ADVANCING THE TERRESTRIAL ECOLOGICAL UNIT INVENTORY WITHIN THE WHITE MOUNTAIN NATIONAL FOREST USING LiDAR

by

Robert A. Colter
B.A. General Agriculture Science, Southern Illinois University, 1998
M.S. Plant and Soil Science, Southern Illinois University, 2001

DISSERTATION

Submitted to the University of New Hampshire
in Partial Fulfillment of
the Requirements for the Degree of

Doctor of Philosophy
in
Natural Resources and Environmental Study
September 2019

This thesis/dissertation has been examined and approved in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Earth and Environmental Science by:

Dissertation Director, Mark J. Ducey, Professor (Natural Resources and the Environment)

Scott W. Bailey, Research Scientist (U.S. Forest Service)

Thomas Lee, Professor (Natural Resources and the Environment)

Gregory Nowacki, R9 Regional Ecologist (U.S. Forest Service)

Michael Palace, Associate Professor (Earth Sciences)

On April 2, 2019

Original approval signatures are on file with the University of New Hampshire Graduate School.

to my mother and father

ACKNOWLEDGEMENTS

I would like to extend my deepest gratitude to my graduate committee, Drs. Mark Ducey, Scott Bailey, Tom Lee, Greg Nowacki and Michael Palace. They have shared with me much of their time and insights.

I would like to send a huge thanks to Olivia Fraser.

I would like to thank Steve Fay, Tom Wagner, Roger Simmons and Stacy Lemieux. And the folks at the White Mountain National Forest.

I would also like to thank Jessica Philippe, Roger Dekett, Robert Long, and Nels Barrett. And the folks at Natural Resource and Conservation Service.

I would like to thank all the field crews for the measurements used in this dissertation.

I would like to thank my family, friends, and colleagues.

Finally, I would like to thank my wife, Melissa Davis, for her support.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

ADVANCING THE TERRESTRIAL ECOLOGICAL UNIT INVENTORY WITHIN THE WHITE MOUNTAIN NATIONAL FOREST USING LiDAR

by Robert A. Colter
University of New Hampshire

Forest land managers need ecological classification to assess and describe resource conditions, vegetation conditions, outcomes resulting from various management prescription scenarios, and communicate environmental effects of land management planning alternatives. However, there is a need to incorporate more ecological classification into the land management plans. The U.S. Forest Service's approach, the Terrestrial Ecological Unit Inventory (TEUI), relies heavily on field data collection and verification of map unit delineations that is time-consuming and costly. Traditional mapping methods far exceed the current financial capacity of the U.S. Forest Service. In order to justify new ecological classification mapping approaches, there needs to be significant evidence that new approaches will create equivalent or superior map products, reduce costs, improve efficiencies and maybe improve accuracy. Therefore the objectives of chapter 2 were to use the Soil Inference Engine (SIE) to partition the areal extent of a project area watershed in the White Mountain National Forest (WMNF) using on topographic metrics derived from Light Detection and Ranging (LiDAR) data including both timber managed and un-managed timber production lands. A total of 189 plots were randomly generated within strata, based on parent material, and topographic metrics using a stratified random sampling approach. The number of plots calculated for stratified random sampling was predominately determined by the number of strata, the acres of timber-managed areas, and budget. 172 of those plots had both vegetation and soils information recorded. The results from chapter 2 showed that stratified random sampling using LiDAR-derived topographic metrics as SIE data inputs were sufficient in capturing the environmental

gradients required by the U.S. Forest Service ecological classification requirements. Additionally, 10 New Hampshire Natural sensitive indicator species were located and recorded in 16% of plots stratified by topographic metrics and parent material. These results suggest this new approach to ecological classification on the WMNF improved the accuracy and efficiency in delineating ecological areas as well as locating the presence of nutrient rich areas.

The objectives of chapter 3 used nonmetric multidimensional scaling (NMDS) to assess the relationship between understory species and environmental variables, including parent material, slope, aspect, elevation, and wetness. The results from chapter 3 showed how both soil properties and topographic metrics correlated with understory species in ordination space. NMDS ordination explained 81.1% of the cumulative variation of understory species presence in three dimensions using soil properties and topographic metrics with a final stress value of 17.3 and a p-value of 0.04. NMDS results also suggested that understory species clustered distinctly within New Hampshire Natural Community types. These results also support the idea that LiDAR-derived topographic metrics could assist in determining where community types are positioned across a landscape. Additional NMDS analysis also showed either soil chemistry or topographic metrics explained nearly equal amounts of cumulative understory species variation. The results from this objective highlights the use of topographic metrics as predictors of understory vegetation, and likely community types, which could be validated in other WMNF watersheds.

Finally, the primary challenge for ecological classification is reducing the cost of traditional unit mapping. Therefore, the objectives of chapter 4 was a conceptual synthesis of the reasoning behind doing ecological classification. Information from the WMNF management plans of 1985 and 2005, and current National and Regional land management direction of the US Forest Service were reviewed. A cost review of ecological classification by stratified random sampling using LiDAR-derived topographic metrics was compared to traditional TEUI mapping methods. In both approaches, the mapping of the plots averaged approximately $989.00 per plot including soil chemistry analysis from U.S. Forest Service Laboratory.

This yielded a total cost of approximately $623,000 for the traditional TEUI compared to approximately $221,000 including the LiDAR acquisition required for stratified random sampling using topographic metrics. This chapter showed that stratified random sampling using LiDAR-derived topographic metrics reduced costs by approximately $402,000, including the additional LiDAR acquisition costs, compared to the traditional TEUI approach.

CHAPTER I

BACKGROUND

1.0 INTRODUCTION

This dissertation integrates forest ecology, soil science, and remote sensing methods to investigate the LiDAR-derived topographic metrics as predictors of relationships between vegetation and soil properties. Land managers need accurate ecological information to make sound land management decisions. The Terrestrial Ecological Unit Inventory (TEUI) is a nested hierarchical land survey that produces natural resource information at multiple spatial scales under the auspices of the National Hierarchical Framework of Ecological Units (Cleland et al. 1997, Winthers et al. 2005). It is a fundamental component of ecosystem management, especially for land management planning and embedded project execution by the U.S. Forest Service. The Forest Service has been working on completing Ecological Landtype (ELT) and Ecological Landtype Phase (ELTp) mapping in the eastern United States for over 40 years. The current cost of the classification and mapping portions of TEUI, however, is prohibitive based on current Forest Service requirements and budgets. Here, we implemented new methods to complete ELT classification and mapping using a stratified random sampling based on LiDAR-derived topographic metrics (vs. the traditional “transects” approach) to generate products at a reduced cost to foster land management decisions.

The TEUI concept integrates both abiotic and biotic ecosystem properties into spatially defined ecological groups and maps them to use on the landscape. Traditional TEUI unit delineation typically uses aerial photos and topographic maps or spatial data combined with Geographic Information Systems (GIS) and a transect-based sampling field campaign. However, this approach is inherently time consuming, field intensive, and requires a large budget. Therefore, there is a significant need across the US Forest Service supporting land management planning efforts to develop more consistent, rapid, and cost-effective method to delineate ecological Land Type (ELT) and Land Type Phase (ELTp) map units.

1.1.1 Ecological Classification

Ecosystems are the place where organisms and the environment interact in the three-dimensional space of Earth (Rowe, 1980). Tansley (1935) introduced the term *ecosystem* by describing how ecological systems are composed of multiple abiotic and biotic factors (Major, 1969). The ecosystem concept is a holistic framework that combines the biological and physical worlds in order to describe, evaluate, and manage the system (Rowe, 1992). Energy, moisture, nutrients, and disturbance gradients are the primary regulators of ecosystem structure and function (Cleland et al., 1997). Multiple environmental and biological factors influence these gradients, including climate, geology, soils, vegetation, fire, and wind, while varying at different spatial and temporal scales (Cleland et. al., 1997).

In order to implement proper ecosystem management, land managers need basic information about the nature and distribution of ecosystems (Cleland et al., 1997). Working definitions of ecosystems supported by field inventories are used to develop the classifications, maps, and descriptions required to properly execute ecosystem management (Cleland et al., 1997). Land managers also need to understand both the ecological patterns and processes of social, physical, and biological interrelationships (Cleland et al., 1997). Land managers must obtain better information about the distribution and interaction of organisms on the lands in which they occur. This includes the demographics of species, the development and succession of communities, the influence of environmental variables, and the effects of human activities and land use on species and ecosystems (Urban et al., 1987).

Multiple biotic and abiotic factors, organized within various spatial scales based on ecosystem characteristics and processes, define the National Hierarchical Framework of Ecological Units (Cleland et. al., 1997). The National Hierarchy compresses an infinite variety of ecosystems and places into a limited number of units based on differences in compositional, structural, and/or functional characteristics (Cleland et. al., 1997).

