which many are continuous gradients without distinct divisions or groups (McElhinny et al., 2005). Furthermore, these attributes tend to develop and interact nonlinearly. Therefore, forest structure may be best measured in terms of actual structural condition rather than such predetermined classes (Kane et al., 2010a; van Ewijk et al., 2011). Furthermore, it can be difficult to ensure that the complete range of existing forest canopy structures are identified in advance. An alternative approach would be to use cluster analysis to group similar LiDAR return distributions and then relate this to known forest canopy structures.

The objective of this study was to develop, test, and demonstrate a typology for the mapping of forest canopy structure (LiDAR Canopy Structure Typology, LCST) over large areas using a publicly available state-wide low-density LiDAR dataset. This typology was
developed using non-hierarchical cluster analysis and applied to large areas using multinomial logistic regression.

4.3 Methods

4.3.1 Remote sensing data

Between 2006 and 2008, Pennsylvania’s Department of Conservation and Natural Resources (DCNR) collected leaf-off low-density LiDAR data and orthographic aerial photography (color, 30.5 cm [1 ft] pixel resolution) for all of Pennsylvania under the PAMAP program. The discrete return LiDAR data were collected and processed by numerous contractors with a 1.4 m average point spacing (2 m maximum), approximately 50 cm diameter footprint, minimum of 2 returns, 30% sidelap, 40° field of view (full angle) and laser pulse rate of 40.6 kHz, resulting in a bare earth vertical accuracy of 18.5 cm RMSE. These data were collected and processed under the US Department of Homeland Security Federal Emergency Management Agency’s (FEMA) Guidelines and Specifications for Flood Hazard Mapping Partners. The LiDAR point clouds, breaklines, LiDAR derived digital elevation model (DEM) and orthophotos are publically available in 9.29 km$^2$ (10,000 × 10,000 ft) tiles. To ensure that only forested areas were included in the analysis, forested areas were extracted using the forest landcover classes of the PAMAP Program Land Cover for Pennsylvania (all remote sensing data are available from http://www.pasda.psu.edu/).

4.3.2 Study site and field data collection

Two datasets were used to develop and validate the LCST. First, field and remotely sensed data from the forested area of four tiles of LiDAR data from central Pennsylvania were used to develop the LCST. Remote sensing data (LiDAR and orthophotos) were available for the entirety of each tile, while field data were available for the portion of each tile that encompassed one of four silvicultural demonstration sites that had been treated between 1993 and 1997 with up to six cutting treatments in adjacent 0.8 ha blocks (21 treatment blocks total). A full inventory of all trees larger than 5 cm in these forest stands was undertaken in the summers of 2009 and 2010. At the time of inventory, all of the stands were fully stocked (McGill et al., 1999); however, the structure of these cutting treatment blocks varied greatly. The control blocks maintained a tall canopy of predominantly large red, black and/or white
oak (Quercus rubra, Q. velutina and Q. alba respectively) and yellow poplar (Liriodendron tulipifera) with sugar or red maple (Acer saccharum and A. rubrum respectively) and other hardwoods in the subcanopy. The clearcut treatment blocks held short, dense, self-thinning pole stands of early successional species (particularly sweet birch [Betula lenta], and yellow poplar). The dense canopy of the diameter-limited thin from the top treatment blocks remained shorter than the surrounding canopy, with a species composition similar to the pre-cut condition. The shelterwood establishment cut blocks consisted of a tall canopy remaining from the initial forest stand, with a secondary canopy of poles in the understory. Finally, the improvement cut and diameter-limited thin from below had returned to a similar composition and structure as the control plots by 2009/2010 (see Chapter 2).

The second dataset of 193 additional tiles encompassing twenty large (8-15 thousand hectares each) randomly selected forested landscapes within Pennsylvania (Figure 4.1) was used to assess the LCST by applying the forest typology (described below) and validating the results against a) the orthographic aerial photos for all twenty landscapes and b) field-data that were collected from 25 random-stratified locations of varying forest structure within two of the twenty landscapes. At each of these field validation locations, the forest structure and species composition were described, oblique photographs were taken, a spherical densiometer was used to estimate canopy cover, canopy top height and estimated canopy cover by height were recorded, and a GPS location was taken.
Figure 4.1. Location of the twenty landscapes analyzed in this study
4.3.3 Data analysis

Remote sensing data from the four development tiles (57,587 cells total) were analysed using a k-means clustering algorithm to define the LCST types. These data were then used to develop multinomial logistic regression equations for applying the typology to the other twenty large landscapes. These analyses were undertaken in R (R Development Core Team, 2009).

Summary statistics to describe the LiDAR point cloud distribution in 0.06 ha (24.4 × 24.4 m or 80 × 80 ft) cells were extracted using FUSION (McGaughey, 2010). LiDAR returns greater than 0.3 m (1 ft) above the digital elevation model were included in these summary statistics; all returns below this were regarded as ground returns. These summary statistics included the mean, 95th percentile, standard deviation, coefficient of variation, kurtosis and skewness of return height. The 95th percentile of return height was used rather than the maximum to mitigate the effect of any singular outlying return. In addition, the proportion of all returns greater than 0.3 m (1 ft) above the digital elevation model was calculated as a relative index of vegetative cover. Finally, a rumple index for the canopy surface was calculated using the GRIDSURFACESTATS algorithm in FUSION by first creating a canopy height model with 9.3 m² (3 × 3 m² or 10 × 10 ft²) sub-cells that were aggregated into 0.06 ha cells (i.e., 8 × 8 sub-cell neighbourhoods) and then calculating the ratio of the rumpled canopy surface area to the planar surface area.

Pennsylvania’s forests are a mixture of deciduous and evergreen species, and the amount of evergreen cover in each cell was variable. While LiDAR studies based on identifying individual trees have utilized the distance between the first and last return to identify the tree as deciduous or evergreen (Liang et al. 2007), it was not known whether the LiDAR height data alone could accurately measure the amount of evergreen foliage within a cell. Due to differences in foliage density, we hypothesized that the laser would interact with evergreen and leaf-off deciduous vegetation differently, distorting the results. The areas occupied by evergreen species in the orthophotos were therefore identified using supervised classification of the three visible light channels with Mahalanobis distance in ENVI (Research Systems Inc. 2005). The number of 30 × 30 cm² (1 × 1 ft²) pixels, which were occupied by evergreen vegetation within each 0.06 ha cell, was then calculated to give a measure of the amount of evergreen foliage within that cell (ranging from 0 to 6400) and converted to a proportion of evergreen abundance.

The appropriate number of clusters for the k-means algorithm were identified by repeating
the analysis for up to 25 clusters and plotting a scree-like plot of the within-cluster sums of squares against the number of clusters. The inflexion point of the curve indicated the appropriate number of clusters; after this point, increasing numbers of clusters gave much smaller reductions in the within-cluster sums of squares (Figure 4.2).

We evaluated several k-means clustering models that varied in terms of which variables were included, whether or not variables were relativized (by range), and how the 95th percentile variable (as a measure of canopy top height) was weighted (e.g., doubly) [see Appendix B for further details]. Each of these models was qualitatively assessed by comparing the resulting cell classifications (LCST types) to field data from the silvicultural demonstration plots and visually comparing the mapped LSCT against orthophotos. Initial classifications inadequately reflected the forest structure as identified in the orthophotography and field data from the silvicultural demonstration plots. The final model described below resolved these misclassifications by first dividing the data into classes based on the 95th percentile of return height and then applying the k-means clustering algorithm within each of these classes. The height classes were chosen on the basis of the Pennsylvania Bureau of Forestry site index classes \(<19.8\) m \((65\text{ ft})\), \(19.8-24.4\) m \((65-80\text{ ft})\), \(>24.4\) m \((80\text{ ft})\)], with additional classes added to capture short vegetation \(<9.1\) m \((30\text{ ft})\)] and to identify cells with extreme outliers \(>45.7\) m \((150\text{ ft})\)]. The number of pixels within each of the resulting classes was approximately even. This final clustering model, which classified cells based on a measure of the predominant top height of the vegetation first and then by complexity of the canopy (variation in return height, LiDAR-derived canopy cover and rumple index), most accurately reflected the canopy structure observed in the field data and orthophotos.

Multinomial logistic regression equations for predicting the cluster membership of each cell to an LCST type were then developed and used to apply the clustering model to the twenty large landscapes. These regression equations were developed on a random subsample of 50,498 cells from the four development tiles with the remaining 7,089 cells retained for validation. Backwards step-wise regression was undertaken utilizing the overall McFadden \(R^2\) and chi-sq likelihood ratio test and significance \(p\)-value of each variable. The k-means cluster for each cell in the validation data set was then compared to the predicted LCST type from the multinomial logistic regressions and the misclassification rate calculated. Only statistically significant models with McFadden \(R^2\) values greater than 0.97 and validation data misclassification rates less than 0.8\% were implemented.

The final LCST model was mapped over the twenty large landscapes using the multino-
Figure 4.2. Scree-like plot of the within-cluster sums of squares against the number of clusters for height class three in the final model (95th percentile of return height between 19.8 and 24.4 m), suggesting that three clusters within this height class are appropriate.
mial logistic regression equations and the mapped LCST types compared to both the aerial orthophotos for all of these landscapes and the field data collected from the 25 locations within two of the landscapes. The percent of correct classification for these locations was calculated.

### 4.4 Results

The final model contains fourteen LCST types, including one for cells without vegetation (no returns above 0.3 m). Within the four classes defined by the 95th percentile of return height ( <9.1 m, 9.1-19.8 m, 19.8-24.4 m, 24.4-45.7 m), k-means clustering identified four types for class 1 and three types each for classes 2 through 4. The 95% confidence intervals of the centroids for each cluster are shown in Table 4.1.

One set of highly statistically significant (p <0.001) predictive (McFadden R$^2$ >0.99) multinomial logistic regression models for LCST was developed for each height class. The confusion matrix for the multinomial logistic regression validation subsample demonstrated a low misclassification rate, with all classes correctly identified more than 99.7% of the time. The multinomial logistic regression coefficients and p-values for height class 1, 2, 3 and 4 are shown in tables 4.2, 4.3, 4.4 and 4.5, respectively.
<table>
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<th>LCST type</th>
<th>Standard Deviation of Return Height (m)</th>
<th>Return Height Coefficient of Variation</th>
<th>Skew of Return Height</th>
<th>Kurtosis of Return Height</th>
<th>95th Percentile of Return Height (m)</th>
<th>Cover (%)</th>
<th>Mean Return Height (m)</th>
<th>Rumpel Index</th>
<th>Evergreen (%)</th>
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<td>3.3–3.6</td>
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<tr>
<td>4.3</td>
<td>7.8–7.9</td>
<td>0.43–0.44</td>
<td>-0.82–0.8</td>
<td>3.03–3.09</td>
<td>28.5–28.7</td>
<td>35.5–35.8</td>
<td>18.9–19.0</td>
<td>4.73–4.77</td>
<td>1.5–1.6</td>
</tr>
<tr>
<td>5</td>
<td>124.4–132.4</td>
<td>1.71–1.78</td>
<td>1.65–1.77</td>
<td>4.18–4.53</td>
<td>350.0–370.8</td>
<td>48.1–50.3</td>
<td>73.2–78.7</td>
<td>3.08–3.28</td>
<td>2.8–4.1</td>
</tr>
</tbody>
</table>
Table 4.2. Mutinomial logistic regression equations for height class 1 (<9.1 m), with LCST 1.1 as the base case. The probability of a cell being a specific LCST is \( \frac{1}{1+e^{-z}} \) where \( z = b_1 + b_2 H_{CV} + b_3 H_{Skew} + b_4 H_{Cover} + b_5 R + b_6 E \), \( H_{CV} \) is the return height coefficient of variation, \( H_{Skew} \) is the skew of return height, \( H_{Cover} \) is the proportion of all returns over 1 ft, \( R \) is the rumple index and \( E \) is the number of evergreen pixels.

<table>
<thead>
<tr>
<th>LCST</th>
<th>Variable</th>
<th>Co-efficient</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.2</td>
<td>intercept</td>
<td>219.40</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>( H_{CV} )</td>
<td>-100.50</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>( H_{Skew} )</td>
<td>-32.405</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>( H_{Cover} )</td>
<td>-2.2185</td>
<td>0.007</td>
</tr>
<tr>
<td></td>
<td>( R )</td>
<td>-10.301</td>
<td>0.058</td>
</tr>
<tr>
<td></td>
<td>( E )</td>
<td>-0.0033172</td>
<td>0.554</td>
</tr>
<tr>
<td>1.3</td>
<td>intercept</td>
<td>-61.381</td>
<td>0.135</td>
</tr>
<tr>
<td></td>
<td>( H_{CV} )</td>
<td>-112.26</td>
<td>0.061</td>
</tr>
<tr>
<td></td>
<td>( H_{Skew} )</td>
<td>-33.439</td>
<td>0.010</td>
</tr>
<tr>
<td></td>
<td>( H_{Cover} )</td>
<td>-0.61424</td>
<td>0.303</td>
</tr>
<tr>
<td></td>
<td>( R )</td>
<td>0.5.4116</td>
<td>0.576</td>
</tr>
<tr>
<td></td>
<td>( E )</td>
<td>0.12840</td>
<td>0.001</td>
</tr>
<tr>
<td>1.4</td>
<td>intercept</td>
<td>37.872</td>
<td>0.077</td>
</tr>
<tr>
<td></td>
<td>( H_{CV} )</td>
<td>-109.2</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>( H_{Skew} )</td>
<td>-29.236</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>( H_{Cover} )</td>
<td>3.5733</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>( R )</td>
<td>-4.8391</td>
<td>0.279</td>
</tr>
<tr>
<td></td>
<td>( E )</td>
<td>0.0062067</td>
<td>0.366</td>
</tr>
</tbody>
</table>

4.4.1 The LCST types

The LCST types for Pennsylvania’s mixed forests were distinguished within height classes primarily on the basis of evergreen abundance as well as distribution of the height returns (i.e., distribution of the canopy among height strata), cover (i.e., canopy cover), and the rumple index (i.e., variability of the canopy) (Figure 4.3, Table 4.6).

4.4.2 Field validation of the LCST

The LCST maps of forest canopy structure accurately reflected the forest structures identified in the orthophotos. The LCST map clearly distinguished clearings without trees, young regenerating forest, and partially harvested forest stands from surrounding intact forest.

Of the 25 field plots within two of the large landscapes, only one (4%) was misclassified.
Table 4.3. Multinomial logistic regression equations for height class 2 (9.1-19.8 m), with LCST 2.1 as the base case. The probability of a cell being a specific LCST is $\frac{1}{1+e^{-z}}$ where $z = b_1 + b_2 H_{CV} + b_3 H_{Skew} + b_4 H_{Cover} + b_5 R + b_6 E$, $H_{CV}$ is the return height coefficient of variation, $H_{Skew}$ is the skew of return height, $H_{Cover}$ is the proportion of all returns over 1 ft, $R$ is the rumple index and $E$ is the number of evergreen pixels.