1.1.2 Ecological Units

Land managers overlay maps of existing vegetation (conditions that change readily) onto ecological maps (which depict potential natural vegetation) to aptly track successional changes overtime within an ecosystem (Cleland et al., 1997). Existing conditions are labeled such as current vegetation, whereas potential conditions such as defined areas of different biological and physical potentials are labeled as ecological units (Cleland et al., 1997). Complexes of life and environment form the basis for defining and mapping ecosystems and the integration of multiple biotic and abiotic factors. Inventories of existing vegetation, air quality, aquatic systems, wildlife, and human elements can help inform TEUI efforts (Cleland et al., 1997). Biotic distributions and ecological processes can then be extrapolated to other similar ecosystems during the mapping process (Cleland et al, 1997). The combination of this information on ecosystems along with our knowledge of various processes facilitates a more ecologically sound approach to resource planning, management, and research (Cleland et al., 1997).

The TEUI approach classifies, maps, and describes ecosystems based on biotic and abiotic factors that comprise the physical environment. The principal landscape elements are physical environmental factors (Winthers et al., 2005). Land managers should combine information on existing vegetation with TEUI products to understand active management impacts and support good land management decisions (Brohman et al., 2005). Current vegetation composition, structure, and patterns become the basis for existing vegetation classification maps (Brohman et al., 2005). In contrast, TEUI uses a broad array of ecological factors (climate, geology, topography, soils, and vegetation) to classify and define land units, thus depicting their ecological potentials (potential natural vegetation). TEUI-based units help define a system's response to disturbance processes and land management activities relative to physical site characteristics and their ecological potential (Brohman et al., 2005).

1.1.3 Ecological Types

A land category consisting of landscape elements, differing from other types in the kind and amount of vegetation and in its ability to respond to natural disturbances and management actions, is defined as an ecological type (Winthers et al., 2005). An ecological type describes, classifies, and characterizes ecosystems based on landscape and site factors, vegetation (existing, historic, and natural potential), disturbance regimes, and state and transition models (Winthers et al., 2005). Ecological type classifications and associated unit maps, when combined with existing vegetation classifications/maps, provide land managers a context for evaluating ecological conditions and resource values (e.g., wildlife habitat, forage, watershed conditions, and timber) (Brohman, et al., 2005). Bourgeron et al. (1994) looked at biotic components and abiotic relationships as significant factors for predicting management response of ecosystems and landscapes due to various management scenarios. Bailey et al. (1994) also described the importance delineating land areas based on similar potential for management to effectively assess ecosystem health.

Describing successional relationships and dynamics is an important component for predicting vegetation responses to various management scenarios or natural disturbance regimes (Brohman, et al., 2005). This requires describing and classifying the plant communities associated with an ecological type (Brohman et al., 2005). The Ecological Land Type Phase (ELTp) is the finest resolution level of ecological units, requiring divisions in landforms of specific variables and vegetation data to form ecological types. Ecological type classification requires analysis and description of relationships among potential natural vegetation (PNV), soils, local climate or microclimate, geomorphology, surficial geology, bedrock geology, and/or hydrology (Winthers et al., 2005). This approach requires analysis on plot inventory data, site-level transect observations, and environmental data (Winthers et al., 2005).

1.1.4 Relationship between Classification and Mapping

Developing high-resolution ecological maps is a long standing challenge for soil scientists and vegetation ecologists (Nowacki, 2003). Soil scientists have traditionally conducted soil surveys on a county-by-county basis. However these surveys, representing a single-resource taxonomy, cannot be used alone when generating ecological units, which represents a multifactor "partonomy" approach (see Nowacki and Sorokine 2003 for details). Ecologists, on the other hand, have focused on developing vegetation-based classifications and maps using multivariate methods and indicator plants (Winthers et al., 2005). As with soil maps, these too suffer from taxonomic limitations and a single-resource perspective. Cleland et al. (1997) proposed to use a multifactor approach simultaneously integrating site, soil, and vegetation to classify ecological types and subsequently delineate ecological map units at various scales. Therefore, TEUIs are an attempt to combine the strengths of these two approaches while incorporating climatic and geologic factors (Winthers et al., 2005). The use of multivariate statistical analysis from vegetation ecology can be helpful teasing apart relationships between potential natural vegetation, existing vegetation, soils, and other landscape elements with other ecological or biological factors (Winthers et al., 2005). Multivariate statistical analysis, however, can be applied to specific soil properties instead of soil taxonomy, in order to incorporate the influences of soil on vegetation (USDA Soil Conservation Service, 1994). Therefore, multivariate statistical analysis is essential for ecological classification at the Ecological Landtype (ELT) and Ecological Landtype phase (ELTp) levels.

1.1.5 Map Unit Delineation

Common TEUI mapping techniques use aerial photos and/or GIS based topographic maps combined with a transect-based field sampling to manually delineate areas. However, neither understory vegetation nor soils can be seen on aerial photos, satellite imagery, or widely available digital elevation maps (DEM) depicting Earth’s bare surface (Winthers et al., 2005). In addition, potential natural vegetation is often is estimated because existing vegetation may not be the ideal representation due to past natural and human disturbances (Winthers et al., 2005). Land managers, therefore, must rely on other landscape element predictors, such as landform, morphometry, and surficial geology. The landscape elements may serve as predictors to the map unit delineation criteria, but may not be necessarily used for the design criteria (Winthers et al., 2005). Map unit delineation criteria can then be selected after elements and associated scale have been selected for map unit design (Winthers et al., 2005).

1.1.6 Historic Vegetation and Disturbance Regimes

Vegetation, as the ultimate expression of living tissue (biomass), is a fundamental component of ecosystems. Vegetation is complex and inherently reflects the abiotic and biotic relationships and disturbance regimes across time and space (Winthers et al., 2005). These relationships become less apparent as humans continue to manipulate vegetation over the course of thousands of years for food and fiber production (Winthers et al., 2005). The core components of vegetation dynamics include existing vegetation, historic vegetation, and potential natural vegetation, and prevailing disturbance regimes (Winthers et al., 2005). All core components are important for understanding vegetation patterns and processes at various spatial and temporal scales. The core components are also essential for ecosystem management, particularly for preparing desired future conditions, silvicultural prescriptions, and ecological restoration plans (Winthers et al., 2005).

1.1.7 Disturbance Regimes

Forest composition, structure, and function around the world are shaped by natural disturbances (Picket and White, 1985; Attiwill, 1994; Reice, 2003). Many forest characteristics are shaped by responses to specific disturbances rather than the result of successional change (Brubaker, 1987). Therefore, disturbance ecology provides the framework for understanding forest ecosystems and is a crucial component of resource management (Engstrom et al., 1999). Disturbances, whether natural or human-caused, change ecosystem characteristics, including species composition and structure, biodiversity, resource productivity, and incidence of disease (Winthers et al., 2005). Since disturbances have significant influences on the biotic portion of ecosystems (e.g., species evolution and adaptations; vegetation compositions and structures), disturbance regimes can be used as a template to design forest management activities. Land managers can emulate those effects of natural disturbance to support native diversity and ecological attributes (Attiwill, 1994, Swetnam et al., 1999). For example, ecosystem restoration through silvicultural intervention can benefit from mimicking natural disturbance regimes, especially after human disturbance (Kimball et al., 1995; Walker et al., 1995; Nowacki and Kramer, 1998; Cissel et al., 1999; Bergeron et al., 2002; Seymour and White, 2002).

1.1.8 Historic Vegetation

Vegetation communities reflect past events as well as contemporary processes. Therefore, ecologists who overlook the past are likely to misinterpret the present (Whitney, 1994). "Stepping back to look forward" is a rationale way of understanding the historical disturbance that has led to current vegetative conditions (Foster, 1998). The origin of current forest conditions can be explained by stand histories (Carvell, 1986). In addition, the restoration of ecological systems requires a thorough understanding of past disturbance that may have negatively altered the stand by either human or natural disturbances or both. Historic vegetation can be displayed in patterns over long time periods spanning thousands of years (Winthers et al., 2005). Land managers should attempt to document vegetation conditions immediately prior to major landscape changes (Whitney, 1994).

1.1.9 Existing Vegetation

Existing vegetation information alone cannot answer important questions about successional relationships based on historical ranges of characteristics as responses to management actions (Brohman et al., 2005). These questions can only be considered by linking information about existing vegetation to the ecological potential of the land and stand history (Brohman et al., 2005). Existing vegetation only represents a single point in time, whereas ecological classifications and map reflects potential natural communities (theoretically the endpoint of succession) based on site conditions and past disturbance regimes (Brohman et al., 2005). Thus, ecological units can be effectively used, when coupled with existing vegetation information, to accurately show successional trajectories for a given piece of land.

1.1.10 Potential Natural Vegetation

Potential natural vegetation (PNV) is the vegetation that would establish if human interference did not occur under past and present climatic and environmental conditions (Winthers et al., 2005). Climate, geology, geomorphology, and soil characteristics can be environmental conditions (Winthers et al., 2005). Recent human-based impacts to the land make it difficult to ascertain PNV; however indicator plants can be used to reasonably estimate PNV conditions.

1.1.11 Utility of Potential Natural Vegetation

Increasingly in the last three decades, a single-state climax concept has been shown to be too simplistic (Cook, 1996). Vegetation on similar sites after disturbance can move toward multiple possible future conditions (Abrams et al. 1985, Winthers et al., 2005). Moreover, the alteration of past disturbance regimes and/or elimination of historically important disturbance drivers (e.g., fire suppression) can allow ecosystems to undergo succession to a new steady state not seen before (Nowacki and Abrams 2008). Potential natural vegetation can be used to describe the land's capability to support specific vegetation communities and always be evaluated in the context of existing and historic vegetation (Winthers et al., 2005). Indicator species are often associated with a distinct habitat (Kricher, 1998). An indicator species is commonly defined as a specific plant species found to only occur or be adapted to certain habit where a specific climate and soil are needed for the plant to survive (Kricher, 1998). Potential natural vegetation can be a useful ecosystem expression even if it is based solely on vegetation characteristics (Winthers et al., 2005). In addition, potential natural vegetation can be viewed as a more permanent feature of the landscape than existing vegetation incorporating the structural and compositional stages of vegetation (Winthers et al., 2005). Potential natural vegetation becomes a more valuable approach when it is combined with other key landscape elements (e.g., soil, landform, climate, and geology) to identify ecological types (Winthers et al., 2005). Although existing vegetation can used to help delineate ecological map units, it is important to remember existing vegetation does not always reflect historic or potential vegetation (Winthers et al., 2005). Existing vegetation and potential natural vegetation classification maps inherently address different questions and should be viewed as complementary (Brohman et al., 2005).

It is more beneficial to integrate existing vegetation information with TEUI products for the purposes of making sound land management decisions (Brohman et al., 2005). Existing vegetation classification maps describe current vegetation composition, structure, and patterns. However, TEUI provides ecological type classifications and defines land units, including the vegetation responses to disturbance processes and land use based on potential natural vegetation and physical site characteristics (Brohman et al., 2005). Land managers are able to evaluate ecological conditions when existing vegetation classifications maps are combined with ecological type classifications and mapped units to select appropriate land management practices based on ecosystem capability.

1.1.12 Field Sampling

Plot data are the basic premise underlying vegetation classification used to inform ecological classification and mapping (Jennings et al., 2004). It is critical to develop and assess a field protocol before data collection can begin. A field protocol ensures consistent, reliable, and statistically valid data are collected to avoid inaccuracies (Jennings et al., 2004). Metadata should be included with all field plot data collection in order to ensure interpretation is correct and the protocol is repeatable (Jennings et al., 2004). There are many approaches to create a sampling design. Configuring plots in areas with relatively uniform physiognomy, floristic composition, and environmental conditions is called preferential sampling (Brohman et al., 2005). However, preferential sampling should locate plots “subjectively without preconceived bias” (Ellenberg and Mueller-Dombois, 1974). This means that plots are carefully selected for relatively uniform vegetation and environmental variables, but are not selected because they “fit” a preconceived community type (Brohman et al., 2005). Objective sampling locates plots systematically or randomly in strata and is also called representative sampling (Jennings et al., 2004).

The “gradsect” technique, or gradient-directed sampling, is one example of an objective approach (Austin and Heylingers, 1991). This technique is a form of stratified random sampling that may be cost effective for sampling vegetation patterns along environmental gradients (Gillison, 1985). The objectivity of sampling can be maintained as long as rejection criteria are clearly defined (Brohman et al., 2005). Representative sampling should be used when the stratification units are large and variable (Ellenberg and Mueller-Dombois, 1974). The best way to account for severe changes in ecological classification and mapping is to use all the tools available for ecological classification. As shown earlier, ecological classification does not just include climax or potential natural vegetation. It also includes all the common variations that can occur in vegetation and soils due to management, succession, and disturbance.

1.2 RESEARCH QUESTIONS AND OBJECTIVES

In light of the above, the objectives of this dissertation were to 1) evaluate the Soil Inference Engine (SIE) as a tool to stratify a watershed in the design phase of a field campaign; 2) assess topographic features (e.g., slope, aspect, elevation) as predictors of ecological units using multivariate statistical analysis; and 3) compare stratified sampling to traditional ecological unit mapping methods to determine if there was a cost reduction. Chapters addressing the aforementioned objectives follow, specifically:

Chapter 2 The Soil Inference Engine (SIE) was used to stratify the project area watershed based on topographic metrics derived from Light Detection and Ranging (LiDAR) data including both timber managed and un-managed timber production lands.

Chapter 3 introduces nonmetric multidimensional scaling (NMDS) and how it can be used to assess the relationship between understory species presence and environmental variables, including parent material, slope, aspect, elevation, and wetness.

Chapter 4 was a conceptual synthesis of the reasoning behind conducting ecological classification and mapping. Information from the White Mountain National Forest management plans of 1985 and 2005, and current National and Regional land management direction of the US

Forest Service were reviewed. A review of the cost of doing ecological classification and mapping by stratified random sampling using LiDAR-derived topographic metrics was analyzed versus a TEUI inventory using a traditional mapping method as outlined by the TEUI Manual (Winthers et al. 2005).

CHAPTER 2

STRATIFIED RANDOM SAMPLING USING LiDAR AND THE SOIL INFERENCE ENGINE FOR TERRESTRIAL ECOLOGICAL UNIT INVENTORY

ABSTRACT

The Forest Service has been working on completing Ecological Landtype (ELT) and Ecological Landtype Phase (ELTp) mapping in the eastern United States for over 40 years. Ecological mapping relies heavily on field data collection to develop the underlining classification and verification of map unit delineations. Traditional mapping techniques use aerial photos and low-resolution topographic maps combined with transect-based field sampling to manually delineate units. This approach is costly and accuracy can be low. In contrast, Light Detection and Ranging (LIDAR) derived data can be used to create high-resolution terrain derivates representative of important forest type predictors (e.g., elevation, aspect, and slope). The Soil Inference Engine (SIE), a software modeling program designed to predict soil types and map their areal extent, was created by the Natural Resource Conservation Service (NRCS) to accurately predict soil types across a landscape using LiDAR-derived terrain products, called topographic metrics. The objective of this chapter was to create and assess the application of a stratified random sampling approach using LiDAR-derived topographic metrics as inputs into the SIE to design an ELT/ELTp inventory across a 17,010 acre watershed in western New Hampshire. A total of 189 plots were randomly generated within strata and 172 plots had both vegetation and soils information recorded. All strata based on slope and drainage were first partitioned based on parent material. There were at least 8 plots per stratum and strata were further divided by timber managed areas and non-timber managed areas. There were 252 understory species recorded

across the 172 plots and 15 total NH Heritage Community Types of vegetation were identified. Additionally, 10 of the 12 sensitive indicator understory species from the New Hampshire Natural Community types were found in a total of 28 plots across the study watershed. This supports that the stratified random sampling approach was successful in partitioning the watershed and still locating sensitive plants indicative of site enrichment. The mean and standard deviation of topographic metrics within each New Hampshire Natural Community type suggests topographic metrics were adequate predictors for high-elevation and flood-plain areas, but did not appear to be as distinct in mid-elevation, slightly sloping community types in well-drained soils. The results also suggest the sampling approach was successful in distributing plots across an array of soil and site conditions within and outside timber managed areas. The application of a stratified random sampling approach based on LiDAR-derived topographic metrics as SIE data inputs appear to be a valid method and valuable for future field campaigns, but more research is needed to better understand the next steps of TEUI across a landscape using topographic metrics as predictors.

2.1 INTRODUCTION

Over several decades, the US Forest Service has been working on completing Ecological Landtype (ELT) and Landtype Phase (ELTp) mapping in the Eastern United States. ELT and ELTp classification and mapping rely heavily on field data for concept building (ecological type creation) and ecological unit delineation and verification. However, traditional mapping techniques are time-consuming and costly. Due to limited budgets and personnel, progress toward completing the mapping has diminished over time. National Forest System lands managed by the U.S. Forest Service need to complete ecological inventories in a shorter time frame so that land managers can incorporate ecological information in developing and assessing management alternatives (USDA, 2005).

Traditional mapping techniques use aerial photos and widely available yet coarse-resolution topographic data combined with a transect-based sampling field campaign to manually delineate units. In 2008, a new effort to use Light Detection and Ranging (LiDAR) to increase inventory efficiency and accuracy of topographic-derived data were explored by the White Mountain National Forest (WMNF). Lefsky et al. (2002) defined LiDAR, as “a remote sensing technology that promises to both increase the accuracy of biophysical measurements and extend spatial analysis into the third (z) dimension (i.e., elevation)”. High-resolution topographic data and estimates of vegetation height, cover, and canopy structure can be made by LiDAR sensors as laser beams intercept the forest canopy. Moreover, this technology advances our mapping efforts by making topography more distinct and visible, thus increasing our capabilities of understanding the total environment (Lefsky et al., 2002). Indeed, the potential exists that our TEUI efforts could benefit greatly by employing LiDAR technology (Lefsky et al, 2002).

More recently, the Soil Inference Engine was created by the Natural Resource Conservation Service (NRCS) to increase efficiencies in predicting soil types using LiDAR-derived terrain products, called topographic metrics. The Soil Inference Engine (SIE) was first used in 2008 to predict soil types in Essex, VT (Mckay, 2008). The SIE is an expert knowledge-based inference model designed for creating soil maps under degrees of truth (fuzzy logic) using remotely sensed data (Mckay, 2008). Parent material is the primary predictor of soil type used in the SIE, but must be manually delineated by the knowledge expert in contrast to other model variables derived from LiDAR. Based on field inventory plot information, the concept of “fuzzy” soil classification assigns degrees of membership values for different soil types to each location (McKay, 2008). In 2008, results from two watersheds in Essex, VT yielded a 74 and 89% accuracy rate in predicting soil series and drainage classes using an independent validation across the watershed (McKay, 2008). In the second validation watershed, the SIE predictions yielded a 71 and 90% accuracy rate. The results were based on a soil parent material of basal till and three soil series consisting of Cabot, Colonel, and Dixfield (McKay, 2008).