<table>
<thead>
<tr>
<th>LCST</th>
<th>Variable</th>
<th>Co-efficient</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.2</td>
<td>intercept</td>
<td>596.79721</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td>$H_{CV}$</td>
<td>44.996922</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td>$H_{Skew}$</td>
<td>5.895332</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td>$H_{Cover}$</td>
<td>-10.312594</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td>$R$</td>
<td>21.338839</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td>$E$</td>
<td>-0.161128</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>2.3</td>
<td>intercept</td>
<td>326.794189</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td>$H_{CV}$</td>
<td>21.503334</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td>$H_{Skew}$</td>
<td>1.854825</td>
<td>0.041</td>
</tr>
<tr>
<td></td>
<td>$H_{Cover}$</td>
<td>-2.764750</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td>$R$</td>
<td>9.792254</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td>$E$</td>
<td>-0.154441</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

The misclassified plot was classified as a LCST 3.2; however, the presence of several large pines in the canopy in addition to deciduous trees indicates it should have been classed as a LCST of 3.1 (i.e., evergreen abundance was underestimated). The remote sensing data of this plot were intermediate between types 3.2 and 3.1, with moderate amounts of evergreen vegetation and 95th percentile of return height between 19.8 and 24.4 m and high LiDAR-derived estimate of canopy cover.
Table 4.4. Multinomial logistic regression equations for height class 3 (19.8-24.4 m), with LCST 3.1 as the base case. The probability of a cell being a specific LCST is \( \frac{1}{1+e^{-z}} \) where \( z = b_1 + b_2 H_{Skew} + b_3 H_{P95} + b_4 H_{Cover} + b_5 H_{Mean} + b_6 R + b_7 E \), \( H_{Skew} \) is the skew of return height, \( H_{P95} \) is the 95th percentile of return height, \( H_{Cover} \) is the proportion of all returns over 1 ft, \( H_{Mean} \) is the mean return height, \( R \) is the rumple index and \( E \) is the number of evergreen pixels.

<table>
<thead>
<tr>
<th>LCST</th>
<th>Variable</th>
<th>Co-efficient</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.2</td>
<td>intercept</td>
<td>396.043238</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td>( H_{Skew} )</td>
<td>-4.659898</td>
<td>0.011</td>
</tr>
<tr>
<td></td>
<td>( H_{P95} )</td>
<td>0.369937</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>( H_{Cover} )</td>
<td>-3.888794</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td>( H_{Mean} )</td>
<td>-0.774204</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td>( R )</td>
<td>12.504752</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td>( E )</td>
<td>-0.145301</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>3.3</td>
<td>intercept</td>
<td>564.069257</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td>( H_{Skew} )</td>
<td>-6.222160</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>( H_{P95} )</td>
<td>0.112064</td>
<td>0.408</td>
</tr>
<tr>
<td></td>
<td>( H_{Cover} )</td>
<td>-9773744</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td>( H_{Mean} )</td>
<td>-0.272930</td>
<td>0.120</td>
</tr>
<tr>
<td></td>
<td>( R )</td>
<td>38.173074</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td>( E )</td>
<td>-0.162082</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

Table 4.5. Multinomial logistic regression equations for height class 4 (24.4-45.7 m), with LCST 4.1 as the base case. The probability of a cell being a specific LCST is \( \frac{1}{1+e^{-z}} \) where \( z = b_1 + b_2 H_{CV} + b_4 H_{Cover} + b_6 R + b_7 E \), \( H_{CV} \) is the return height coefficient of variation, \( H_{Cover} \) is the proportion of all returns over 1 ft, \( R \) is the rumple index and \( E \) is the number of evergreen pixels.

<table>
<thead>
<tr>
<th>LCST</th>
<th>Variable</th>
<th>Co-efficient</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>4.2</td>
<td>intercept</td>
<td>458.700768</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td>( H_{CV} )</td>
<td>-3.278044</td>
<td>0.351</td>
</tr>
<tr>
<td></td>
<td>( H_{Cover} )</td>
<td>-5.258491</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td>( R )</td>
<td>10.646421</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td>( E )</td>
<td>-0.119414</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>4.3</td>
<td>intercept</td>
<td>468.257224</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td>( H_{CV} )</td>
<td>-19.077307</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td>( H_{Cover} )</td>
<td>0.9526211</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td>( R )</td>
<td>55.727434</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td></td>
<td>( E )</td>
<td>-0.130312</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>
Table 4.6. Description of LCST types

<table>
<thead>
<tr>
<th>LCST Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.1</td>
<td>Very short deciduous vegetation with a variable canopy height including: regenerating stands with scattered fast growing individuals (stump sprouts or fast growing species) or small residuals mixed with smaller seedling regeneration or stands with patchy short regeneration. These cells are characterised as having a 95th percentile of return height less than 9.1 m tall but with relatively high variation in the return height (high coefficient of variation, standard deviation, large positive skew and high rumple index). Also, the LiDAR-derived cover estimate is high and the amount of evergreen foliage is low.</td>
</tr>
<tr>
<td>1.2</td>
<td>Very short deciduous vegetation with very low estimated LiDAR-derived canopy cover. These cells are characterised as having a 95th percentile of return height less than 9.1 m tall, with a small positive skew, low rumple and low amount of evergreen foliage.</td>
</tr>
<tr>
<td>1.3</td>
<td>Very short evergreen vegetation that have a 95th percentile of return height less than 9.1 m tall, high amounts of evergreen foliage within the cell, with low skew, and moderate cover.</td>
</tr>
<tr>
<td>1.4</td>
<td>Taller regenerating stands with a canopy top height (95th percentile of LiDAR return height) less than but close to 9.1 m tall. These are dense pole stands of deciduous forests that are rapidly self-thinning due to high competition. In terms of the remote sensing data, they have a small positive skew, high LiDAR-derived cover estimates and low amount of evergreen foliage.</td>
</tr>
<tr>
<td>2.1</td>
<td>Short evergreen stand (generally coniferous) which have a top canopy height (95th percentile of LiDAR return height) between 9.1 and 19.8 m tall. These cells are also characterised as having high amounts of evergreen foliage, very high LiDAR-derived cover estimates, and low rumple index.</td>
</tr>
<tr>
<td>2.2</td>
<td>Short deciduous stand with top canopy height between 9.1 and 19.8 m tall, with an open canopy and an understory that includes at least sparse evergreen shrubs or saplings (generally coniferous, mountain laurel or rhododendron). These stands have a 95th percentile of return height between 9.1 and 19.8 m tall with low LiDAR-derived cover estimates and high rumple index.</td>
</tr>
<tr>
<td>LCST Type</td>
<td>Description</td>
</tr>
<tr>
<td>-----------</td>
<td>---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>2.3</td>
<td>Short stand with dense simple canopy that is between 9.1 and 19.8 m tall, and very few to no evergreen shrubs and saplings in the understory. The 95th percentile of return height is between 9.1 and 19.8 m, with high cover values and low evergreen foliage amounts.</td>
</tr>
<tr>
<td>3.1</td>
<td>Medium height evergreen stand with a top canopy height between 19.8 and 24.4 m. These cells have a 95th percentile of return height between 19.8 and 24.4 m tall with high amounts of evergreen foliage, and high LiDAR-derived estimates of canopy cover and low rumple index.</td>
</tr>
<tr>
<td>3.2</td>
<td>Medium height stand with dense simple canopy with a top canopy height between 19.8 and 24.4 m, and few to no evergreen shrubs or saplings in the understory. These cells are characterised by having a 95th percentile of return height between 19.8 and 24.4 m tall with low amount of evergreen foliage but high cover estimates.</td>
</tr>
<tr>
<td>3.3</td>
<td>Medium height stand with an open canopy, a top canopy height between 19.8 and 24.4 m and an understory that includes sparse evergreen shrubs or saplings. The estimated cover is low with a high rumple index and a 95th percentile of return height between 19.8 and 24.4 m tall.</td>
</tr>
<tr>
<td>4.1</td>
<td>Tall evergreen stand with a canopy top height greater than 24.4 m. The 95th percentile of return height is between 24.4 and 45.7 m tall, with high amounts of evergreen foliage, very high LiDAR-derived canopy cover estimates, and a low rumple index.</td>
</tr>
<tr>
<td>LCST Type</td>
<td>Description</td>
</tr>
<tr>
<td>-----------</td>
<td>-------------</td>
</tr>
<tr>
<td>4.2</td>
<td>Tall deciduous stand with dense simple canopy with a top canopy height greater than 24.4 m and few to no evergreen shrubs or saplings in the understory. These cells have a 95th percentile of return height is between 24.4 and 45.7 m tall with low amounts of evergreen foliage and high LiDAR-derived canopy cover estimates.</td>
</tr>
<tr>
<td>4.3</td>
<td>Tall stand with a top canopy height greater than 24.4 m but with an understory that includes sparse evergreen shrubs or saplings. These cells have a 95th percentile of return height between 24.4 and 45.7 m tall but with relatively low estimated cover and a high rumple index.</td>
</tr>
<tr>
<td>6</td>
<td>No-vegetation as identified by a lack of returns greater than one foot above the DEM. This may be due to clearings, wide roads, skid sites, wetlands or rivers that are equal to or larger than one cell in area.</td>
</tr>
</tbody>
</table>
Figure 4.3. LCST types for Pennsylvanias mixed forests. 95th percentile of return height increases across the LCST types from left to right. Types with high canopy evergreen amounts are at the top. Types in the middle rows have low amounts of canopy evergreen with a high variation in return height and relatively low LiDAR-derived canopy cover. Types in the bottom row have low amounts of both canopy evergreen, with low variation in return height and high LiDAR-derived canopy cover.
4.5 Discussion

4.5.1 Pennsylvania’s LCSTs

The LCST presented here is a cost-effective accurate way to quickly map general forest structure over large areas. It has the potential to be scaled up to map the forest structure of the whole state of Pennsylvania as the data are available. Such mapping of forest canopy structure over large areas could provide information used to identify candidate forest stands for different silvicultural prescriptions such as pre-commercial or commercial thinning, create detailed habitat models over large areas (e.g., for white tailed deer), or develop ecosystem classification systems (ECS). For instance, the forests of Pennsylvania are currently under attack from several invasive pests, including gypsy moth, hemlock woolly adelgid, emerald ash borer and Asian longhorned beetle (McWilliams et al., 2007) and this LCST may assist in identifying forest stands that are most vulnerable to these pests where susceptibility is associated with specific forest structural conditions. For example, gypsy moth attack is higher in stands with high proportions of hardwood species (Gottschalk, 1993) (LCST types 2.2, 2.3, 3.2, 3.3, 2.4 and 4.3), gypsy moth predators populations are denser in diverse forest structures (Muzika et al., 2004) (LCST types 2.2, 3.3 and 4.3) and tree mortality due to gypsy moth is higher in older, highly productive sites (Gottschalk, 1993) (LCST types 4.2 and 4.3); indicating a high risk for stands classified as LCST 4.2. Furthermore, if the LiDAR data collection is repeated in the future, this typology could also be used as a forest health monitoring tool by comparing changes in LCST of the individual cells over time.

Previous approaches to mapping the forest area of Pennsylvania used remote sensing with multispectral data to identify broad landcover types (deciduous, mixed and evergreen forests). These approaches did not provide information on forest structure (e.g., PAMAP Program Land Cover for Pennsylvania available from http://www.pasda.psu.edu/). Detailed vegetation mapping of public lands have been undertaken by Pennsylvania’s Bureau of Forestry using a combination of multispectral and field data; however, these have been labor intensive and expensive activities with limited scope due to the lack of access to private land. Similarly, data acquisition under the US Department of Agriculture’s Forest Inventory Analysis (FIA, http://www.fia.fs.fed.us/) is labour intensive and expensive and only yields spatially coarse data. The LCST has the advantages of providing spatially explicit data on forest structure using a publicly available dataset for the entire state.
4.5.2 Potential application of the typology

Development of this LCST has demonstrated the potential for a cost-effective use of widely available topographic leaf-off low density discrete-return small-footprint LiDAR for mapping forest canopy structure despite the relatively low density of returns. Similar approaches could be applied to other areas where nation- or state-wide LiDAR datasets are available, but would need to be tailored to the individual characteristics of these datasets.

Similar to this study, Kim (2010) also used multivariate cluster analysis of LiDAR point cloud characteristics; however, the author used it to identify the species of individual tree crowns. Both Kim (2010) and the present study demonstrate that foliage with similar structures tend to have similar LiDAR point cloud characteristics. These forest structures cluster together without the need to assign groups \textit{a priori} (whether they are species or forest structure types). Approaches used elsewhere to determine forest structural characteristics from LiDAR have tended to use regression methods to focus on one attribute of forest structure at a time, e.g. basal area (Lefsky et al., 1999; Means et al., 2000; Andersen et al., 2005b), not on the canopy structure as a whole; however, habitats are rarely defined by just one aspect of forest structure (McElhinny et al., 2005). The combination of tree density, canopy height, tree size, vertical foliage profile etc. contributes to forest structure and the approach used here describes the forest structure as a whole in broad classes, but does not provide detailed estimates of tree characteristics. The selection of data to include in the analysis (i.e., the inclusion of evergreen abundance and 95th percentile of return height) clearly impacts the LCST types derived. However, this provides the opportunity to design a LCST that is region- or purpose-specific. Where forest structure habitat models for specific species are required, the approach of Vierling et al. (2011a) would be advantageous. Their approach examines the LiDAR point cloud characteristics as a direct predictor of a specific species’ abundance.

Although LiDAR datasets with higher density of returns may allow the use of smaller cells (with similar numbers of returns per cell) and thus more detailed mapping, the 24.4 × 24.4 m cell size used in this analysis was sufficient to capture a large enough number of returns to ensure consistency of return statistics. In addition, combinations of LCST types in neighbouring cells may provide information on the forest structure of whole stands or landscapes.

The leaf-off nature of this dataset produced a LCST that reflected the internal structure of the canopy rather than merely the upper surface (Brandtberg et al., 2003), but corresponding
orthophotos (same time period, same scale) were required to accurately identify areas of high evergreen abundance. However, other multispectral data may be used to identify areas of high evergreen foliage instead (Quackenbush et al., 2000). Further, the inclusion in future classifications of return intensity data that have been normalized to account for variations caused by surface type, atmospheric condition, and time of day (Yoon et al., 2008) may negate the need for additional remote sensing data to identify the amount of evergreen foliage.
Chapter 5

Revealing landscape patterns in forest structure across site and management type

5.1 Abstract

Forest structure varies over the landscape and land managers are increasingly focusing on managing forest structures at the landscape scale. The current study investigates forest structure patterns over large landscapes using novel remote sensing techniques to identify the pattern of forest structure and investigate the relative importance of two drivers: site and management. LiDAR Canopy Structure Typology (LCST, a measure of forest structure) was mapped over twenty large landscapes in Pennsylvania using topographic LiDAR data and aerial ortho-photography and analyzed at both the local and landscape scales.

At the local scale, the LCST of each cell (24.4 × 24.4 m) was analyzed using ANOVA and LDA in terms of both topography and management type (non-government, Pennsylvania Bureau of Forestry, Pennsylvania Bureau of State Parks and Pennsylvania Game Commission). The results indicated that both topography and land management type had significant influences on forest structure; however, combined they only explained 32% of the variation in forest structure.

At the landscape scale, the spatial patterns of the LCST types were analyzed and con-
trasts among Bailey’s eco-provinces and the four land management types were made. There were significant differences in forest structure among Bailey’s eco-provinces and management types. Fragmentation of forest structure within forested lands was found particularly on non-government lands, which contained a higher proportion of short vegetation types, higher patch density, and greater heterogeneity among neighboring patches. This within-forest fragmentation is likely to have implications for both biodiversity and ecosystem services.

The results of this study suggest that differences in ownership and management philosophy influence forest structure that can be observed at the landscape scale. The techniques used in this study may be adapted to specific habitat or ecosystem service requirements and be used as a robust method for analyzing landscapes in terms of species habitat requirements or specific forest management goals.

5.2 Introduction

Forest structure has been somewhat vaguely defined as the type, size, shape, and spatial arrangement of the bio-physical components of a forested ecosystem both within a stand and across landscapes (Spies, 1998; McElhinny et al., 2005). Increasingly, land managers are focusing on both forest structural diversity (Mizunaga et al., 2010; Duduman, 2011) and landscape-scale management (Franklin and Forman, 1987; Pearson and McAlpine, 2010). This is likely due to an increased awareness of ecosystem processes and the need to consider whole ecosystems when managing land (Yaffee, 1999).

Topography interacts with climate, geology, soils and biotic factors; all of which are intimately linked with light, heat, water, chemical availability and disturbance regimes (Ellenberg, 1968; Barnes et al., 1998) at the local scale. Combined, all of these factors influence plant growth and form (Ellenberg, 1968; Barnes et al., 1998), and therefore forest structure. As such, topography has been used to predict forest productivity in numerous studies (e.g., Carmean, 1965; Bolstad et al., 2001; Wang et al., 2005) and has also been linked to disturbance regimes (Brokaw and Grear, 1991; Hadley, 1994; Lentile et al., 2006), tree density and basal area (Elliott et al., 1999; Clark and Clark, 2000) and coarse woody debris (Gale, 2000). At the landscape scale, the environment can be classified into eco-provinces (Bailey, 1980, 1983), which each have different geologic, topographic, climatic and ecological histories and processes. These processes are intimately linked and their combination will hypothetically produce a different landscape pattern of forest structure (Freligh, 2002). Variation in these
topographic and other drivers at the landscape scale creates a patchwork pattern of forest structure, which in turn affects ecological processes (Turner, 1989; Spies, 1998).

Landscape ecology has traditionally focused on describing patch-work patterns of contrasting land covers (e.g., forest versus grassland), under a patch-matrix-corridor paradigm (Forman and Godron, 1981; Farina, 2006). This paradigm describes landscapes as being entirely composed of three components: patches that are relatively homogeneous non-linear areas contrasting with their surroundings, a matrix that dominates the landscape, and corridors that are homogenous linear areas connecting patches. In contrast to the traditional approach of landscape ecology, this study is concerned with the patchwork of structure within a single landcover (forest). While theories of within-forest successional mosaics (Watt, 1947; Bormann and Likens, 1979; Frelich, 2002) have been developed, relatively little work has attempted to quantify the pattern of forest structure across large landscapes, probably due to the intensive fieldwork required (Bobiec, 1998; Oldeman, 1990; Bobiec et al., 2000) and the paucity of detailed forest structure information from established multi- and hyper-spectral remote sensing techniques (Campbell, 2007).

The delineation of a patch is dependent on the context of the inquiry. Generally, forest management has used the stand as the management unit, which is defined as a “contiguous group of trees sufficiently uniform in species composition, arrangement of age classes, site quality, and condition to be a distinguishable unit” (Smith et al., 1997; Nyland, 2002). However, this definition and therefore the delineation of stands is highly dependent on the intensity of management. Alternatively, Oldeman (1990) took an ecological approach to defining a within-forest patch, defining a forest eco-unit as “…the unit of vegetation which started its development at the same moment and on the same surface”. Historically, studies that have used a landscape approach to investigate forest structure have involved intensive field work to identify and map forest mosaics (Oldeman, 1990; Bobiec, 1998; Bobiec et al., 2000). Studies of forest dynamics rely on mapping patches of forest developmental phases based on forest structure (White et al., 1985; Torquebiau, 1986). However, mapping boundaries of different development phases in forest stands is subjective (Nagel et al., 2007). The development of LiDAR (Light Detection and Ranging) provides a new tool for researchers and land managers, increasing the efficiency and precision of forest structure mapping over large landscapes. Landscapes that have been mapped in terms of patch types can then be further quantified using a number of indices such as the distributions of patch type, size, isolation, diversity and edge effects (McGarigal and Marks, 1994). Each of these features
influence habitat resource variety and availability, and therefore habitat suitability at the
landscape scale. To fully describe landscape patterns it is helpful to compute a number of
indices for a more complete insight into key landscape features.

Land managers have a variety of goals and associated land-management practices that
are also hypothesized to be a key driver in landscape patterns. For example, much of
Pennsylvania’s forests were cleared prior to the mid 20th century (Klein and Hoogenboom,
1973; Stevens, 1956). Subsequent management by various management types have had
different objectives and different associated management practices. Pennsylvania’s Bureau
of Forestry (BoF) aims to conserve the state’s forests while utilizing the timber and mineral
resources they provide by “Managing State Forests under sound ecosystem management,
to retain their wild character and maintain biological diversity while providing pure water,
opportunities for low density recreation, habitats for forest plans and animals, sustained
yields of quality timber, and environmentally sound utilization of mineral resources” (BoF,
2010). Furthermore, the BoF sustainable forest resource management plan restricts the
silvicultural techniques that may be used and specifically requires green tree retention when
harvesting forests (BoF, 2003). In contrast, the objective of Pennsylvania’s Bureau of State
Parks (BoSP) is to “provide opportunities for enjoying healthful outdoor recreation and serve
as outdoor classrooms for environmental education” through the conservation of natural,
scenic, aesthetic and historical values (BoSP, 2010). The purpose of the Pennsylvania Game
Commission (PGC) is to “protect, propagate, manage and preserve the game or wildlife” [The
Game and Wildlife Code Title 34 Chpt. 3b Sec. 322] on their lands. Lastly, non-government
forest, which accounts for 71% of Pennsylvania forest land, is managed by landowners for
a variety of management objectives, generally without the advice of professional foresters
(McWilliams et al., 2007). These landowners predominantly own small parcels of land,
with 64% of private land owners holding less than ten acres (Metcalfe, 2010). Each of these
management types have different land management philosophies with different goals and
utilize different management techniques. There are concerns that fragmentation may occur
within forests, with changes in the pattern of forest structure (Lindenmayer and Fischer,
2006, p. 103). The rate and pattern of forest harvesting (which differs depending on the
management goals and techniques employed) may influence the forest structure pattern, and
therefore influence ecosystem functions (e.g. hydrological and geomorphic processes) and
the availability of habitat resources (Lindenmayer and Fischer, 2006). While it is clear that
the hard edges which occur between forest and non-forest land cover affect many species’
habitats and behaviors, it is also possible that subtle within-forest edges may act as barriers for some species (Lindenmayer and Fischer, 2006, p. 118).

The current study used LiDAR data and aerial photography to map forest structure (LiDAR Canopy Structure Topology, LCST) across the landscape and investigate the relative importance of the environment (topography and eco-province) and land management at both local and landscape scales. Furthermore, this study investigated the influence of management type on landscape-scale forest structure and analyzed the landscape patterns of forest structure to investigate within-forest fragmentation.

5.3 Material and methods

5.3.1 Study Sites

Twenty large landscapes in Pennsylvania were selected by first randomly selecting five points within the state. At each point, the nearest large (8-15 thousand hectares) forest area [delimited by cadastral boundaries (ERRI PSU, 1996b,a; DCNR, 2009; PGC, 2009; DCNR, 2010) and data tile extents described below] was selected that belonged to each of four management types: Bureau of Forestry, Bureau of State Parks, Pennsylvania Game Commission and non-government land. These twenty forested landscapes are located within the two major physiographic provinces occurring in Pennsylvania; the Appalachian Plateaus and the Ridge and Valley (Figure 4.1; Sevon, 2000). Each of these provinces is dominated by different forest types and geological and ecological processes.

The Appalachian Plateaus (including Bailey’s Laurentian Mixed Forest and Eastern Broadleaf (Oceanic) Provinces; Bailey, 1980, 1983) occupies approximately 60% of Pennsylvania, being characterized by land above 365 m asl, local relief less than 120 m, with “...regionally gentle and locally abrupt increments to extensive areas of high plateaus and mountain ridges...” (Shultz, 1999). The soils are formed from shale, sandstone, limestone and glacial till (Shultz, 1999). The Appalachian Plateaus have a typical continental climate with changeable temperatures, cold temperatures (particularly in the North), frequent precipitation, mean annual precipitation of 100 cm, daily temperature ranges of 10-15°C and 130-180 frost free days annually (Waltman et al., 1997; Shultz, 1999). The northern portion of Pennsylvania’s Appalachian Plateaus is dominated by the Laurentian Mixed Forest ecoregion that is characterized by northern hardwoods (Barrett, 1980; Barnes et al.,
that will perpetuate themselves through gap-phase dynamics in the absence of severe
disturbances (Walker, 1999). In contrast, mixed mesophytic forests are prevalent in the
Eastern Broadleaf (Oceanic) Provinces and in the south-western portion of Pennsylvania’s
Appalachian Plateaus (Barrett, 1980; Barnes et al., 1998).

In contrast, the Ridge and Valley physiographic province (containing Bailey’s Central
Appalachian Broadleaf Forest-Coniferous Forest-Meadow Province; Bailey, 1980, 1983) is
composed of folded and faulted sedimentary rock forming a band of alternating elongated
mountain ridges and valleys with soils formed from shale, sandstone and limestone (Shultz,
1999). The Ridge and Valley has montane climate, with large temperature extremes and
daily temperature ranges, annual precipitation of 111 cm of which much is snow, and a
mean frost free period of between 180 to 140 days each year (Shultz, 1999; Waltman et al.,
1997). This province is dominated by mixed-oak (or oak-hickory or oak-chestnut) forest,
often with an ericaceous shrub understory (Barrett, 1980; Barnes et al., 1998). Prior to the
20th century, this forest type was probably perpetuated by periodic fires (Abrams, 1992;
Brose et al., 2001).

5.3.2 Remote Sensing

Between 2006 and 2008, the Pennsylvania Department of Conservation and Natural Re-
sources (DCNR) collected leaf-off low-density LiDAR data and orthographic aerial photograph-
ry (color, 30.5 cm [1 ft] cell resolution) for all of Pennsylvania under the PAMAP program.
The discrete return LiDAR data was collected and processed by numerous contractors with
a 1.4 m average point spacing (2 m maximum), approximately 50 cm diameter footprint,
minimum of 2 returns, 30% sidelaq, 40° field of view (full angle) and laser pulse rate of
40.6 kHz, resulting in a bare earth vertical accuracy of 18.5 cm RMSE. These data were
collected and processed under the US Department of Homeland Security Federal Emergency
Management Agency’s Guidelines and Specifications for Flood Hazard Mapping Partners.
The LiDAR point clouds, breaklines, LiDAR derived digital elevation model (DEM) and
orthophotos are publically available in 9.29 km² (10000 × 10000 ft) tiles (all remote sensing
data is available from http://www.pasda.psu.edu/).
5.3.3 Data Analysis

Utilizing the remote sensing data, the forest structure of the 20 large landscapes was mapped by LiDAR Canopy Structure Typology (LCST) type in $24.4 \times 24.4$ m cells. The LCST is divided into 14 types based on the predominant top height of the canopy, amount of evergreen foliage in the canopy, and within-cell structural diversity (see Figure 4.3 for definitions of the types). To ensure that only forest areas were included in the analysis, forested areas were extracted using the forest landcover classes of the PAMAP Program Land Cover for Pennsylvania (PSU, 2007).

At the local scale, topographic variables including topographic wetness index (TWI; Beven and Kirkby, 1979), elevation, slope, planar curvature ($3 \times 3$ cell neighbourhood), profile curvature ($3 \times 3$ cell neighbourhood), state plane co-ordinates, and Northness and Eastness of aspect (Hengl and Reuter, 2009) were calculated from the LiDAR derived DEM for each cell.

Detailed information on the specific management practices within each of the twenty large landscapes was not available; however, land management boundaries for Pennsylvania’s national parks (ERRI PSU, 1996a), national forests (ERRI PSU, 1996b), state forests (DCNR, 2010), state parks (DCNR, 2009) and state gamelands (PGC, 2009) were available. Non-government land was defined as land that did not fall under state or federal management, but may include family-owned, private industry and non-profit or NGO (non-government organization) managed lands.

A random sample of 19,880 cells was selected from the 20 large landscapes to examine the relationship between topographic variables and forest structure (i.e., LCST) at the local scale. ANOVA (for continuous variables) and Chi-square tests (for discrete variables) were used to investigate the relationship between LCST type and topographic variables individually and linear discriminant analysis (LDA) was implemented to investigate the cumulative relationship between management type, topography, and LCST types. LDA is a multivariate statistical technique that finds the linear functions of independent variables that best discriminate a priori groups by maximizing the ratio of among-class to within-class variance (McCune et al., 2002). It is similar to logistic regression; however, the focus of LDA is on describing the multivariate correlation structure, rather than forming predictive models (McCune et al., 2002).

Landscape statistics for each of the twenty landscapes were calculated by LCST type using FRAGSTATS (McGarigal and Marks, 1994), including percent of total landscape in
each LCST, mean patch area, patch area coefficient of variation, patch density, normalised landscape shape index (nLSI), perimeter to area ratio, edge density (ED), contrast weighted edge density (CWED), total edge contrast index (TECI), Euclidean nearest neighbor, and interspersion & juxtaposition index (IJI). The 8-neighbour rule was imposed for all cell-based indices. The relationship between each of these landscape statistics and LCST type was tested using ANOVA. Furthermore, the relationship between each of these landscape statistics and individual landscapes, location cluster (the landscape sampling cluster), management type and Bailey’s eco-province was also tested using ANOVA, retaining LCST type in the model. Where the results were statistically significant ($\alpha = 0.05$), follow-up paired t-tests with Holm’s (1979) multiple comparison correction were undertaken.