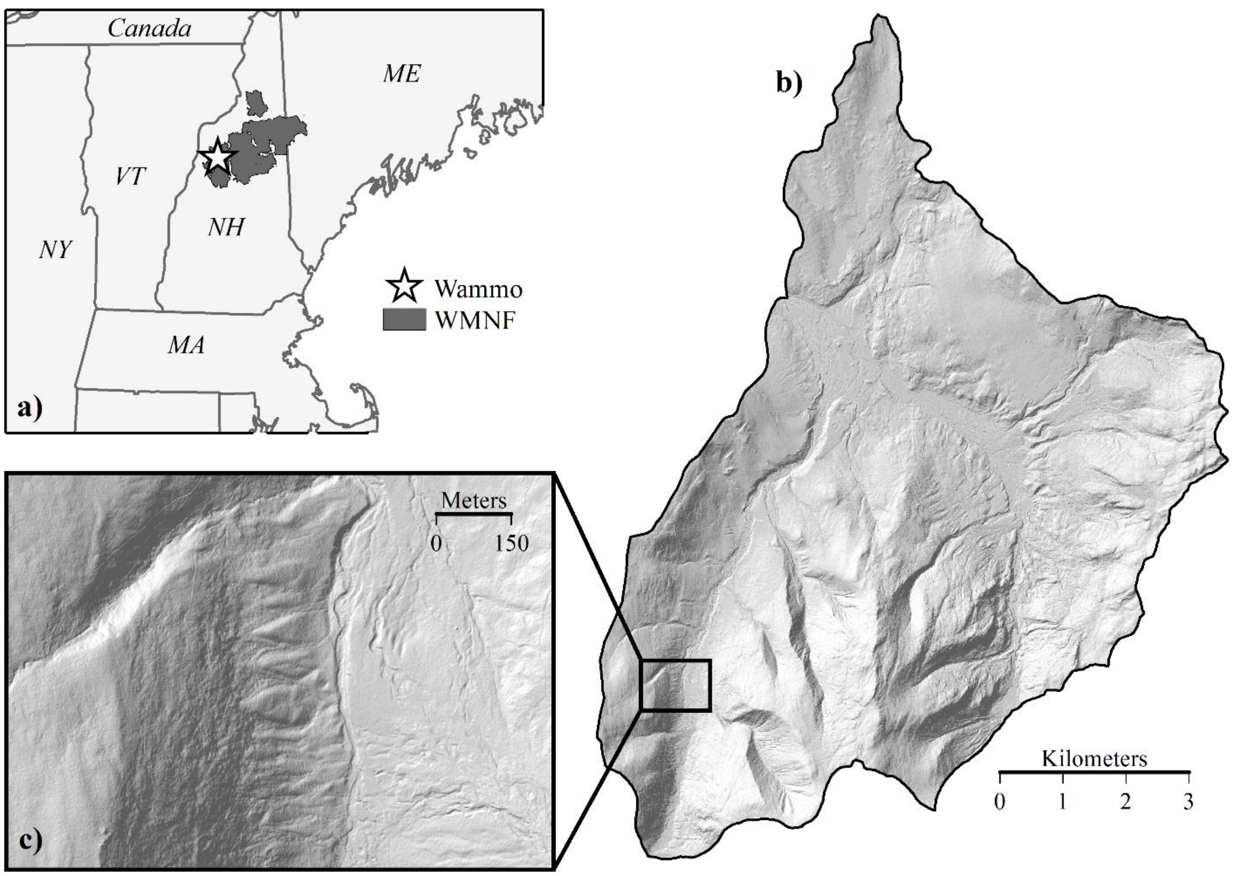
Therefore, the objective of this chapter was to create and assess the application of stratified random sampling using LiDAR-derived topographic metrics as Soil Inference Engine data inputs to design an ELT/ELTp field campaign.

2.2 METHODS

2.2.1 Study Area

The White Mountain National Forest (WMNF) covers approximately 800,000 acres located in north-central New Hampshire and adjacent western Maine. This study was centered on the Upper Wild Ammonoosuc watershed, a single 17,010 acre watershed in the western New Hampshire portion of the WMNF. The Upper Wild Ammonoosuc watershed (Wammo) was selected because it encompasses most forest types and soils found within the WMNF. Here, the US Forest Service owns 16,245 acres, with the remaining acreage being privately owned. The Wammo watershed has an elevation gradient ranging from 336 to 1,462 meters. Dominant vegetation types include northern hardwood, spruce-fir, and mixed-species forests (McNab & Avers, 1994). Annual precipitation averages 90-180 cm and total annual snowfall ranges from 250-400 cm (McNab & Avers, 1994). The soils tend to be Spodosols, spanning the suborders of Aquods (wet), Cryods (cold), Humods (high organic matter), and Orthods (ordinary spodosols) (USDA, 2006).

Figure 2.1: Inset map a) shows the White Mountain National Forest (WMNF) external boundaries in gray within the Northeastern U.S. as well as the location of the Wammo study area within the WMNF marked by a five point star. Map b) shows a 1 meter shaded relief map derived from LiDAR within the 17,010 acre Wammo watershed. Inset map c) also shows a 1 meter shaded relief map within the Wammo watershed at a finer scale to highlight the differences in roughness used to delineate parent material.



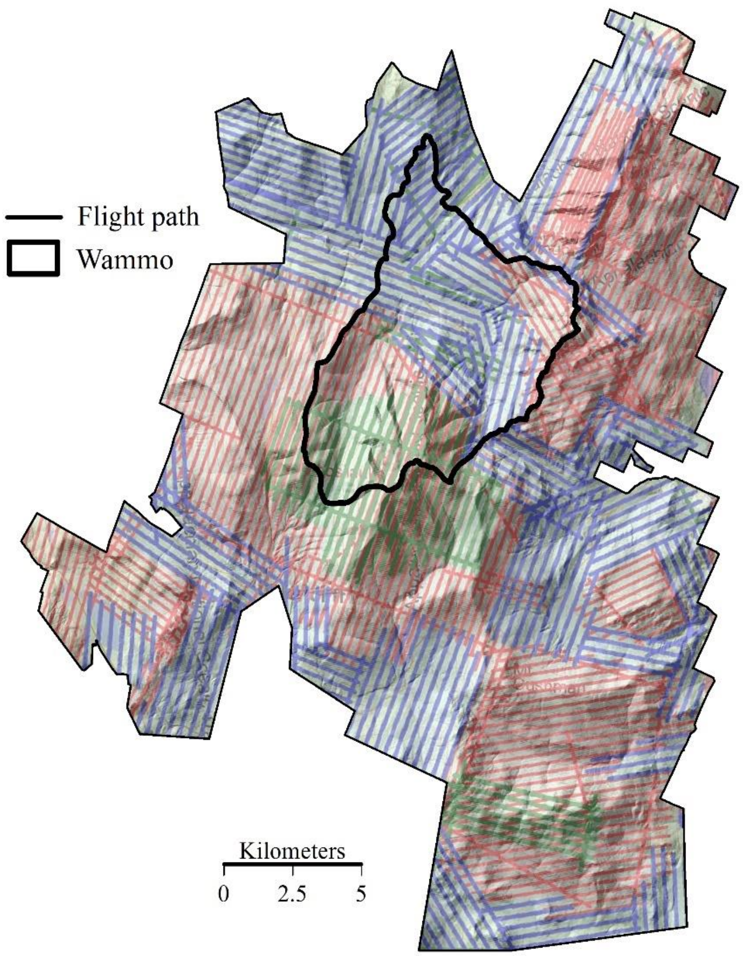
2.2.2 LiDAR Acquisition

In 2010, for this study, the WMNF contracted Photo Science, Inc. to acquire LiDAR for the western third of the WMNF in New Hampshire. The primary acquisition requirements were: 1) 1-meter nominal spacing and 2) leaf-off conditions. Photo Science subsequently acquired the desired data on November 2010 and April 2012 for the Wammo study area, during conditions with no snow and stream flows at or below normal levels. The WMNF LiDAR acquisition were planned most efficiently at 1,158 meters AGL using 30% overlap using a GEMINI Airborne Laser Terrain Mapper (ALTM) sensor. The scan frequency was 49.3 Hz and a total scan angle of 27 degrees (+13.5 and -13.5 degrees from NADIR). This resulted in a planned resolution of 0.548 per meter across and along track for average point spacing of 3 points per square meter.

The altitude and pulse rates were selected due to the point spacing results working around the atmospheric constraints of the laser. These settings provide a system vertical accuracy of better than 18 cm. Final accuracy was improved with QC ground control points being used to remove any vertical bias. Each LiDAR LAS file (per tile) produced by Photo Science was in both LAS1.2 format using Point Record Format #1, with POSIX time stamps and ASCII (x,y,z) format and included first return, last return, and one or more intermediate returns. Each return contained information regarding X, Y, and Z locations, return number, classification, GPS time and intensity.