The mean patch area of the patches within a landscape mosaic is a fundamental measure of landscape patterns. Patch size has important implications for ecosystem functioning. For example, a minimum area of habitat may be required to provide enough resources to be useful for a species. In addition, the coefficient of variation of patch area is a measure of the variation in patch area across the landscape. Patch density is influenced by patch area and is a measure of the number of individual patches within one hundred hectares on average, but does not convey information about the size or spatial distribution of patches (McGarigal and Marks, 1994).

Normalized landscape shape index (nLSI) is a measure of aggregation and ranges from 0 to 1, with 0 indicating a single simple shaped patch and 1 indicating maximum disaggregation or a checkerboard pattern (McGarigal and Marks, 1994). Specifically, it equals the total perimeter of a class (given the number of cells occupied) minus the minimum perimeter possible for a maximally aggregated class (given the number of cells occupied), divided by the maximum minus the minimum class perimeter (McGarigal and Marks, 1994).

The shape of the patches may be important in addition to the size of patches. For example a large habitat patch that is long and narrow may not provide as much shelter as a similar sized patch that is compact. Furthermore, where a patch has a complex shape, environmental edge effects may reach further into the core of the patch and erode the habitat value of a patch. The perimeter-to-area ratio is a simple measure of patch shape with small ratios corresponding to compact patches with simple shapes and large ratios indicating a complex shape with convoluted edges; however, this measure is influenced by patch size because an increase in patch size will cause a decrease in the perimeter-area ratio (McGarigal and Marks, 1994).

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ED is simply a measure of the length of edge between patches per hectare; however, ED assumes that all edges have an equivalent influence on ecological processes (McGarigal and Marks, 1994). CWED modifies this measure by weighting the edge density by an index of contrast between the neighboring patches (McGarigal and Marks, 1994). Where the contrast between patches is high, the edge will have more severe environmental gradients and therefore will be more likely to act as a barrier to ecological processes (e.g., species movement). Similarly, TECI is a relative measure of the contrast along all of the patch perimeters in a landscape, expressed as a percentage (McGarigal and Marks, 1994). Both the CWED and TECI were estimated using a symmetrical similarity matrix between LCST types constructed by ranking structural similarities between 0 and 1, in 0.25 increments, based on the height class of the LCST type and the amount of evergreen canopy (i.e., 0 = dissimilar, 1 = indistinguishable).

Mean Euclidean nearest neighbor distance is the mean direct distance between patches of the same type and is a measure of patch isolation (McGarigal and Marks, 1994). Where patches of the same type are in close proximity and isolation is low, individuals of a species may move between habitat patches more easily. Furthermore, ecological processes that require a minimum patch area may still function when smaller individual patches are in close proximity.

The interspersion and juxtaposition index (IJI) indicates the level of patch interspersion or intermixing (as opposed to individual cell aggregation) and ranges between 0 and 100 (McGarigal and Marks, 1994). When IJI equals 100, all patch types are equally adjacent to all other patch types (maximum juxtaposition and interspersion); as IJI reduces to 0, the patch type adjacencies become increasingly unevenly distributed with some combinations of neighboring patch types being more common than others.

To further examine the mosaic of patches at the landscape scale, area-richness curves of the twenty landscapes were constructed by calculating the mean LCST type richness of a moving window with a variable neighbourhood size. Both Log and Power species-area relationship functions (Dengler, 2009) were fitted using linear least-squares regression and the z-values were extracted. The z-value is the slope of the species-area relationship in log-log or semi-log space, respectively. The relationship between the z-values and LCST type richness at 1.5 ha (5 × 5 cells), 13.4 ha (15 × 15 cells), and 53.6 ha (30 × 30 cells) neighbourhood sizes, location cluster, management type and Bailey’s eco-province was tested using ANOVA with follow up paired t-tests with Holm’s (1979) multiple comparison correction.
5.4 Results

LCST types were mapped across the 20 large landscapes in $24.4 \times 24.4$ m cells. Figure 5.1 is an example of this LCST mapping, with a hill-shaded elevation model and aerial photo for comparison.
Figure 5.1. LCST map within Rothrock State Forest (a), with the hill-shade of the digital elevation model (b) and orthographic aerial photo (c).
Table 5.1. P and $R^2$ values from individual ANOVA analyses of topographic variables against LCST type

<table>
<thead>
<tr>
<th>Topographic Variable</th>
<th>P value</th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>TWI</td>
<td>&lt;0.0001</td>
<td>0.020</td>
</tr>
<tr>
<td>elevation</td>
<td>&lt;0.0001</td>
<td>0.059</td>
</tr>
<tr>
<td>slope</td>
<td>&lt;0.0001</td>
<td>0.069</td>
</tr>
<tr>
<td>planar curvature</td>
<td>&lt;0.0001</td>
<td>0.005</td>
</tr>
<tr>
<td>profile curvature</td>
<td>&lt;0.0001</td>
<td>0.007</td>
</tr>
<tr>
<td>state plane easting</td>
<td>&lt;0.0001</td>
<td>0.029</td>
</tr>
<tr>
<td>state plane northing</td>
<td>&lt;0.0001</td>
<td>0.105</td>
</tr>
<tr>
<td>eastness of aspect</td>
<td>0.23</td>
<td>0.001</td>
</tr>
<tr>
<td>northness of aspect</td>
<td>0.77</td>
<td>0.001</td>
</tr>
</tbody>
</table>

5.4.1 Forest Structure at the local scale

Individual ANOVA analysis of the LCST types and each topographic variable show that while topographic wetness index (TWI), elevation, slope, planar curvature, profile curvature and state plane co-ordinates (northing and easting) are all significantly related to LCST type, the coefficient of determination for each of these variables is low (Table 5.1). Each topographic variable individually provides little predictive power for LCST type. Eastness and northness of aspect were not significantly related to LCST type.

The chi-square test of cell LCST type counts by management type was significant ($P < 0.001$), with non-government land having proportionally higher amounts of unvegetated within-forest clearings (LCST 6), sparse and very short vegetation (LCST 1.2), and short evergreen vegetation (LCST 2.1) than all of the other management types. BoSP had proportionally higher amounts of tall evergreen vegetation (LCST 4.1) and tall structurally-simple deciduous vegetation (LCST 4.2) compared to the other management types (Table 5.2).
Table 5.2. Mean percentage of landscapes in each LCST type by management type

<table>
<thead>
<tr>
<th>Management type</th>
<th>6</th>
<th>1.1</th>
<th>1.2</th>
<th>1.3</th>
<th>1.4</th>
<th>2.1</th>
<th>2.2</th>
<th>2.3</th>
<th>3.1</th>
<th>3.2</th>
<th>3.3</th>
<th>4.1</th>
<th>4.2</th>
<th>4.3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-government</td>
<td>3.8</td>
<td>0.1</td>
<td>1.8</td>
<td>0.3</td>
<td>1.0</td>
<td>4.0</td>
<td>14.5</td>
<td>15.6</td>
<td>4.4</td>
<td>15.0</td>
<td>15.3</td>
<td>3.0</td>
<td>11.5</td>
<td>9.5</td>
</tr>
<tr>
<td>BOF</td>
<td>0.2</td>
<td>0.2</td>
<td>0.8</td>
<td>0.0</td>
<td>1.5</td>
<td>3.0</td>
<td>15.1</td>
<td>13.3</td>
<td>3.8</td>
<td>16.7</td>
<td>16.3</td>
<td>2.5</td>
<td>13.0</td>
<td>13.5</td>
</tr>
<tr>
<td>PGC</td>
<td>0.5</td>
<td>0.2</td>
<td>1.0</td>
<td>0.0</td>
<td>0.9</td>
<td>2.7</td>
<td>10.6</td>
<td>14.6</td>
<td>3.3</td>
<td>15.0</td>
<td>13.8</td>
<td>2.6</td>
<td>19.9</td>
<td>14.6</td>
</tr>
<tr>
<td>BoSP</td>
<td>0.6</td>
<td>0.0</td>
<td>0.6</td>
<td>0.0</td>
<td>0.1</td>
<td>1.9</td>
<td>3.3</td>
<td>12.6</td>
<td>2.4</td>
<td>18.7</td>
<td>10.1</td>
<td>17.1</td>
<td>22.6</td>
<td>9.7</td>
</tr>
</tbody>
</table>
The linear discriminant analysis (LDA) of these topographic variables and management type against LCST type resulted in a significant model (P <0.0001), but the proportion of error not explained by the model (Wilks $\lambda$) was 0.68. Furthermore, this model with all topographic variables resulted in the correct identification of just 26.9% of the LCST types. The proportion of correct identification of very short vegetation LCST types (0, 0, 0%, respectively) and evergreen vegetation LCST types (0, 0, 0.1, 2%, respectively) were very low in contrast to the other deciduous forest LCST types (38, 46, 16, 20, 33 and 42%, respectively).

The proportion of trace for each of the first five linear discriminant (LD) variables was 0.55, 0.28, 0.07, 0.05 and 0.03 respectively; with the three largest normalized coefficients for each LD variable being: 8.997 (TWI), -8.020 (non-government land) and 5.793 (northness of aspect) for the first LD variable; -6.806 (non-government land), 4.916 (planar curvature) and 3.832 (profile curvature) for the second LD variable; -9.205 (elevation), -6.230 (eastness of aspect) and -4.338 (northness of aspect) for the third LD variable; -9.909 (eastness of aspect), -8.135 (PGC land), and -7.499 (TWI) for the fourth LD variable; and -9.535 (state plane easting), -8.697 (elevation) and 7.521 (northness of aspect) for the fifth LD variable.

5.4.2 Forest Structure at the landscape scale

5.4.2.1 Prevalent forest structures

The percent of the landscapes occupied by the various LCST types was significantly different (P <0.0001), with the pairwise t-tests with Holm’s multiple comparison adjustment indicating that there were two groups (P <0.0001) of LCST types. Un-vegetated clearings (LCST 6), very short (LCST 1.1,1.2,1.3 and 1.4) and evergreen (LCST 2.1, 3.1 and 4.1) types had lower mean prevalences than the other deciduous LCST types. In contrast, there were no significant differences among management types (P = 0.29), Bailey’s eco-provinces (P=0.13), or location cluster (P = 0.26). The standard deviations overall and by individual landscape, management type, Bailey’s eco-provinces and location clusters were all larger than the means, indicating that variation in the percent of landscape occupied varied greatly.

5.4.2.2 Patch area and density

Mean patch areas were significantly different among LCST types (P <0.0001), and Bailey’s eco-provinces (P = 0.009), with patches in the Laurentian Mixed Forest Province being
significantly larger than those in Central Appalachian Broadleaf Forest-Coniferous Forest-Meadow Province (P <0.05, Table 5.3). However, there were no significant differences among individual landscapes, location cluster, or management types (P >0.05).

The mean patch area coefficient of variation was significant different among LCST types (P <0.0001), with small coefficients of variation in very short (LCST 1.1, 1.2, 1.3 and 1.4) and evergreen (LCST 2.1, 3.1 and 4.1) types and large coefficients in other deciduous vegetation (LCST 2.2, 2.3, 3.2, 3.3, 4.2 and 4.3) types. There was also a significant difference among individual landscapes (P <0.0001), but not in terms of location cluster, Bailey’s eco-provinces or management types (P >0.05, Table 5.3).

The density of patches was significantly different among LCST types (P <0.0001) with dense patches in short to tall deciduous (LCST 2.2, 2.3, 3.2, 3.3, 4.2 and 4.3) types and sparse patches in very short (LCST 1.1, 1.2, 1.3, 1.4) and evergreen (LCST 2.1, 3.1 and 4.1) types in-between. Individual landscapes were significantly different in terms of patch density (P <0.0001), but location clusters were only marginally significantly different (P <0.05). Patch densities were significantly different among management types (P <0.0001, Table 5.3), with higher densities on non-government land than both BoSP and PGC (P <0.05), but not BoF (P >0.05) (Figure 5.2). Significant patch density differences were also seen among Bailey’s eco-provinces (P <0.001, Table 5.3).
Figure 5.2. Examples of non-government (a), Bureau of Forestry (b), Pennsylvania Game Commission (c) and Bureau of State Park (d) managed forest LCST's.
5.4.2.3 Patch shape

There were significant differences in patch shape among LCST types (P <0.0001), with very short (LCST 1.1, 1.2, 1.3, 1.4) types and the medium height evergreen (LCST 3.1) type having higher nLSI and short dense deciduous (LCST 2.3) and tall variable deciduous (LCST 4.3) types having a lower nLSI than the remaining types (P <0.05). There were no significant patch shape differences among individual landscapes, location clusters, Bailey’s eco-provinces or management types (all P >0.1, Table 5.3).

Similarly, there were significant perimeter area ratio differences among LCST types (P <0.0001), with un-vegetated forest clearings (LCST 6) having significantly lower perimeter-to-area-ratios and very short vegetation types (LCST 1.1, 1.2, 1.3, 1.4) having high ratios (P <0.05). There were no significant perimeter-to-area-ratio differences among individual landscapes, location clusters, Bailey’s eco-provinces or management types (all P >0.1).

5.4.2.4 Patch edge and contrast

Edge density (ED) was significantly different among LCST types (P <0.0001), with marginally significant differences among individual landscapes (P <0.05), but no significant differences among location clusters, Bailey’s eco-provinces or management types (P >0.05, Table 5.3).

Contrast weighted edge density (CWED) was significantly different among LCST types by (P <0.0001), with low CWED in very short and evergreen vegetation LCST types, and high CWED in other deciduous vegetation LCST types. In contrast to edge density, contrast-weighted edge density was also significant different among individual landscapes (P <0.01), location clusters (P <0.05), and Bailey’s eco-provinces (P <0.05, Table 5.3), but not among management types (P >0.05). The CWED in the Laurentian Mixed Forest Province was higher than in both the Central Appalachian Broadleaf Forest-Coniferous Forest-Meadow and Eastern Broadleaf (Oceanic) Provinces.

Similarly, total edge contrast index (TECI) was significantly different among LCST types (P <0.0001), with low TECI values for un-vegetated forest clearings (LCST 6) and short vegetation (LCST 2.1, 2.2 and 2.3) types, moderate TECI values for other deciduous types (LCST 1.1, 1.2, 1.4, 3.2, 3.3, 4.2 and 4.3), and high TECI values for evergreen (LCST 1.3, 2.1, 3.1 and 4.1) types. TECI values a differed significantly among individual landscapes (P <0.0001), location clusters (P <0.0001) and Bailey’s eco-provinces (P <0.0001, Table 5.3), but not among between management types (P >0.05).
5.4.2.5 Patch isolation and proximity

The mean Euclidean nearest neighbor distance was significantly different among LCST types \( P < 0.0001 \); specifically, the very short evergreen (LCST 1.3), very short but highly variable canopy height (LCST 1.2) and un-vegetated forest clearing (LCST 6) types had longer distances between patches than the remaining classes. Patch isolation was not significantly different among individual locations, location clusters, Bailey’s eco-province and management types (all \( P > 0.1 \), Table 5.3).

Patch interspersion was significantly different among LCST types \( P < 0.0001 \), with tall forest (LCST 4.1, 4.2 and 4.3) types having a lower IJI, and very short vegetation (LCST 1.1, 1.2, 1.3 and 1.4) types having a higher IJI than the remaining LCST types. IJI values were significantly different among individual landscapes \( P < 0.0001 \), location clusters \( P < 0.005 \), Bailey’s eco-provinces \( P < 0.0001 \), Table 5.3) and management types \( P < 0.05 \), with both non-government land and Laurentian Mixed Forest Province having a higher IJI (indicating higher interspersion), respectively.
Table 5.3. Mean of landscape forest structure metrics by management type and eco-province, including: patch area, coefficient of variation (CV) of patch area, patch density, normalized landscape shape index (nLSI), edge density (ED), contrast weighted edge density (CWED), total edge contrast index (TECI), Euclidean nearest neighbor distance, and interspersion and juxtaposition index (IJI).

<table>
<thead>
<tr>
<th>Management type</th>
<th>Patch area (ha)</th>
<th>CV of patch area</th>
<th>Patch density (number per 100 ha⁻¹)</th>
<th>nLSI</th>
<th>ED (m ha⁻¹)</th>
<th>CWED (m ha⁻¹)</th>
<th>TECI (%)</th>
<th>Euclidean nearest neighbor distance (m)</th>
<th>IJI (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>BOF</td>
<td>0.44</td>
<td>4.10</td>
<td>10.72</td>
<td>0.57</td>
<td>36.49</td>
<td>21.18</td>
<td>47.72</td>
<td>147.67</td>
<td>64.02</td>
</tr>
<tr>
<td>BoSP</td>
<td>0.46</td>
<td>4.30</td>
<td>8.16</td>
<td>0.56</td>
<td>27.66</td>
<td>16.33</td>
<td>46.91</td>
<td>137.32</td>
<td>64.64</td>
</tr>
<tr>
<td>Non-government</td>
<td>0.34</td>
<td>3.76</td>
<td>11.66</td>
<td>0.60</td>
<td>33.91</td>
<td>19.47</td>
<td>46.14</td>
<td>136.94</td>
<td>66.05</td>
</tr>
<tr>
<td>PGC</td>
<td>0.45</td>
<td>4.49</td>
<td>8.59</td>
<td>0.58</td>
<td>31.00</td>
<td>17.60</td>
<td>47.17</td>
<td>142.52</td>
<td>62.34</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>EcoProvince</th>
<th>Patch area (ha)</th>
<th>CV of patch area</th>
<th>Patch density (number per 100 ha⁻¹)</th>
<th>nLSI</th>
<th>ED (m ha⁻¹)</th>
<th>CWED (m ha⁻¹)</th>
<th>TECI (%)</th>
<th>Euclidean nearest neighbor distance (m)</th>
<th>IJI (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Central Appalachian broadleaf forest</td>
<td>0.38</td>
<td>4.25</td>
<td>9.51</td>
<td>0.59</td>
<td>30.64</td>
<td>17.39</td>
<td>46.05</td>
<td>132.93</td>
<td>63.41</td>
</tr>
<tr>
<td>Central Appalachian coniferous forest</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Central Appalachian meadow</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Eastern broadLeaf (Oceanic)</td>
<td>0.50</td>
<td>3.72</td>
<td>6.29</td>
<td>0.60</td>
<td>25.53</td>
<td>13.33</td>
<td>45.75</td>
<td>146.90</td>
<td>58.63</td>
</tr>
<tr>
<td>Laurentian mixed forest</td>
<td>0.48</td>
<td>4.10</td>
<td>10.59</td>
<td>0.57</td>
<td>35.35</td>
<td>21.04</td>
<td>48.42</td>
<td>151.65</td>
<td>66.13</td>
</tr>
</tbody>
</table>
5.4.2.6 Structural diversity

Area-richness curves of the twenty landscapes were constructed (Figures 5.3 and 5.4) and both log- and power-species area richness curves were fitted using linear least-squares regression. All models were significant \((P < 0.001)\); however, the log model was a better fit than the power model in terms of the coefficient of determination for 15 of the 20 landscapes (all \(R^2\) values >0.9). The z-value is a measure of the rate of increase in richness with the increase in neighbourhood area; however, there were no significant z-value differences among location clusters, Bailey’s eco-provinces or management types \((P >0.05)\).

Mean LCST type richness in a 1.5 ha neighborhood was not significantly different among location clusters \((P >0.05)\); however, there were significant differences among management types \((P = 0.018)\) and Bailey’s eco-provinces \((P = 0.011)\), with non-government land having a significantly higher LCST richness compared to BoSP and PGC \((P <0.05)\) and Laurentian
Mixed Forest province higher LCST richness than the Central Appalachian Broadleaf Forest-Coniferous Forest-Meadow province. Mean LCST type richness at either a 13.4 ha or 53.6 ha neighbourhood was not significantly different among location clusters, management types, or Bailey’s eco-provinces ($P > 0.05$).

### 5.5 Discussion

At the local scale ($24.4 \times 24.4$ m), measured topographic variables (excluding aspect) and management type were significantly related to forest structure; however, all these variables combined only explained 32% of the variation in forest structure. Topographic wetness index (TWI) highlights areas of low slope with large upslope contributing areas and was the most important variable in the LDA, followed by management type (particularly non-
government land) and topographic measures of aspect, elevation and curvature, respectively. The poor prediction rates for very short vegetation and evergreen vegetation in the LDA, compared to the other deciduous types, indicates that the presence of very short vegetation or evergreens were poorly predicted by topographic features or management type. Land managers use a variety of techniques to achieve land management goals and it is likely that the low level of prediction was due to the variation in specific land management activities undertaken by land managers at specific locations, i.e., time since harvesting was most likely an important determinant of short LCST types. Unfortunately detailed information regarding these specific management activities was not available and could not be included in this study.

The significant differences in the proportion of different forest structure types among land management types at the local scale, with non-government land management units containing greater amounts of very short and low cover, very short evergreen, and short evergreen types, and BoSP land holding greater amounts of tall vegetation types, reflects the different forest management objectives of these groups. These results indicate that there are greater levels of harvesting in forests managed by non-government managers, leading to different forest structures. In contrast, the landscape-scale analysis indicated that there were high levels of variation in the proportion of forest structure types and therefore no statistically significant trends in terms of forest structure type prevalence within Bailey’s eco-province or across management types.

It was hypothesized that there would be landscape-scale forest structure differences among Bailey’s eco-provinces because of differences in geologic, topographic, climatic and ecological histories and processes. Significant difference of mean patch area, patch density, CWED, TECI, IJI and structural richness at small neighborhood sizes among eco-provinces uphold this hypothesis. However, the lack of significant differences of ED among Bailey’s eco-provinces suggests that there is a difference in terms of the juxtaposition of forest structures but not a prevalence of edges. The mean patch area and structural differences between neighboring patches tended to be greater in the Laurentian Mixed Forest Province than the Central Appalachian Broadleaf Forest-Coniferous Forest-Meadow Province, indicating that the disturbance regime in the Laurentian Mixed Forest Province may be dominated by larger disturbances that create more pronounced boundaries (Chapin et al., 2011). Despite significant differences in patch areas, the mean patch areas are relatively small and not very different among the three eco-provinces, ranging from 0.38-0.50 ha. Similarly small mean
patch areas may be the result of past land use history in that most of the forests in Pennsylvania originate from land clearance at the turn of the last century (Stevens, 1956; Klein and Hoogenboom, 1973) and are all relatively similar in age (McWilliams et al., 2007). The smaller mean patch area and low edge contrast between neighboring patches in the Central Appalachian Broadleaf Forest-Coniferous Forest-Meadow Province may be due to low levels of disturbance, reflecting the fact that the historical disturbance regime of fire in the Central Appalachian Broadleaf Forest-Coniferous Forest-Meadow Province has been suppressed by modern land management. Whereas, the relatively small mean patch area in the Laurentian Mixed Forest Province is consistent with a gap-phase forest disturbance regime that perpetuates these forests in the absence of severe disturbances (Walker, 1999; Chapin et al., 2011).

The higher edge contrast in the Laurentian Mixed Forest Province is likely to influence current ecological processes. Abrupt edges are associated with steeper gradients in the physical environment, for example edges between tall forest and short vegetation may receive more wind and light, and therefore have a drier environment than softer edges that occur among tall forest types (Chapin et al., 2011). Landscape-scale forest structure also influences disturbance regimes, with fine-scale mosaics tending to be perpetuated. For example, specific forest structures may be less flammable and a mosaic of forest structures may act as natural barriers to the spread of fire, preventing the occurrence of large scale fire disturbances (Chapin et al., 2011). Similarly, some forest structures may be more resilient to windthrow than others, and mosaics of forest structure may prevent large-scale blow-downs.

Management was also found to be a significant factor in terms of landscape patterns measured by patch density, IJI and structural richness at small neighborhood sizes. There was a higher diversity of forest structure types on non-government land than other management types, consistent with Chapin et al. (2011), and an increased prevalence on very short and short types. In addition, non-government land also showed greater density of patches and differences between neighboring patches. These differences between non-government land and BoSP, BOF and PGC lands lends support to concerns over the fragmentation of forest structure within forestered lands on non-government lands. The differences between non-government and BoF land may also reflect the silvicultural restrictions placed on BoF lands under Pennsylvania’s sustainable forest resource management plan, which specifically requires green tree retention (0.9-1.9 square meters of live basal area) when harvesting (BoF, 2003). Non-government land does not have this restriction. Green tree retention (as required
on BoF land), retains mature forest structural attributes and reduces the impact of harvesting on ecological processes (Franklin et al., 1997; Chapin et al., 2011). As there are only few small areas of old-growth forests left in Pennsylvania (Smith, 1989; Davis, 1993), the implications of this fragmentation in contrast to pre-settlement forest conditions are difficult to ascertain.

Similarly, Bobiec et al. (2000) found that commercial forestry management altered the pattern of forest structure over the landscape when contrasted with primeval national park forests in the oak-lime-hornbeam forests of Bialowieza, Poland. Commercial forestry reduced variation in patch size, increased the dominance of young successional patches and homogenized the landscape. While the forest types and management approaches in Bobiec et al. (2000) and the current study are not directly comparable, both studies nonetheless show that land management influences forest structure over the landscape. Furthermore, commercial forestry practices and the maintenance of near-natural landscape forest structure patterns are compatible management objectives if forests are managed strategically (Bobiec et al., 2000).

Unlike the fragmentation of forests by non-forest landcover, the landscape connectivity of within-forest fragmentation likely remains high as high levels of refugia and cover remain; however, there are changes to the environment and available habitat resources. For example, the amount of herbaceous browse is strongly influenced by forest canopy density. While negative effects of within-forest fragmentation on forest interior species are expected; edge and pioneering species may benefit (Farina, 2006). In addition, effects on other ecological processes are probable, such as increases in water run-off and nutrient leaching due to increased prevalence of very short and short vegetation (Swank et al., 2001). This fragmentation is also likely to have cascading effects. For instance, white-tailed deer (*Odocoileus virginianus* Zimm.) are an edge-browsing species (Williamson and Hirth, 1985) known to be long-distance seed dispersers of both native and invasive species (Myers et al., 2004). Consequently, it is possible that this within-forest fragmentation may lead to greater long-distance seed dispersal of edge species by deer and increased invasion of weed species.

The within-forest fragmentation under non-government management is likely to be influenced by the parcelization of forest ownership in Pennsylvania. Sixty-three percent of Pennsylvania’s non-government forest owners own fewer than 4 hectares (Metcalf, 2010). Generally, it is difficult to manage economically such small forest parcels for timber products on a sustainable basis; furthermore, non-government forest owners are generally reluctant to
work across boundaries (Hill, 2011) and are not bound by federal and state sustainable forest policies. Parcelization is likely to continue to worsen, with 9% of private forest landowners planning to subdivide and sell their land and a further 52% planning to leave their land to multiple heirs (Gruver, 2010).

This study demonstrates a robust method to analyze and investigate forest structure at the landscape scale. It was found that at the local scale, the influence of topography (and the intimately associated environment) outweighed the influence of management on forest structure; however, management (particularly non-government management) still remained influential. At the landscape scale, both Bailey’s Eco-province (the environment) and management type were both influential on forest structure landscape patterns. Worryingly, evidence of within-forest fragmentation of non-government lands was found, with likely impacts on both biodiversity and ecosystem services. Further work is needed to quantify the specific requirements of species or ecological services to further understand the implications of this within-forest fragmentation.
Chapter 6

Conclusions

The overall objective of this dissertation was to examine the effects of land management on forest structure at both the stand and landscape level. Specifically, it investigated the effect of five types of silvicultural cutting on forest structure, composition and carbon storage in mixed-oak hardwood forests. Furthermore it developed a LiDAR Canopy Structure Topology (LCST) to map and investigate forest structure at the landscape scale, contrasting both sites (topography and eco-province) and management types.

6.1 Summary of findings

6.1.1 Objective 1

To investigate the effect of clear-cutting, improvement thinning, diameter-limited thinning from the top, diameter-limited thinning from below and the initial shelterwood cut on the forest structure and carbon stock in mixed oak-hardwood forest stands.

The results of Chapter Two confirm that both disturbance intensity and the strata disturbed influence a forest’s response to partial disturbances. Low-intensity disturbances maintained a single cohort structure, while the two high-intensity partial disturbances responded differently. While the intense partial disturbance that affected a number of forest strata
developed a multi-cohort structure as predicted by the model of Oliver and Larson (1990), the intense partial disturbance that affected only the tallest strata did not. The strata affected and intensity of the disturbance both influenced the severity of the disturbance (sensu Chapin et al., 2002) and therefore modified the response of the forest.

In terms of the effect of silvicultural disturbances on forest structure, it was hypothesized that partial cutting would initially increase structural diversity at the stand level, while clearcutting would decrease structural diversity. Chapter Two demonstrated that the effect of partial cutting on structural diversity immediately post-harvest was dependent on the type of cut applied. Specifically, the thin from below and the top treatments decreased the coefficient of variation of diameter at breast height initially; however, the improvement and shelterwood establishment cuts maintained the pre-harvest coefficient of variation of diameter at breast height.