Although the WMNF LiDAR acquisition project was designed to map existing vegetation, the LiDAR acquisition specifications selected were the minimum specifications necessary to achieve the desired results. Cost of LiDAR acquisition prohibited obtaining a higher number of points per return. The cost of the LiDAR specified for this acquisition was $2.00 an acre. A higher point-per-square-meter resolution would have doubled the cost. In addition, the drastic differences in terrain across a range of flood plains, moderate to steep slopes, and across an elevation gradient of approximately 1,100 meters was also limiting and contributed to increased costs. Figure 2.2 shows the flight pattern needed in order to gain the specified LiDAR specifications of 3 points/m^2.

Figure 2.2: The LiDAR flight paths on November 2010 and April 2012 are depicted in red, blue, and green lines representing the different transects needed to achieve a standardized resolution across the western portion of the WMNF. The Upper Wild Ammonoosuc watershed (Wammo) study area is depicted with a black outline.



LiDAR flights are generally flown in a straight back-and-forth motion to save costs in fuel and plane time, however the flight pattern in the Wammo acquisition was flown in multiple directions. This flight pattern was necessary due to the drastic differences in elevation as the capabilities of the plane were not able to compensate quickly enough to maintain data quality and safety of the crew. Drastic differences in elevation also contributed to the LiDAR acquisition taking multiple years. The LiDAR acquisition costs were more than predicted because multiple plane and crew trips were needed to the project area at different times in the spring and fall to meet the specifications required of leaf off and snow free conditions due to the high elevation variability.

2.2.3 Topographic Metrics

LiDAR data can be derived or processed to provide accurate measurements of important landscape features or attributes that drive potential natural vegetation, such as elevation, aspect, and slope. These landscape features can serve as proxies for various soil and hydrologic properties that can also drive potential natural vegetation. For example, while working in a New York forest, Gauch and Stone (1979) identified moisture gradients as a primary vegetation driver, therefore a proxy for surficial wetness would be beneficial for identifying other mechanisms influencing vegetation. Seibert et al. (2007) researching boreal forests in Sweden reported correlations between topographic indices such as topographic wetness index (TWI) and soil characteristics such as pH. Therefore, topographic metrics were created from LiDAR-derived digital elevation models (DEMs) as the inputs in the SIE to stratify the Wammo study area. The topographic metrics used for the Wammo study area were derived from LiDAR included elevation, aspect, slope, and topographic wetness computed in ArcGIS© (ArcMap, version 10.3) software. A 1-meter DEM was created from only LiDAR ground returns, coarsened to 5 meter through mean cell aggregation and filled using an algorithm that maintains the downslope gradient (Wang and Liu, 2006). A DEM resolution of 5 meter was selected because it was shown to strongly correlate with ground water fluctuations and land survey measurements (Gillin et al., 2015). Slope was calculated using maximum slope algorithm (Travis et al., 1975). Topographic wetness index (TWI) (Beven and Kirkby, 1979) was calculated with the upslope accumulated area (UAA) computed from a multiple flow direction algorithm and slope.

2.2.4 Soil Inference Engine

The Soil Inference Engine (SIE) is an expert user knowledge-based inference model using remotely sensed data such as LiDAR, designed for creating soil raster maps by looking at the range of soil characteristics across a landscape (Shi, 2013). Soil types for each location have a range of characteristics for soil classification and the SIE performs the soil predictions based on the range of characteristics across a landscape (McKay, 2008). The values are meant to represent the similarities of a given soil to those soil types (Shi, 2013). Rule-based reasoning is used by the SIE to calculate the ranges of the characteristic membership values and represent the similarities of a given soil to be predicted to those soil types defined (Shi, 2013).

The primary input variable in the SIE process for the Wammo study area was the areal extent of six different parent material types (Table 2.1). Parent material was defined according to NRCS (Schoeneberger, 2012) and delineated by NRCS personnel using visual interpretation of 1-meter LiDAR-derived shaded relief maps combined with field verification. The high-resolution shaded relief maps enable the expert soil scientist to distinguish a transition in parent material by a change in roughness on Earth’s bare surface. For example, bedrock-controlled soils were very rough based on the shaded relief map, whereas ablation and basal till commonly have a relatively smooth surface signature (McKay, 2008). Each topographic metric was then reclassified into groups as the additional SIE variable inputs based on ranges most commonly associated with soil types within each parent material. For example, slope was classified into six groups representing

0-8%, 9-15%, 16-35%, 36-60%, and greater than 60%. A total of 189 plots were randomly generated within strata and a total of 11 strata (Table 2.1) consisting of slope and drainage class were used across the Wammo study area. The field campaign took place over two years where a total of 88 plots were completed in 2013 and a total of 99 plots were completed in 2014.

2.2.5 Management Areas

The 2005 WMNF Management Plan split the Wammo watershed into different management areas consisting of timber treatment areas, alpine area, snowmobile recreation, and non-snowmobile recreation (USDA, 2005). Since this project was designed for the WMNF, a higher number of plots was located in highly managed timber areas (135 plots) rather than non-timber managed (54 plots). The purpose of the increased number of plots in these areas was also to capture any differences the SIE model may have missed. The timber managed area, including inholdings, consisted of 10,688 acres and the unmanaged timber areas consisted of 6,322 acres.

2.2.6 Stratified Random Sampling

Stratified random sampling was selected for distributing ELT plots across the Wammo. This method of sampling has been shown to reduce overall soil prediction error since points are uniformly allocated over the study area proportional to the distribution of soil type (Hengl et al., 2003). The topographic metrics that correspond to important environmental variables driving vegetation patterns in the WMNF included elevation, slope, aspect, topographic wetness, and parent material. Previous studies have shown that using a stratified random sampling rather than simple random sampling can result in a greater number of presences and a higher accuracy of future model predictions (Guisan et al., 2006). It has been shown using a stratified random sampling reduces costs and improves accuracy (Guisan et al., 2006).

2.2.7 Stratified Plots by LiDAR-derived Classes

A total of 189 plots were randomly generated within strata and 172 plots had both vegetation and soils information recorded (Figure 2.3). All strata based on slope and drainage were first partitioned based on parent material (Table 2.1). In addition, there were at least 8 plots per strata and strata were further divided by timber and non-timber managed areas. For example, this resulted in 63 plots in timber managed areas and 12 plots in non-timber managed areas within basal till. There were at least 10 plots per parent material and more than 12 plots in both timber and non-timber managed areas.

2.2.8 Site Information

Once plots were randomly stratified using SIE, the plots were located on the ground using a Trimble Pro XH GPS receiver and the plot center was monumented with a buried magnet. This monumented location became the actual plot location and may differ slightly from the original UTM coordinates due to small GPS errors. The Trimble Pro XH receiver GPS was located over the monument and began collecting approximately 900 points per location to achieve accuracy. Continuously Operating Reference Station (CORS) data from the National Geodetic Survey and Trimble Pathfinder software were later used to obtain approximately 1-2 meter horizontal precision of plot center after differential corrections. If the specified UTM coordinate fell within open water, or a location that was determined to be physically unsafe (e.g., in a road, on a cellar hole), or in a location where mechanical disturbance had substantially modified the natural soils (e.g., old road, landing), then the plot center and the monuments were displaced by 5 meters in a random direction until the sample point was not in the previous feature and determined safe to work.

Plot information was typed into a Panasonic Toughbook to ensure data recording was efficient and accurate. Information collected included the plot number, soil type, and UTM coordinates as well as the names of field crew, date of sampling and the general plot location information (e.g., landmarks, routes,). Any visual evidence of disturbance such as recent logging, skid trails, fresh stumps, decayed stumps, stone walls, and windthrow were also noted. General conditions surrounding the plots were taken, including site homogeneity, any departures in overall vegetation structure/composition and their approximate distance/direction, apparent landform, and other peculiarities. Finally, the community vegetation type based on the New Hampshire Natural Community key was visually evaluated and recorded in the field (Sperduto and Kimball, 2011).

2.2.9 Vegetation and Soil Sampling Protocol

The overstory composition and structure were measured including on all woody stems greater than 2.5 cm diameter at breast height (DBH). Woody stems less than 2.5 cm DBH or shorter than breast height, and all herbaceous species, were treated as understory species. For all living and dead woody stems of 2.5 cm DBH or greater within the appropriate size/distance relationship, the DBH, distance from plot center, bearing from plot center, species, decay status, and cavity presence were recorded. Woody stems within a 4.23 meter fixed radius were recorded if stems measured between 2.5 cm and 12.6 cm DBH. Woody stems within a 10 meter fixed radius were recorded if stems measured greater than 12.7 cm. Tree height measurements were recorded based on a metric BAF 2.25 m2/ha (using Spiegel-relascope, 1.5 bars) for all trees found with a metric

BAF 4 m^2/ha (using Spiegel-relascope, 2 bars). Total height of the trees based on the tallest tree element (live or dead) as well as height to base of crown (live trees only) was recorded. Crown radius toward the plot center, and away from the plot center (live trees only) were also recorded. The understory composition and structure were captured using a 10meter fixed radius plot. The scientific name along with the plant type code and sociability code (Sperduto and Kimball, 2011) were also recorded. Ocular estimate of maximum height was recorded, to nearest 0.5 meter if less than 2 meters and to the nearest meter if taller than 2 meters and ocular estimate of percent cover.