Furthermore, it was hypothesized that as time since cutting increased, structural diversity would approximate conditions similar to the control. Chapter Two confirmed that this is generally true; however, the shelterwood establishment treatment had an increased coefficient of variation of diameter at breast height between one and fifteen years post-harvest and a higher canopy roughness after 15 years (as measured by LiDAR) due to the growth of a secondary canopy. Furthermore, the thin from the top treatment maintained similar canopy roughness, but shorter height than the control, indicating that this treatment remained structurally different from the control.

In addition, it was hypothesized that the untreated controls would continue to change over time, because these forests were still undergoing succession; however, these changes would be relatively small when compared to the treated plots. Chapter Two confirmed this hypothesis, with small changes in both the forest structure and composition of the control plots over the fifteen years of measurement.

In Chapter Two, we also demonstrated that structural resilience was greater than compositional resilience, with the composition of the treated plots remaining different from the control, but the forest structure returning to be similar to the untreated condition in most of the treatments. In addition, an incomplete shelterwood (establishment cut only) could be used to increase forest structural diversity; however, this must be balanced by the increased dominance of shade-tolerant regeneration. Finally, the specific compositional response to partial cuts are complex and context-specific, and their use could increase structural complexity at the landscape level.
In terms of the effect of silvicultural disturbances on above-ground carbon stock, it was hypothesized that all cutting techniques would reduce the carbon stock, but that the level of reduction would depend on the severity and type of cutting. Furthermore, it was hypothesized that carbon sequestration would increase after cutting to replace the reduced carbon stock, but that the level and rate of increase would depend on the severity and type of cutting. The results of Chapter Three confirm both of these hypotheses. Specifically, it was found that the clear-cutting treatment removed the most carbon stock and had the highest carbon periodic annual increment in the first 15 years post harvest, but stored less carbon than the other treatments in the long term due to a shift in species composition. Unlike the other partial cutting treatments, the thin from below treatment did not have a greater carbon periodic annual increment over the first fifteen years than the control plots; however, in the long term, all of the partial cutting treatments stored similar levels of carbon.

Furthermore, it was hypothesized that the untreated controls would increase in carbon stock over time, because these forests were still undergoing succession; however, these changes would be relatively small when compared to the treated plots. Chapter Three confirmed this hypothesis, with small increases in carbon stock in both the medium and long term.

In addition, in Chapter Three we found that while these forests are still aggrading, the no-cut was best option for carbon storage. However, if a cut is needed to provide supply of wood, the improvement cut was ideal, providing moderate wood supplies, moderately high cPAI and relatively high carbon in the long term. Furthermore, improvement cutting is compatible with the implementation of longer rotations that have been suggested as another way to increase carbon storage (Lorenz and Lal, 2009). Generally, it was found that management greatly impacted stand structure, composition and above-ground carbon storage at the stand scale.

6.1.2 Objective 2

To develop LiDAR methods to quantify forest structural diversity over landscape scales

Chapter Four developed an informative LiDAR Canopy Structure Topology (LCST) using a novel combination of statistical techniques: k-means clustering with multi-nomial logistic regression. This LCST uses publicly available topographic LiDAR (leaf-off, wide scan angle and low return density) and aerial orthographic photos to map forest structure in a raster format. This LCST had 14 types based on predominant height of vegetation, presence of
evergreen vegetation in the canopy and the complexity of the vegetation with a correct classification rate of 96%.

6.1.3 Objective 3

To examine the pattern of forest structural diversity across the landscape, and examine the relationship between the forest management type and landscape-level structural diversity.

Using the LCST developed in Chapter Four, forest structure was mapped across 20 large landscapes in Pennsylvania. The relationships between both forest management type and topography and forest structure were investigated at the local scale. The pattern of forest structure at the landscape scale in terms of the patchwork mosaic was also compared between eco-provinces and four forest land management types.

Topography was hypothesized to be associated with forest structure patterns at the local scale, because of the inter-relationships among topography, edaphic factors, climatic factors, disturbance regimes, site productivity, species composition and silvicultural techniques. Chapter Five demonstrated that there was a significant relationship between topography (topographic wetness index, elevation, slope, planar and profile curvature, state plane coordinates) and forest structure; however, the relationship explained relatively little of the variation in forest structure. Furthermore, management type and typography failed to explain 68% of the variation in forest structure (LCST).

At the landscape level, eco-provinces were found to have significantly different landscape patterns of forest structure with significant differences in mean patch size, patch density, contrast weighted edge density, total edge contrast index, interspersion and juxtaposition index, and forest structural richness at small scales. This supports the hypothesis that these differences among eco-provinces are likely due to differences in geologic, topographic, climatic and ecological histories and processes. The Laurentian Mixed Forest Province tended to have larger mean patch areas with greater heterogeneity between neighboring patches than the Central Appalachian Broadleaf Forest-Coniferous Forest-Meadow Province.

At the landscape scale, it was hypothesized that different forest management types would result in different landscape-level structural diversity patterns as different forest management philosophies are employed to achieve their varied objectives. Chapter Five demonstrates that there is a difference between non-government and public forest landscapes in terms of within-forest mosaics, but few differences were observed among the landscape forest structure of
public lands managed for different objectives.

Furthermore, it was hypothesized that forest management types with comprehensive planning and philosophies and objectives that do not preclude timber harvesting (i.e. Pennsylvania’s State Forests) would reduce patch richness and increase average patch size at the landscape scale as these forests are generally manipulated at the stand level. We found that there was no reduction in patch richness, nor an increase in average patch size on Bureau of Forestry managed land; however, on non-government land, where timber harvesting also occurs, there was a higher diversity of forest structure types than other forest management types.

Due to the haphazard nature of private forest management, it was hypothesized that structural diversity at the landscape scale would be greater than that of public land, but it would have a prevalence of low structural diversity patches due to forestry practices such as high-grading and complete clearcutting that are not generally practiced by public forest managers. The results presented in Chapter Five are consistent with this hypothesis as they indicate that there was a higher diversity of forest structure types on non-government land, with a greater prevalence of short forests and greater densities of forest structure patches with greater heterogeneity between neighboring patches than other forest management types. These results suggest that fragmentation of the within-forest structure may be occurring in privately managed forest; in addition to any forest fragmentation that may be occurring.

6.2 Overall conclusions and future directions

The studies presented in this dissertation show that management has a great impact on forest structure and carbon storage at both the stand and landscape levels. Management modifies the underlying influence of the environment, resulting in the realized forest structure patterns on the landscape. As such, managers need to consciously incorporate the effects of their actions on forest structure into their management decisions at both the stand and landscape levels.

At the stand level, it has been shown that forest management impacts forest structure and carbon storage and that specific silvicultural techniques can either maintain, increase or decrease both forest structural diversity and carbon storage. The importance of partial cutting strategies to achieve specific forest structure and carbon storage goals was highlighted, supporting calls for greater use of these techniques in managing forests as complex ecosys-
tems for multiple outcomes (Seymour et al., 2002; Drever et al., 2006; Puettmann et al., 2009).

Evidence of within-forest fragmentation of structure was found on non-government lands. Given that private forest land accounts for 71% of the forest land in Pennsylvania (McWilliams et al., 2007; Gruver, 2010), this trend deserves attention. While the effects of within-forest fragmentation are unlikely to be as severe as the fragmentation of forests by non-forest land cover, there are likely to be impacts on forest habitat and ecosystem functioning. While it is important to respect and preserve the rights of private landowners, efforts to improve forest management on private lands through policy incentives and public education are warranted. While fragmentation may be a result of the prevalence of small landholdings in the private forest estate (Metcalf, 2010), it is not inconceivable that greater professional involvement in private forest management may lead to reduced within-forest fragmentation because modern professional forestry training emphasizes the importance of ecosystem processes and the need for landscape-scale planning. Only an estimated 8% of private forest owners have sought professional forestry advice (McWilliams et al., 2007). Mechanisms and incentives for private forest owners to cooperate across ownership boundaries may also improve forest management through the pooling of resources and support services.

Furthermore, this dissertation shows that topographic LiDAR can be used for both topographic and vegetation modeling. Programs such as PAMAP, which create publicly available statewide LiDAR datasets, could provide information about forest habitats for wildlife, forest and ecosystem managers, planners and researchers. While these datasets are not collected under ideal conditions for very detailed vegetation studies, they are adequate for landscape-scale modelling of forest structure and provide more detailed information than is currently available from other remote sensing techniques.

As LiDAR data were collected for the entire state of Pennsylvania, it will be possible to map the forest structure of all of Pennsylvania’s Forests using the LCSFT developed here. Similar datasets are also available for other regions and a similar approach may be implemented to develop a LCSFT to map the forest structure of those regions. Furthermore, forest structure indices for specific goals or species could also be developed by differentially weighting LiDAR point cloud inputs that directly relate to the vegetation characteristics of interest. For example, species-specific habitat maps could be created based on the vegetation preferences of the specific species of interest. Forest carbon storage could also be mapped over the landscape, highlighting areas of high carbon storage that should be protected and
areas where carbon storage could potentially be increased through forest management.

Repeated collections of LiDAR data over the same region could also assist in the monitoring of forest structure changes over time. Such repeated measures of forest structure have important implications for forest health monitoring, allowing for detailed mapping of forest health trends. Such methods could assist in the early detection of forest health issues and generate hypotheses as to their causes and potential solutions. Forest carbon storage trends could also be more accurately mapped, assisting with the development of climate change mitigation policies.

Many of the published LiDAR studies combine LiDAR with other remote sensing techniques. In this dissertation, LiDAR was combined with aerial orthographic photography to map forest structure. Future studies may benefit from the use of data from multi- or hyper-spectral sensors rather than aerial orthophotography as these sensors are able to provide information on a greater range of wavelengths. While the visible spectrum wavelengths used in this study were satisfactory, multi- and hyper-spectral sensors can be used to detect wavelengths in the infra-red spectrum that may be more informative for vegetative studies. The combination of LiDAR and hyper-spectral data may allow for the identification of individual species (e.g., differentiate coniferous regeneration and ericaceous shrub understory species) and quantification of forest composition as well as structure (Asner and Martin, 2008).

A handful of studies in the published literature have taken the voxel (volumetric pixel) approach to LiDAR for forest structure modelling (Lee et al., 2004; Coops et al., 2007; Mascaro et al., 2011). This approach creates a three-dimensional model of the forest from LiDAR returns based on the density of LiDAR returns within a three-dimensional lattice of cuboid cells. By using this approach, assumptions regarding the height distribution of the LiDAR returns are not required and there is no need to calculate statistical parameters to describe the distribution of the LiDAR returns. While a voxel approach may lead to a development of a better LCST, further research is needed to investigate the appropriateness of using this approach with topographic (leaf-off, discrete-return, wide point spacing, wide scan angle) LiDAR.

It was hoped that the LCST developed in this dissertation may be able to characterize the vegetation of the whole forest structure, including the sub-canopy vegetation through the use of discrete return leaf-off LiDAR. While this classification was able to identify forest areas with evergreen understories, it was unable to identify those with deciduous understories. It is likely that the discretization settings of the LiDAR system were not sensitive
enough to record small peaks in the return signal corresponding to the small branches of de-
ciduous shrubs. Future studies that investigate the influence of these discretization settings
on LiDAR point clouds and the detection of understory vegetation in leaf-off discrete return
LiDAR would be beneficial to the future development of better LiDAR-based forest structure
typologies; however, the specific discretization settings of commercial LiDAR systems tend
to be proprietary (Gatziolis and Andersen, 2008).
Appendix A

Allometric equations for the above ground biomass of selected common Eastern hardwood understory species


A.1 Abstract

Allometric equations were formulated for predicting the above ground biomass of six groups of forest understory species (autumn olive, Elaeagnus umbellata Thunb.; blueberry, Vaccinium angustifolium Aiton, V. corymbosum L. and V. pallidum Aiton; hawthorn, Crataegus spp.; Honeysuckle, Lonicera spp.; multiflora rose, Rosa multiflora Thunb.; and viburnum, Viburnum acerifolium L. and V. dentatum L) common to Eastern hardwoods using basal diameter and/or height. As measured by fit index (FI), basal diameter or height alone explained between 51 and 93% of the variation in oven-dry weight; this increased to 75-96% when both basal diameter and height were used as predictors. Data were collected at four
sites throughout Pennsylvania, but an evaluation of the importance of site as a blocking factor found site not to be statistically significant; therefore the equations presented here may be utilized in a variety of forested sites within the greater mid-Atlantic region.

A.2 Introduction

Estimates of biomass are useful indicators of productivity, forest fire fuel loads, wildlife habitat and carbon storage. Using allometric equations for predicting the biomass of vegetation from simple metrics is a common and widely accepted technique (Elliott and Clinton, 1993; Williams and McClanahan, 1984). The biggest advantage of these allometric equations is that they allow for the easy estimation of biomass without time consuming and expensive destructive sampling.

Extensive reviews of such equations for North American forest trees have shown the abundance of useful equations for the overstory of a forest (Jenkins et al., 2003a); however, fewer allometric equations have been produced for the understory vegetation (e.g., Elliott and Clinton, 1993). For example, no appropriate biomass equations were found in the literature for the following common exotic and native understory species: autumn olive (Elaeagnus umbellata Thunb.), blueberry (Vaccinium angustifolium Aiton, V. corymbosum L. and V. pallidum Aiton), hawthorn (Crataegus spp.), honeysuckle (Lonicera spp., e.g., L. morrowii A. Gray and L. maackii (Rupr.) Maxim.), multiflora rose (Rosa multiflora Thunb.) and viburnum (Viburnum acerifolium L. and V. dentatum L). Allometric equations for estimating the oven-dry weight from stem basal diameter and shrub height for these six species groups have been developed and are presented here.

A.3 Materials and methods

A.3.1 Study sites and field methods

The four study sites used in this study are part of a larger silvicultural demonstration and are widely distributed in both location and environmental factors (Table A.1). Stands were classified as red oak - mixed hardwood or as northern hardwood/red oak - mixed hardwood transitional forest (Fike, 1999) with upland oak site indices (Carmean et al., 1989) between 49-82 and stocking (McGill et al., 1999) between 65-109%.
Table A.1. Characteristics of the study sites, including forest type (Fike, 1999), upland oak site index (SI) (Carmean et al., 1989), stocking (McGill et al., 1999), aspect, elevation, and soil type (Anon., 2008). Study sites were located in the Bald Eagle State Forest (BE), State Gamelands 211 (SGL), Stone Valley Experimental Forest (SVEF), and Tiadaghton State Forest (TIAD).

<table>
<thead>
<tr>
<th>Site</th>
<th>Location</th>
<th>Forest type</th>
<th>SI</th>
<th>Stocking (%)</th>
<th>Aspect</th>
<th>Elevation (ft)</th>
<th>Soil type</th>
</tr>
</thead>
<tbody>
<tr>
<td>BE</td>
<td>Union County, PA</td>
<td>Red oak-mixed hardwood</td>
<td>75</td>
<td>82-88</td>
<td>SE</td>
<td>920</td>
<td>Buchanan gravelly loam and very stony loam</td>
</tr>
<tr>
<td>SGL</td>
<td>Dauphin County, PA</td>
<td>Red oak-mixed hardwood</td>
<td>56</td>
<td>76-109</td>
<td>SSE</td>
<td>520</td>
<td>Calvin very stony silt loam</td>
</tr>
<tr>
<td>SVEF</td>
<td>Huntingdon County, PA</td>
<td>Red oak-mixed hardwood</td>
<td>49</td>
<td>66-93</td>
<td>SW</td>
<td>1040</td>
<td>Blairton and Brinkerton silt loams</td>
</tr>
<tr>
<td>TIAD</td>
<td>Lycoming County, PA</td>
<td>Transitional northern hardwood/red oak-mixed hardwood</td>
<td>82</td>
<td>65-100</td>
<td>E</td>
<td>1020</td>
<td>Oyuanga and Loardstown very stony loams</td>
</tr>
</tbody>
</table>
At each site a random sample of approximately 25 individuals representing the size range present at the site was chosen (Table A.2). Where the species was uncommon at a site, fewer individuals were collected. Each individual was between 30 cm tall and 2.5 cm diameter at breast height (dbh). Basal diameter and height of each individual stem were recorded and the stem was clipped at ground level. The above ground portion of the stems was collected in the field, kiln dried at 100°C until a constant weight was achieved, and the final weight recorded. Plant materials are usually dried at 60 - 105°C, with the lower temperatures used to prevent volatilization of compounds which may affect chemical compositional analysis (Forrest, 1968; Bonham, 1989). Drying plant materials at 100°C compared to 70°C may reduce the weight of the sample up to 2-4% (Forrest, 1968; Snowdon et al., 2001); however, this higher temperature is consistent with the drying practices used for other forest and plant materials such as soil, wood, and aquatic plant samples.
Table A.2. Summary data of samples collected, including the range of both basal diameters and heights used to fit regression models for oven-dry weight of above-ground biomass. BE, Bald Eagle State Forest; SGL, State Gamelands 211; SVEF, Stone Valley Experimental Forest; TIAD, Tiadaghton State Forest.

<table>
<thead>
<tr>
<th>Species</th>
<th>Site</th>
<th>n</th>
<th>Basal diameter range (cm)</th>
<th>Height range (m)</th>
<th>Oven-dry weight range (g)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Autumn olive</td>
<td>SVEF</td>
<td>27</td>
<td>0.2-4.1</td>
<td>0.58-3.52</td>
<td>3.7-923.1</td>
</tr>
<tr>
<td>Blueberry</td>
<td>BE</td>
<td>22</td>
<td>0.3-1.2</td>
<td>0.40-1.14</td>
<td>3.1-71.3</td>
</tr>
<tr>
<td></td>
<td>SGL</td>
<td>28</td>
<td>0.2-2.9</td>
<td>0.41-2.47</td>
<td>3.7-591.3</td>
</tr>
<tr>
<td></td>
<td>SVEF</td>
<td>31</td>
<td>0.2-1.0</td>
<td>0.4-1.39</td>
<td>2.8-127.8</td>
</tr>
<tr>
<td>Hawthorn</td>
<td>SGL</td>
<td>17</td>
<td>0.3-5.6</td>
<td>0.4-7.01</td>
<td>5.0-3481.6</td>
</tr>
<tr>
<td></td>
<td>SVEF</td>
<td>19</td>
<td>0.3-2.7</td>
<td>0.56-3.13</td>
<td>4.8-639.3</td>
</tr>
<tr>
<td>Honeysuckle</td>
<td>SVEF</td>
<td>22</td>
<td>0.3-6.0</td>
<td>0.77-3.90</td>
<td>3.8-2485.3</td>
</tr>
<tr>
<td>Multiflora rose</td>
<td>SGL</td>
<td>9</td>
<td>0.3-1.2</td>
<td>0.41-1.90</td>
<td>3.4-44.7</td>
</tr>
<tr>
<td></td>
<td>SVEF</td>
<td>24</td>
<td>0.2-2.2</td>
<td>0.41-4.15</td>
<td>3.1-443.7</td>
</tr>
<tr>
<td></td>
<td>TIAD</td>
<td>25</td>
<td>0.2-1.5</td>
<td>0.39-3.58</td>
<td>2.2-262.0</td>
</tr>
<tr>
<td>Viburnum</td>
<td>BE</td>
<td>21</td>
<td>0.3-1.0</td>
<td>0.30-1.56</td>
<td>2.3-43.6</td>
</tr>
<tr>
<td></td>
<td>SGL</td>
<td>25</td>
<td>0.3-1.1</td>
<td>0.43-2.13</td>
<td>3.8-131.7</td>
</tr>
<tr>
<td></td>
<td>SVEF</td>
<td>28</td>
<td>0.2-1.5</td>
<td>0.51-2.56</td>
<td>3.6-204.6</td>
</tr>
</tbody>
</table>
A.3.2 Data analysis

Models for fitting understory biomass allometric equations typically use natural logarithmic transformations of the dependent and independent variables (e.g., Ohmann et al., 1976; Smith and Brand, 1983; Elliott and Clinton, 1993; Buech and Rugg, 1995) or power functions (e.g., Grigal and Ohmann, 1977; Roussopoulos and Loomis, 1979; Ohmann et al., 1981). In this study, the Box-Cox transformation procedure indicated that natural logarithmic transformations would be appropriate for these data sets. As the type of data collected varies by user, we tested allometric models for oven-dry weight with basal diameter only, height only, and with both height and diameter as predictors. Linear regression was used to fit the following equations using the statistical package R (R Development Core Team, 2009):

\[
\ln(ODW) = a + (b \times \ln(BD)) \quad (A.1)
\]
\[
\ln(ODW) = a + (b \times \ln(H)) \quad (A.2)
\]
\[
\ln(ODW) = a + (b \times \ln(H)) + (c \times \ln(BD)) + (d \times \ln(H) \times \ln(BD)) \quad (A.3)
\]

where \( \ln \) is the natural logarithm, ODW is the oven-dry weight in grams, BD is basal diameter in centimeters, H is height from root collar to stem tip in meters, and a, b, c and d are regression coefficients for their respective terms. When both basal diameter and height were used (Equation A.3), an interaction factor was also included initially, and removed if the coefficient was not statistically significant.

While \( R^2 \) is a good indicator of model fit to the transformed data, it does not indicate the overall fit of the model based on the untransformed dependent variable. Therefore, the average bias, standard error of the estimate (SEE) and fit index (FI) based on Schlaegel (1981) were calculated and used to evaluate the model performance. All three of these statistics are based on the residuals in the measured units, not transformed units. The fit index ranges between 0 and 1, and is interpreted in a manner analogous to \( R^2 \).

When allometric equations of logarithmic dependent variables are back-transformed to the original scale, the results give the geometric mean rather than the arithmetic mean. To correct this bias, we applied the ratio estimator correction factor following Snowdon (1991). To examine the applicability of these equations across a range of sites, it was important to examine whether site as a blocking factor was a significant predictor of oven-dry weight. A
fourth equation was also fitted, adding indicator variables representing the four study sites to the terms in equation three with the appropriate interaction terms. The significance of the coefficients of the indicator variables was tested using a t-test with the null hypothesis that the coefficient is equal to 0. Where the coefficients are not significant, site is not an important predictor of oven-dry weight and the equations may be applicable across a range of sites.

A.4 Results and discussion

The coefficients for the fitted allometric equations, as given by Equations A.1-A.3, are presented in Tables A.3-A.5 respectively. Model $R^2$ values between 0.67 and 0.98 were achieved, with the majority of models giving values above 0.90. As measured by FI, basal diameter or height alone explained between 51 and 93 % of the variation in oven-dry weight; this increased to 75-96 % when both basal diameter and height were used as predictors. All of the models tested were statistically significant with p-values $<0.001$. Inclusion of the statistically significant interaction term between basal diameter and height in the honeysuckle allometric equation caused the main effect of basal diameter to be no longer statistically significant; however, where a higher order term (such as an interaction term) is included in the model, all associated lower order terms should be maintained even if they are not statistically significant (Aiken et al., 1991).
Table A.3. Coefficient estimates, their standard errors (in parentheses), coefficient of determination, average bias, standard error of the estimate (SEE), and fit index (FI) for allometric equations based on basal diameter as given by Equation A.1. P-values of both intercept (a) and coefficient (b) were $<0.001$ for all species.

<table>
<thead>
<tr>
<th>Species</th>
<th>a</th>
<th>b</th>
<th>$R^2$</th>
<th>Average bias (g)</th>
<th>SEE (g)</th>
<th>FI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Autumn olive</td>
<td>3.7993 (0.0672)</td>
<td>2.169 (0.0876)</td>
<td>0.96</td>
<td>14.12</td>
<td>76.25</td>
<td>0.93</td>
</tr>
<tr>
<td>Blueberry</td>
<td>3.6685 (0.0576)</td>
<td>1.8205 (0.0750)</td>
<td>0.88</td>
<td>5.43</td>
<td>49.20</td>
<td>0.70</td>
</tr>
<tr>
<td>Hawthorn</td>
<td>3.6834 (0.1030)</td>
<td>2.3405 (0.1709)</td>
<td>0.85</td>
<td>90.05</td>
<td>548.64</td>
<td>0.75</td>
</tr>
<tr>
<td>Honeysuckle</td>
<td>3.7992 (0.2306)</td>
<td>1.7880 (0.2724)</td>
<td>0.67</td>
<td>137.52</td>
<td>676.54</td>
<td>0.51</td>
</tr>
<tr>
<td>Multiflora rose</td>
<td>4.1203 (0.1118)</td>
<td>2.2455 (0.1264)</td>
<td>0.85</td>
<td>9.21</td>
<td>71.44</td>
<td>0.60</td>
</tr>
<tr>
<td>Viburnum</td>
<td>3.8799 (0.0760)</td>
<td>2.3936 (0.1090)</td>
<td>0.87</td>
<td>3.96</td>
<td>34.51</td>
<td>0.81</td>
</tr>
</tbody>
</table>
Table A.4. Coefficient estimates, their standard errors (in parentheses), coefficient of determination, average bias, standard error of the estimate (SEE), and fit index (FI) for allometric equations based on stem height as given by Equation A.2. P-values of both intercept (a) and coefficient (b) were <0.001 for all species.

<table>
<thead>
<tr>
<th>Species</th>
<th>a</th>
<th>b</th>
<th>R²</th>
<th>Average bias (g)</th>
<th>SEE (g)</th>
<th>FI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Autumn olive</td>
<td>2.5469 (0.1196)</td>
<td>3.0497 (0.1914)</td>
<td>0.91</td>
<td>38.30</td>
<td>206.80</td>
<td>0.85</td>
</tr>
<tr>
<td>Blueberry</td>
<td>3.6176 (0.0754)</td>
<td>2.4228 (0.1383)</td>
<td>0.80</td>
<td>5.18</td>
<td>42.21</td>
<td>0.78</td>
</tr>
<tr>
<td>Hawthorn</td>
<td>3.1645 (0.1026)</td>
<td>2.1273 (0.1525)</td>
<td>0.85</td>
<td>105.47</td>
<td>651.16</td>
<td>0.59</td>
</tr>
<tr>
<td>Honeysuckle</td>
<td>3.2821 (0.1167)</td>
<td>3.2012 (0.1991)</td>
<td>0.92</td>
<td>84.05</td>
<td>403.66</td>
<td>0.77</td>
</tr>
<tr>
<td>Multiflora rose</td>
<td>2.4740 (0.1003)</td>
<td>1.5060 (0.1412)</td>
<td>0.67</td>
<td>16.14</td>
<td>126.03</td>
<td>0.31</td>
</tr>
<tr>
<td>Viburnum</td>
<td>2.8171 (0.0498)</td>
<td>1.9530 (0.0891)</td>
<td>0.87</td>
<td>3.77</td>
<td>32.87</td>
<td>0.77</td>
</tr>
</tbody>
</table>
**Table A.5.** Coefficient estimates, their standard errors (in parentheses), coefficient of determination, average bias, standard error of the estimate (SEE), and fit index (FI) for allometric equations based on both basal diameter and height as given by Equation A.3. P-values of intercept (a), and coefficients (b, c, and d) were $<0.001$ for all species, except: a $P < 0.001$, b $P < 0.003$, c $P < 0.001$, d $P = 0.81$, e $P = 0.031$.

<table>
<thead>
<tr>
<th>Species</th>
<th>a</th>
<th>b</th>
<th>c</th>
<th>d</th>
<th>$R^2$</th>
<th>Average bias (g)</th>
<th>SEE (g)</th>
<th>FI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Autumn olive</td>
<td>3.1522 (0.1311)</td>
<td>1.1981 (0.2556)</td>
<td>1.1968 (0.1962)</td>
<td>0.4206 (0.1157)</td>
<td>a 0.98</td>
<td>05.70</td>
<td>30.77</td>
<td>0.90</td>
</tr>
<tr>
<td>Blueberry</td>
<td>3.6920 (0.0497)</td>
<td>0.9256 (0.1700)</td>
<td>1.4977 (0.1404)</td>
<td>0.4155 (0.1361)</td>
<td>b 0.92</td>
<td>0.12</td>
<td>1.12</td>
<td>0.96</td>
</tr>
<tr>
<td>Hawthorn</td>
<td>3.3269 (0.0680)</td>
<td>1.0583 (0.1435)</td>
<td>1.1827 (0.1554)</td>
<td>0.3472 (0.0966)</td>
<td>c 0.96</td>
<td>24.75</td>
<td>155.60</td>
<td>0.75</td>
</tr>
<tr>
<td>Honeysuckle</td>
<td>3.1582 (0.1315)</td>
<td>2.8930 (0.2897)</td>
<td>0.0540 (0.2226)</td>
<td>0.4743 (0.2026)</td>
<td>d 0.94</td>
<td>4.11</td>
<td>21.31</td>
<td>0.80</td>
</tr>
<tr>
<td>Multiflora rose</td>
<td>3.4097 (0.1197)</td>
<td>1.0299 (0.1332)</td>
<td>1.5894 (0.1340)</td>
<td>0.7757 (0.1409)</td>
<td>e 0.93</td>
<td>1.95</td>
<td>15.28</td>
<td>0.80</td>
</tr>
<tr>
<td>Viburnum</td>
<td>3.3090 (0.0727)</td>
<td>1.2616 (0.1203)</td>
<td>1.3391 (0.1329)</td>
<td>0.5500 (0.1388)</td>
<td>0.95</td>
<td>0.56</td>
<td>4.97</td>
<td>0.91</td>
</tr>
</tbody>
</table>
The residuals for each model are approximately randomly distributed around 0 (Figures A.1-A.3), and the average bias and SEE are relatively small, indicating that there is little bias in the equations. The correction factors for the bias that arises from logarithmic back transformations are given in Table A.6.
Figure A.1. Plots of residuals (y axis) versus fitted values (x axis) for allometric equations based on basal diameter (Equation A.1) for autumn olive (A), blueberry (B), hawthorn (C), honeysuckle (D), rose (E), and viburnum (F).
Figure A.2. Plot of residuals (y axis) versus fitted values (x axis) for allometric equations based on height (Equation A.2) for autumn olive (A), blueberry (B), hawthorn (C), honeysuckle (D), multiflora rose (E), and viburnum (F).
Figure A.3. Plot of residuals (y axis) versus fitted values (x axis) for allometric equations based on height and basal diameter (Equation A.3) for autumn olive (A), blueberry (B), hawthorn (C), honeysuckle (D), multiflora rose (E), and viburnum (F).