One soil pit was dug per plot location and located within the plot. A full soil profile was characterized per NRCS standards. The NRCS standards include describing and sampling soil profiles based on genetic horizons and Munsell color, texture, structure, moist consistence, presence of redoximorphic features, rooting density, and coarse fragment content (Schoeneberger, 2012). Soil samples for chemical analysis were collected from the pit profile by the height of the horizon and width of the pit including the first 10 cm of the Oa horizon, the first 10 cm of the B horizon and the first 10 cm of the C horizon.

All soil samples were then air-dried, sieved to remove particles >2 mm, homogenized and split to generate a subsample for chemical analysis. Samples were measured for pH in 0.01 mol/L CaC_{l2} (Robarge and Fernandez, 1987). All samples were analyzed for carbon and nitrogen on a CN elemental analyzer (CE-Elantech Thermo FlashEA 1112 Series NC Soil Analyzer) using pulverized subsamples. Soil standards obtained from the North American Proficiency Testing program were used to standardize the instrument. Exchangeable cations were measured in an extract obtained from a mechanical vacuum extractor using 1 M NH_4OAc buffered at pH 4.8.

Cation concentrations were measured with an Agilent inductively coupled plasma spectrometer (Agilent Technologies 700 Series ICP-OES) at the US Forest Service laboratory in Durham, NH. Reference samples of Oa and Bs horizons from Vermont were included in all analytical streams and yielded values of C, N, pH, and exchangeable cations comparable to the median values reported in an interlaboratory study (Ross et al., 2015).

2.2.10 Descriptive Summaries

Descriptive summaries partitioned by indicator species and NH Natural Community Types, mean and standard deviation, were calculated based on the plot locations extracted from the two dimensional topographic metric data to determine how plots distributed across strata (Table 2.1) as stated by the TEUI Tech Guide (Winthers et al., 2005). In addition, mean and standard deviation topographic metric values based on the 12 sensitive indicator species listed by NH Natural Community type (Sperduto and Engstrom, 1995), NH Natural Community Types, and soil series are reported. Sensitive indicator species can be useful when trying to type out natural communities as that indicator species will be only found in that given natural vegetation community. In the case of the 12 sensitive indicator species assessed in this study, they are all indicators of enriched sites important to the WMNF from a forest management perspective (Sperduto and Kimball, 2011).

2.3 RESULTS

2.3.1 Indicator species and NH Heritage Community Types by Topographic metrics

There were 252 understory species recorded across the 172 plots and 15 total NH Heritage Community Types were identified. Sperduto and Engstrom (1995) identified 12 sensitive understory indicator species for the WMNF and 10 of those indicator species were found in a total of 28 plots across the Wammo watershed. Table 2.2 shows the number of plots by sensitive indicator understory species (six letter species code) along with the number of plots that were in timber managed or non-timber managed areas. The following 10 sensitive understory indicator species were indicators of enriched sites: *Botrychium virginianum* (rattlesnake fern), *Aralia racemosa* (spikenard), *Carex plantaginea* (plantain-leaved sedge), *Carex leptonervia* (snake root), *Carex laxiflora* (lax sedge), *Caulophyllum thalictroides* (blue cohosh), *Laportea canadensis* (wood-nettle), *Osmorhiza claytonii* (sweet cicely), *Solidago flexicaulis* (zig-zag goldenrod), *Viola pubescens* (downy yellow violet) (Sperduto and Engstrom, 1995).

Table 2.1: The acres and proportion of the watershed covered by topographic metric classes (slope and wetness) and parent material as well as the number of plots in each category based on timber managed and non-timber managed areas within the Wammo.

Strata	Managed (acres)	Unmanaged (acres)	Total	Proportion of watershed (%)	n (managed)	n (unmanaged)
0-8% Slope	1373.6	95.3	1468.9	8.6%	27	10
9-15% Slope	2247.8	261.5	2509.3	14.8%	24	9
16-35% Slope	4391.1	2050.3	6441.4	37.9%	33	17
36-60% Slope	1142.0	1156.0	2298.0	13.5%	13	5
> 60% Slope	506.0	207.2	713.2	4.2%	7	6
Wet	116.7	222.3	339.0	2.0%	5	9
Dry	905.3	2324.8	3230.0	19.0%	18	6
Parent material	**Managed (acres)**	**Unmanaged (acres)**	**Total**	**Proportion of watershed (%)**	**n (managed)**	**n (unmanaged)**
ATI	3100.8	314.8	3415.6	20.1%	28	13
ATI_ALL/Outwash	878.3	40.2	918.5	5.4%	20	9
BTI	3908.4	378.7	4287.2	25.2%	63	12
BDR_4	1944.0	1096.8	3040.8	17.9%	4	1
BDR_5	762.1	4098.9	4861.0	28.6%	16	23
ORM	93.2	18.7	111.9	0.7%	0	0
Total	10686.7	5948.2	16634.9		131	58

Figure 2.3: The Wild Ammonoosuc (Wammo) watershed is outlined in black with the different parent material types represented by associated colors (on left). Wammo watershed also outlined in black with different stratified classes derived from LiDAR and the Soil Inference Engine represented by different colors (on right).

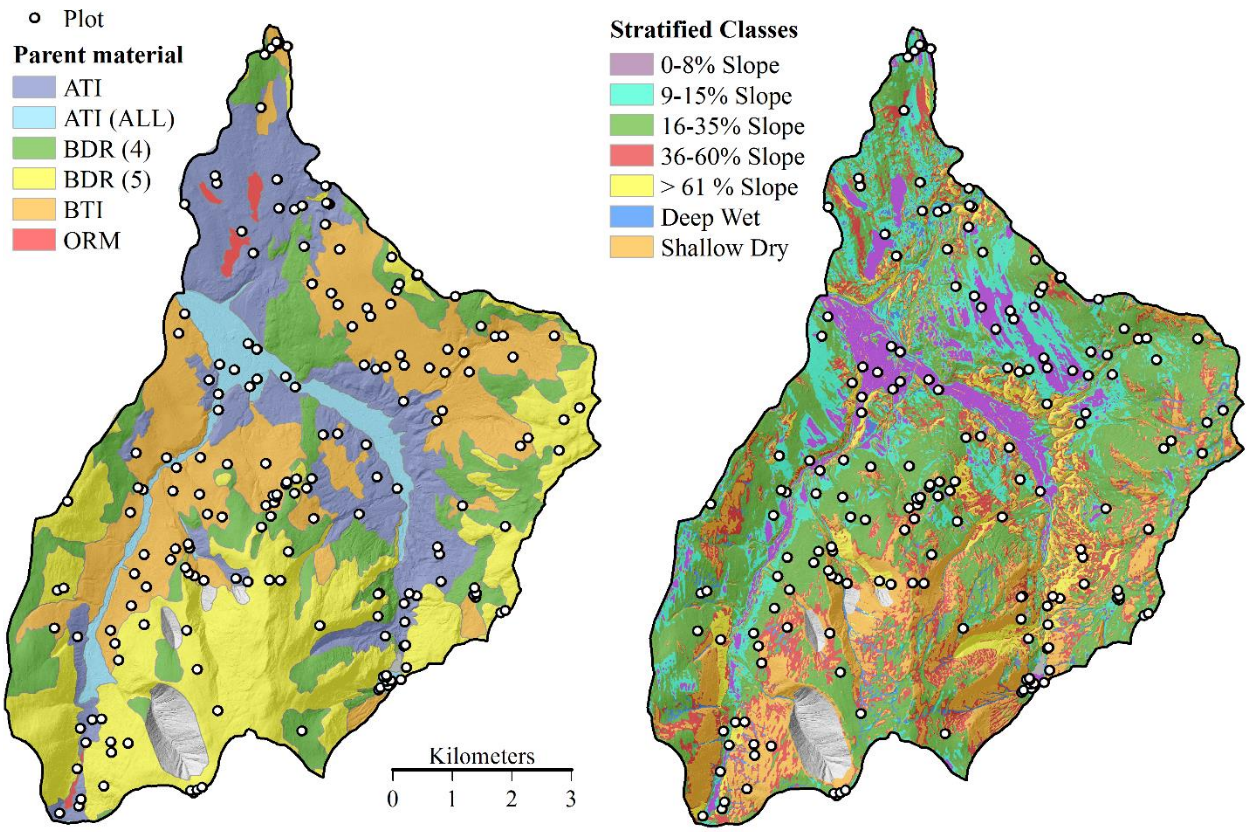


Table 2.2 also shows the mean and standard deviation of the topographic metric values of the elevation, aspect, slope and wetness (if the species occurred more than once) of each. 6 of the total 28 plots had more than one sensitive understory indicator species occur in the same plot. Only 4 plots that had any of these indicator species were within the non-timber managed areas.

Table 2.2: Mean and standard deviation by indicator species and New Hampshire Heritage Community type of elevation (m), aspect (degrees), slope (%), and topographic wetness index (TWI) calculated from a 5 meter LiDAR-derived DEM.

Indicator species	n (managed)	n (unmanaged)	Elevation	(SD)	Aspect	(SD)	Slope	(SD)	TWI	(SD)
ARARAC	2	1	552.3	(51.4)	302	(27.2)	0.12	(0.03)	9.5	(0.7)
BOTVIR	1	0	408.9		31.3		0.12		6.5	
CARPLA	2	0	364.7	(11.0)	184.7	(131.6)	0.1	(0.07)	8.6	(1.0)
CARLEP	5	3	650.8	(68.5)	151.7	(110.5)	0.2	(0.12)	9	(1.6)
CARLAX	1	0	611.1		306.3		0.18		7	
CAUTHA	2	0	381.3	(27.6)	42.1	(10.9)	0.14	(0.03)	8	(1.6)
LAPCAN	5	0	427.2	(66.6)	109.9	(82.5)	0.12	(0.07)	7.4	(1.5)
OSMCLA	4	1	551.7	(83.6)	192.3	(142.0)	0.14	(0.04)	8.2	(1.2)
SOLFLE	10	0	480.3	(115.8)	183.1	(134.8)	0.11	(0.06)	9.3	(1.1)
VIOPUB	3	0	379.4	(22.7)	133.5	(129.5)	0.11	(0.06)	7.8	(1.3)
Heritage codes	**n (managed)**	**n (unmanaged)**	**Elevation**	**(SD)**	**Aspect**	**(SD)**	**Slope**	**(SD)**	**TWI**	**(SD)**
26A	2	2	582.6	(15.4)	88.4	(35.4)	0.18	(0.13)	6.5	(0.4)
26B	1	0	399.7		162.7		0.15		9	
28A	2	3	627.5	(121.3)	144.3	(71.2)	0.07	(0.05)	9.7	(2.0)
29A	0	6	1,055.50	(123.4)	235.7	(140.7)	0.25	(0.09)	7.1	(1.2)
29B	1	13	877.2	(67.0)	242.6	(93.7)	0.33	(0.17)	7.8	(1.6)
37A	4	7	663.5	(109.4)	223.3	(115.7)	0.27	(0.13)	8	(1.7)
37B	14	0	515.5	(125.8	198	(119.7)	0.21	(0.17)	8.2	(1.8)
41A	7	2	504.5	(62.2)	199.9	(111.0)	0.16	(0.14)	7.1	(1.2)
43A	2	0	523.4	(99.7)	258.8	(36.8)	0.17	(0.08)	7.4	(1.1)
43B	46	18	579.5	(86.0)	189.8	(112.8)	0.21	(0.14)	7.8	(1.9)
4A	4	0	462.4	(81.5)	207.6	(122.3)	0.14	(0.13)	8	(1.1)
4B	21	1	526.5	(86.2)	208.2	(98.1)	0.15	(0.06)	8.7	(1.2)
52A wetlands	0	1	721.9		298.2		0.11		9.2	
54B wetlands	1	0	400.4		188.3		0.06		7.1	
6A wetlands	5	0	380.4	(12.7)	30.8	(26.5)	0.04	(0.02)	9.7	(0.5)

Table 2.3: Mean and standard deviation by soil series, as determined by the soil pit description, of elevation (m), aspect (degrees), slope (%), and topographic wetness index (TWI) calculated from a 5 meter LiDAR-derived DEM.

Soil series	n (managed)	n (unmanaged)	Elevation	(SD)	Aspect	(SD)	Slope	(SD)	TWI	(SD)
Abram	2	1	621.0	203.0	181.5	111.4	0.24	0.10	7.3	1.5
Adirondack	22	5	550.5	95.2	186.2	93.9	0.18	0.12	7.6	1.3
Alluvium	3	0	461.9	127.7	219.3	179.1	0.06	0.04	8.0	0.8
Berkshire	2	3	799.4	172.0	285.2	24.2	0.45	0.08	7.9	1.3
Cabot	4	0	508.9	45.7	166.7	94.5	0.05	0.02	11.3	1.5
Colluvium	0	3	678.2	34.9	183.7	174.0	0.46	0.06	7.8	1.8
Colonel	14	3	588.8	77.3	252.4	84.4	0.19	0.12	7.7	1.6
Danforth	2	5	591.6	102.5	186.6	112.1	0.34	0.17	7.5	0.9
Dixfield	22	3	571.5	76.4	172.7	129.8	0.25	0.14	7.1	1.3
Dixmont	2	0	452.5	48.5	192.6	222.2	0.16	0.01	6.8	0.9
Glebe	0	1	936.3		24.5		0.04		6.1	
Houghtonville	1	0	691.2		305.0		0.40		7.7	
Knob	0	1	817.1	156.8	216.1	123.3	0.40	0.33	6.6	2.7
Lombard	1	0	714.1		129.5		0.21		9.0	
Londonderry	0	1	1032.3		21.6		0.35		5.5	
Lyman	4	2	721.4	81.7	225.6	98.3	0.24	0.15	7.7	2.7
Lyme	5	0	389.9	20.1	118.1	113.9	0.02	0.02	8.3	0.4
Madawaska	3	0	382.3	12.5	23.0	32.3	0.04	0.02	7.5	0.7
Mahoosuc	1	2	904.3	286.7	142.0	96.5	0.29	0.13	9.3	2.5
Marlow	1	0	592.3		204.3		0.06		9.2	
Monadnock	2	1	507.6	92.3	220.9	154.5	0.11	0.08	7.4	1.4
Moosilauke	0	1	678.9		282.4		0.10		12.2	
Pillsbury	0	1	718.9		29.4		0.13		5.7	

Rawsonville	0	1	601.3		274.0		0.54		7.4	
Rockrift	0	1	598.4		82.6		0.14		10.9	
Roundabout	1	0	379.5		14.2		0.06		7.1	
Rumney	1	0	366.8		65.2		0.02		8.4	
Saddleback	0	1	901.6		299.8		0.37		7.7	
Skerry	2	0	397.6	62.1	186.3	188.4	0.14	0.04	9.0	0.8
Stratton	1	1	931.4	399.0	224.5	167.0	0.22	0.09	7.3	2.0
Sunapee	11	11	568.1	124.3	167.4	113.4	0.16	0.10	7.5	1.9
Tunbridge	3	1	656.0	173.2	120.2	128.7	0.20	0.08	8.0	1.9
Wilmington	14	3	535.0	75.8	210.4	109.3	0.14	0.12	9.3	2.3
Wonsqueak	0	1	721.9		298.2		0.11		9.2	

Table 2.2 also shows the 15 NH Heritage Community codes based on types (Sperduto and Kimball, 2011) recorded in the study area along with indication of whether it was located in the timber managed or non-timber managed plot. The mean and standard deviation of each topographic metric, including elevation, aspect, slope and wetness (if the species occurred more than once) is also listed by NH Heritage Community code.

2.3.3 Soil Series by Topographic metrics

Although the goal for ecological classification is to map by soil variables rather than by soil series, it is still worthwhile knowing how the series align themselves by topographic metric used to stratify plots to determine the best method for prediction soils. Table 2.3 shows the soil series as identified by NRCS by topographic metric and if the soil occurred in a managed timber plot or non-timber managed plot. The top three soil series, all basal till soils but differing in drainage, occurring at the most plots were Adirondack, Dixfield, and Colonel.

2.4 DISCUSSION

The objective of this chapter was to create and assess the application of stratified random sampling using LiDAR-derived topographic metrics as Soil Inference Engine (SIE) data inputs to design an ELT/ELTp field campaign. The results presented in Table 2.1 support the TEUI requirement that plots be well distributed across environmental gradients. Since the accuracy of the SIE relies so heavily on parent material, even distribution of plots within each parent material was crucial in designing this field sampling campaign. The results shown in Table 2.2 support the stratified random sampling approach as successful in locating sensitive indicator species. Because the goal of ecological classification is to aid decision makers in making sound forest management decisions, it was important to know if strata derived from topographic metrics as inputs in the SIE model captured indicator plant species of enrichment. Although only 4 of the 28 plots had sensitive indicator species in unmanaged areas, the environmental conditions of the unmanaged area may not contain ideal stand conditions to support sensitive species. For example, the areal extent of the unmanaged areas starts at mid elevation ranges to the top of the Mt. Moosilauke. The presence of sensitive species in 24 plots within the managed areas suggests the past management history did not disturb the conditions necessary to support indicator species. However, because those 24 plots have been actively managed, it is possible the overstory is not representative of the understory lending to the importance of collecting both vegetation layers when mapping.

In addition, the results presented in Table 2.2 regarding the mean and standard deviation of topographic metrics within each New Hampshire Heritage type (Sperduto and Kimball, 2011) suggest topographic metrics were adequate predictors for high-elevation and flood-plain areas. For example, "High-elevation balsam fir forest" (29A, Sperduto and Kimball, 2011) typically occurs at higher elevations up to the krummholz area and is very prone to windthrow. This community type had a mean elevation of 1,055 meters (a standard deviation of 123.4) and the mean slope was 25% (a standard deviation of 0.1). This community type is usually found at high elevations with steep slopes. The topographic metrics descriptive summaries successfully represents those conditions.