<table>
<thead>
<tr>
<th>Species</th>
<th>Stem height model (Equation A.1)</th>
<th>Basal diameter model (Equation A.2)</th>
<th>Stem height and basal diameter model (Equation A.3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Autumn olive</td>
<td>1.3320</td>
<td>1.1012</td>
<td>0.9642</td>
</tr>
<tr>
<td>Blueberry</td>
<td>1.2206</td>
<td>1.2281</td>
<td>1.0042</td>
</tr>
<tr>
<td>Hawthorn</td>
<td>1.9457</td>
<td>1.6732</td>
<td>0.9004</td>
</tr>
<tr>
<td>Honeysuckle</td>
<td>1.3845</td>
<td>1.8708</td>
<td>1.0141</td>
</tr>
<tr>
<td>Multiflora rose</td>
<td>1.7919</td>
<td>1.3202</td>
<td>1.0555</td>
</tr>
<tr>
<td>Viburnum</td>
<td>1.1681</td>
<td>1.1588</td>
<td>1.0209</td>
</tr>
</tbody>
</table>

The blocking factor site was tested as a predictor for the oven-dry weight of blueberry, hawthorn, multiflora rose and viburnum; autumn olive and honeysuckle were only present at one site each and thus testing was not possible. When the indicator variables for site were included in the model with both basal diameter and height, the coefficients for the site indicator variables were not significant (p-values 0.11 - 0.84) and only modest increases in the variation explained were seen (Table A.7). The interaction terms relating to the site indicator variables were also not statistically significant (p-values 0.14 - 0.98). Consequently, the understory biomass allometric equations presented here may be applied to variety of forested sites within Pennsylvania.

A.5 An example

To estimate the biomass of a viburnum shrub with a basal diameter of 1.3 cm and a height of 2.2 m, allometric equation 3 based on both basal diameter and height, the coefficients from Table 5, and the bias correction factor (CF) from Table 6 would be used as follows:

\[
\ln(ODW) = a + b \times \ln(H) + c \times \ln(BD) + d \times \ln(H) \times \ln(BD)
\]

\[
= 3.3090 + 1.2616 \times \ln(2.2) + 1.3391 \times \ln(1.3) + 0.5500 \times \ln(2.2) \times \ln(1.3)
\]
Table A.7. Model P value and site dummy variable coefficient P values for the developed allometric equations based on site, basal diameter and height. SGL, State Gamelands 211; SVEF, Stone Valley Experimental Forest; TIAD, Tiadaghton State Forest. INTER refers to a P value range for interaction coefficients involving site indicator variables.

<table>
<thead>
<tr>
<th>Species</th>
<th>Base case</th>
<th>P value for site indicator variable at:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>SGL</td>
</tr>
<tr>
<td>Blueberry</td>
<td>BE</td>
<td>0.11</td>
</tr>
<tr>
<td>Hawthorn</td>
<td>SGL</td>
<td>N/A</td>
</tr>
<tr>
<td>Multiflora rose</td>
<td>SGL</td>
<td>N/A</td>
</tr>
<tr>
<td>Viburnum</td>
<td>BE</td>
<td>0.64</td>
</tr>
</tbody>
</table>

= 4.7688

\[
\text{MedianODW} = e^{4.7688}
\]

= 117.7778 g

\[
\text{MeanODW} = \text{MedianODW} \times CF
\]

= 117.7778 g \times 1.0209

= 120.2 g
Appendix B

Development process for the LiDAR Canopy Structure Topology (LCST)

The LiDAR Canopy Structure Topology (LCST) was developed in a step-by-step iterative process by changing the variable inclusion, variable relativization, and weighting of the 95th percentile of return height at each step to modify the K-means clustering algorithm as described in Table B.1. The appropriate number of clusters for each iteration was identified by repeating the analysis for up to 25 clusters and plotting a scree-like plot (see chapter 4 for details). The clustering of data points was then qualitatively assessed by examining the distribution of the cluster centroids, comparing the resulting cell classifications to the field data from the silvicultural demonstration plots and visually comparing the mapped clusters against aerial photos. Model 6 is the preferred model as it accurately reflected the top height of the canopy, canopy density, variation in foliage height and level of evergreen foliage.

Similar to Ferraro (2008), after applying K-means clustering to the sample data, a statistical modeling technique was used to be able to apply this classification to data not included in the original analysis (i.e., to areas outside the initial four tiles of sample data). In this study, multinomial logistic regression equations were developed as described in Chapter 4.
Table B.1. Description of the iterative LCST development

<table>
<thead>
<tr>
<th>Model</th>
<th>Inputs</th>
<th>Model</th>
<th>Critique of resulting LCST types</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Mean, standard deviation, coefficient of variation, kurtosis, skew, and 95th percentile of return height and return intensity, proportion of all returns greater than 1 ft above the digital elevation model, canopy height model rumple index and evergreen pixel count</td>
<td>K-means clustering with 8 clusters and all variables relativised by their range</td>
<td>This analysis includes all available data with relativization to ensure the weighting of each variable equally. The centroids of the resulting clusters suggest that the classification is heavily influenced by the intensity values of the returns. Intensity values of the returns were uncorrelated with return height statistics and the laser intensity was adjusted during data collection to ensure laser backscatter. Furthermore, while the use of normalized intensity values has shown promise for land-cover mapping, intensity values are unlikely to be useful for vegetation mapping due to their variability (Yoon et al., 2008). Therefore, return intensity data was excluded from further analyses.</td>
</tr>
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<td>2</td>
<td>Mean, standard deviation, coefficient of variation, kurtosis, skew, and 95th percentile of return height, proportion of all returns greater than 1 ft above the digital elevation model, canopy height model rumple index and evergreen pixel count</td>
<td>K-means clustering with 7 clusters with all variables relativised by their range</td>
<td>The cluster centroids and comparisons of the mapped clusters against both the aerial photos and field data from the silviculture demonstrations plots suggest that the clusters reflect the level of evergreen foliage in the canopy and variation in foliage height well, but do not reflect the top height nor density of the canopy.</td>
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### Table

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<thead>
<tr>
<th>Model</th>
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<th>Critique of resulting LCST</th>
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<tbody>
<tr>
<td>3</td>
<td>Mean, standard deviation, coefficient of variation, kurtosis, skew, and 95th percentile of return height, proportion of all returns greater than 1 ft above the digital elevation model and canopy height model rumple index</td>
<td>K-means clustering with 7 clusters with all variables relativised by their range</td>
<td>The evergreen pixel count was excluded from this analysis to assess its inclusion in addition to the LiDAR data. The cluster centroids and comparisons of the mapped clusters against both the aerial photos and field data from the silviculture demonstrations plots show that without the evergreen pixel count variable the LCST is unable to differentiate between evergreen and leaf-off deciduous forest canopies. However, in the leaf-off state evergreen and deciduous canopies are not comparable; therefore, all future analyses include the evergreen pixel count variable.</td>
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<td>4</td>
<td>Mean, standard deviation, coefficient of variation, kurtosis, skew, and 95th percentile of return height, proportion of all returns greater than 1 ft above the digital elevation model, canopy height model rumple index and evergreen pixel count</td>
<td>K-means clustering with 5 clusters</td>
<td>The variables were not relativized by their range to assess the need for relativization. Therefore, the variables are simply weighted by their innate range in values, with variables with large ranges more heavily weighted than those with small ranges. The cluster centroids and comparisons of the mapped clusters against both the aerial photos and field data from the silviculture demonstrations plots show that the resulting clusters are highly influenced by the evergreen pixel count variable which has a very large range, and poorly reflects canopy top height. Furthermore, this analysis and previous analyses show that it is unable to separate outliers in the dataset with cells with 95th percentile of return heights &gt;400 ft found across all clusters.</td>
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<td>5a</td>
<td>Mean, coefficient of variation, kurtosis, skew, and 95th percentile of return height, proportion of all returns greater than 1 ft above the digital elevation model, canopy height model rumple index and evergreen pixel count</td>
<td>K-means clustering with 9 clusters with all variables relativised by their range</td>
<td>The standard deviation of return height was highly correlated with the 95th percentile of return height. To assess the effect of multi-collinearity on clustering, the standard deviation of return height was removed from the analysis; however marginal tables of cluster membership between this model and Model 2 suggests that they remain similar despite the absence of this variable.</td>
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<td>5b</td>
<td>Mean, coefficient of variation, kurtosis, skew, and 95th percentile of return height, proportion of all returns greater than 1 ft above the digital elevation model, canopy height model rumple index and evergreen pixel count</td>
<td>K-means clustering with 7 clusters with all variables relativised by their range</td>
<td>To further assess the effect of multi-collinearity, Model 5 was re-run with only 7 clusters to be directly comparable to Model 2. This showed that the membership of the clusters remained the same despite the absence of the standard deviation of return height variable and that this variable contributes little additional information to the analysis. The standard deviation of height was therefore left out of all further models.</td>
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<td>6</td>
<td>Mean, coefficient of variation, kurtosis, skew, and 95th percentile of return height, proportion of all returns greater than 1 ft above the digital elevation mode, canopy height model rumple index and evergreen pixel count</td>
<td>K-means clustering in five 95th percentile of return height classes with all variables relativised by their range: 0-30, 30-65, 65-80, 80-150 and &gt;150ft. The height classes are derived from the Pennsylvania Bureau of Forestry site classifications (Brose et al., 2008) with additional divisions for very short and tall outlying values. 4 clusters were applied for the 0-30 height class, and 3 clusters each for the 30-65, 65-80 and 80-150 ft height classes. No clustering was undertaken on the &gt;150ft outliers height class.</td>
<td>The cluster centroids and comparisons of the mapped clusters against both the aerial photos and field data from the silviculture demonstrations plots show that this model with divisions by the 95th percentile of return height accurately reflect the top height of the canopy, canopy density, variation in foliage height and level of evergreen foliage. By a priori classifying by 95th percentile of return height, this variable is heavily weighted above the other variables. This additional weighting on the 95th percentile is superior to both Models 2 and 5 by reflecting top height of the canopy in addition to other vegetation characteristics. This was the preferred model.</td>
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<td>Mean, coefficient of variation, kurtosis, skew, and 95th percentile of return height, proportion of all returns greater than 1 ft above the digital elevation model, canopy height model rumple index and evergreen pixel count</td>
<td>K-means clustering in five 95th percentile of return height classes with all variables relativised by their range: 0-30, 30-65, 65-80, 80-150 and &gt;150ft. The height classes are derived from the Pennsylvania Bureau of Forestry site classifications (Brose et al., 2008) with additional divisions for very short and tall outlying values. 3 clusters were applied to each of the height classes, except the &gt;150ft outliers height class which was not clustered.</td>
<td>For simplicity, fewer numbers of clusters are preferred if possible. To maintain consistency across the height classes, the number of clusters per height class were reduced to 3; however, the cluster centroids and comparisons of the mapped clusters against the aerial photos show that this model does not truly reflect the variation in short vegetation. Older even-aged silvicultural treatments (primarily clearcuts and completed shelterwoods) with dense pole stands were clustered with recent overstory removals with very short shrubby vegetation.</td>
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<td>8</td>
<td>Mean, coefficient of variation, kurtosis, skew, and 95th percentile of return height, proportion of all returns greater than 1 ft above the digital elevation model, canopy height model rumple index and evergreen pixel count</td>
<td>K-means clustering with 6 clusters with all variables relativised by their range and weighting on the 95th percentile of height variable by adding this variable to the analysis twice</td>
<td>The 95th percentile of return height was added multiple times to the model in an attempt to increase the weighting of this variable. However, as demonstrated by Models 5a and 5b, multicollinearity does not affect cluster membership. A marginal table of the resulting cluster memberships from this model against those of model 5 suggest that cluster membership in these two models is very similar.</td>
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<td>9a</td>
<td>Mean, standard deviation, coefficient of variation, kurtosis, skew, and 95th percentile of return height, proportion of all returns greater than 1 ft above the digital elevation model, canopy height model rumple index and evergreen pixel count</td>
<td>K-means clustering with 7 clusters, all variables relativised by their range and 3-fold weighting on the 95th percentile of height variable</td>
<td>The 95th percentile of return height was multiplied by three to increase the weighting of this variable. Comparisons of the cluster centroids; comparisons of the mapped clusters against both the aerial photos and field data from the silviculture demonstrations plots and the marginal table of the cluster membership against those from Model 2 show that the within-cluster variation of the 95th percentile of return height variable has not been reduced. This model does not reflect the top height of the canopy accurately.</td>
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<td>9b</td>
<td>Mean, standard deviation, coefficient of variation, kurtosis, skew, and 95th percentile of return height, proportion of all returns greater than 1 ft above the digital elevation model, canopy height model rumple index and evergreen pixel count</td>
<td>K-means clustering with 7 clusters, all variables relativised by their range and 5-fold weighting on the 95th percentile of height variable</td>
<td>The 95th percentile of return height was multiplied by five to further increase the weighting of this variable. The cluster centroids and comparisons of the mapped clusters against both the aerial photos and field data from the silviculture demonstrations plots show that while the resulting clusters accurately reflect the top height of the canopy as desired, they no longer accurately reflect the level of evergreen foliage in the canopy, variation in foliage height well, or density of the canopy.</td>
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<td>Mean, standard deviation, coefficient of variation, kurtosis, skew, and 95th percentile of return height, proportion of all returns greater than 1 ft above the digital elevation model, canopy height model rumple index and evergreen pixel count</td>
<td>Recursive hierarchical K-mean clustering with all variables relativised by their range (similar to the methods of Kim, 2010)</td>
<td>This method of repeating the K-mean clustering analysis on Model 2 clusters resulted in an unwieldy number of clusters (&gt;20). The cluster centroids and comparisons of the mapped clusters against both the aerial photos and field data from the silviculture demonstration plots suggest that the data do not warrant such fine division, and that it is difficult to delineate these clusters from field data.</td>
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</table>


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