On the other hand, there were 5 plots "Balsam fir floodplain/silt plain wetland" NH Natural Community type (6A, Sperduto and Kimball, 2011). This community type typically has balsam fir with red-maple and forms a forested zone above flooded areas. This community type had a mean elevation derived from the LiDAR consisting of 380 meters (a standard deviation of 12.7), a 4% slope (a standard deviation of 0.02), and a wetness index of 9.7 (a standard deviation of

0.5). This is also consistent with the general landscape conditions used to describe the ideal condition for this community type.

However, the descriptive summaries for mid-elevation, slightly sloping community types in well-drained soils did not appear to be as distinct based on topographic metrics. These include combinations of “Northern hardwood-spruce-fir forest” (26A, Sperduto and Kimball, 2011) typically found on basal till or rocky soils, “Hemlock-oak -northern hardwood forest” (41A, Sperduto and Kimball, 2011) found on rocky slopes and till soils up to elevation of 610 meters and “Sugar maple-beech-yellow birch forest” (43B, Sperduto and Kimball, 2011) found on ablation tills below 760 meters. All community types resulted in mean elevations of 582.6, 504.5, and 579.5 respectively. Further analysis is needed to determine if, based on topographic metrics, there are enough differences in those community types to accurately delineate those units.

The results presented in Table 2.3 suggest the stratified random sampling approach as successful in distributing plots based on soil series in terms of timber managed areas verses non-timber managed areas. For example, Dixfield and Colonel were two of the three basal till parent material soils series McKay (2008) concentrated on when validating the SIE model in Essex, VT. In addition, the Wonsqueak series, a wetland soil, was located in one non-timber managed area at an elevation of 722 meters, an aspect of 298 degrees, a mean slope of 11%, and a wetness value of 9.2. This type of plot should not be managed for timber because it is too wet for mechanized operation. In another example, the Madawaska series, a moderately well drained outwash soil, was recorded in three timber managed plots at an elevation of 382 meters (standard deviation of 12.5), aspect of 23 degrees (standard deviation of 32), a mean slope of 36% (standard deviation of 0.02), and a wetness index of 7.5 (standard deviation of 0.7). This type of plot can be managed for timber because elevation and wetness are appropriate for mechanized operation. Limitations need to be placed on this analysis as it only looks at timber managed plots versus unmanaged for timber plots and does not look at the vegetation for correlation with the series.

2.5 CONCLUSIONS

LiDAR-derived topographic metrics as SIE data inputs appears to be a valid method for stratified random sampling for ecological classification. However, more work is needed to further refine the inventory and vegetation analysis to increase the boundary accuracy of ecological units. One way to do this would be to automate the parent material delineations to ensure delineation is accurate. Currently, this process still requires expert soil knowledge to delineate, however if the process were to become automated, the delineation accuracy might increase or decrease the cost. More analysis is also needed between the understory species and the overstory species in the timber managed areas to identify which components of the overstory may be in a state of transition compared to the understory. It may be possible given the age of the overstory, in the non-managed timber areas (last managed around the turn of the 20th century), the overstory and understory could both be representative of the climax species at which point there may be other predictors that could improve accuracy and time. Finally, more study is needed to evaluate if there are more indicator species to assist community typing. In this study, only 12 understory sensitive indicator species for enriched sites were selected as defined by Sperduto and Kimball, (2011), however there may be additional sensitive indicator species available for classification and ELT/ELTp delineation.

CHAPTER 3

ASSESSING UNDERSTORY SPECIES RELATIONSHIPS WITH SOIL PROPERTIES AND TOPOGRAPHIC METRICS USING NONMETRIC MULTIDIMENSIONAL SCALING

ABSTRACT

Land managers need terrestrial ecological unit inventory (TEUI) products to assess and describe resource conditions, vegetation conditions, outcomes resulting from various management prescription scenarios, and communicate environmental effects of land management planning alternatives. The U.S. Forest Service approach to ecological classification relies heavily on field-data collection and map-unit verification that is time-consuming and costly. The White Mountain National Forest (WMNF) covers approximately 800,000 acres located in north-central New Hampshire and adjacent western Maine has not completed ecological classification at the scale required by the National TEUI guidelines (Winthers et al. 2005). However, recent research suggests that remotely sensed data, such as LiDAR, can be important predictors of both vegetation and soil properties. Therefore, the objective of this chapter was to assess soil properties and topographic metrics (e.g., slope, aspect, elevation and wetness) derived from LiDAR as predictors of understory species presence across a 17,010 acre watershed in western New Hampshire using multivariate statistical analysis. Specifically, the project area concentrated on a single watershed called the Upper Wild Ammonoosuc (Wammo) in the western portion of the White Mountain National Forest (WMNF). A total of 189 plots were randomly generated within strata, parent material and topographic metrics using a stratified random sampling approach. One hundred and seventy two of those plots had both vegetation and soils information recorded. The presence of 252 understory vegetation species were also recorded across the 172 plots and a total of 15 NH Natural Community types were identified. The understory vegetation

presence were used to analyze the significance of environmental gradients on vegetation since the study watershed had intense land disturbances potentially influencing the overstory species to a state not representative of potential natural vegetation. Sperduto and Engstrom (1995) identified 12 sensitive indicator understory species across the WMNF and 10 of those species were found in 28 of the 172 plots across the Wammo watershed. Nonmetric multidimensional scaling (NMDS) was used to investigate the soil properties and topographic metrics as environmental gradients associated with understory species in ordination space. NMDS ordination explained 81.1% of the cumulative variation of understory species presence in three dimensions using soil properties and topographic metrics with a final stress value of 17.3 and a p-value of 0.04. NMDS results suggested that understory species clustered distinctly within New Hampshire Natural Community types. These results suggest that LiDAR-derived topographic metrics and availability of soil nutrients could assist in determining where community types are positioned across a landscape. Additional NMDS analysis also showed either soil chemistry (Ca, C, and Al) or topographic metrics explained nearly equal amounts of cumulative understory species variation. The results from this study highlight the use of LiDAR-derived topographic metrics as predictors of understory vegetation and likely community types which could be validated in other WMNF watersheds.

3.1 Introduction

Ecosystems are the place where organisms and the environment interact in the three-dimensional space of Earth (Rowe, 1980). Tansley (1935) introduced the term ecosystem by describing how ecological systems are composed of multiple abiotic and biotic factors (Major, 1969). The ecosystem concept is a holistic framework that combines the biological and physical worlds in order to describe, evaluate, and manage the system (Rowe, 1992). Energy, moisture, nutrients, and disturbance gradients are the primary regulators of ecosystem structure and function (Cleland et al., 1997). Multiple environmental and biological factors influence these gradients, including climate, geology, soils, flora, fire, and wind, while varying at different spatial and temporal scales (Cleland et al., 1997).

Forest vegetation is complex and reflects the abiotic and biotic relationships across time and space (Winthers et al., 2005). These relationships are less obvious as humans continue to manipulate vegetation (Winthers et al., 2005). The core components of vegetation dynamics include historic vegetation, disturbance regimes, existing vegetation, and potential natural vegetation and are important for understanding vegetation patterns and processes at different spatial and temporal scales. (Winthers et al., 2005). The core components are also essential for ecosystem management, particularly for preparing desired future conditions, silvicultural prescriptions, and ecological restoration plans (Winthers et al., 2005). Existing vegetation information alone cannot answer important questions about successional trajectories based on historical range of characteristics as responses to management actions (Brohman et al., 2005).

These questions can only be considered by combining information about potential natural vegetation and existing vegetation (Brohman et al., 2005). An existing vegetation classification only represents a single point in time whereas the current plant community reflects the history of a site (Brohman et al., 2005). Because of these disturbance factors, existing vegetation often does not represent the potential natural vegetation under current environmental conditions (Brohman et al., 2005). Vegetation on similar sites after a disturbance can move toward multiple possible future conditions (Winthers et al., 2005). Potential natural vegetation can be used to describe the land's capability to support specific vegetative ecosystems and can be evaluated in the context of existing and historic vegetation (Winthers et al., 2005). In addition, potential natural vegetation can be viewed as a more permanent feature of the landscape than existing vegetation (Winthers et al., 2005). However, understory vegetation is able to withstand past disturbances (e.g. timber harvesting) on the landscape whereas the overstory vegetation often reflects these past disturbances (Gilliam, 2007). In forest ecosystems, structure and function can be determined significantly by understory vegetation (Gilliam, 2007). In this chapter, understory vegetation presence was used to analyze the significance of environmental gradients on vegetation since the study watershed had intense land disturbances potentially influencing the overstory species to a state not representative of potential natural vegetation.

More recent approaches to ecological classification use biophysical variables where both biological and physical chemical criteria are evaluated (Leak, 1982). Habitat types described on the basis of vegetation, soils, and glacial deposit fit the biophysical approach (Mueller-Dombois, 1965). For example, Leak (1982) delineated ecological units at Bartlett Experimental Forest (BEF) in the central portion of the White Mountain National Forest (WMNF) using biological, physical, and chemical conditions. Although vegetation across the White Mountain National Forest can be highly varied, Leak (1982) suggests that this variation can be explained with climate and the mineralogy of the parent material. In the Leak (1982) approach to delineating units, habitats tend to be small from a few to greater than 40 hectares within a given climatic mineralogical zone and supporting a distinct vegetation growing on a specific soil type.

The approach explored at BEF is very similar to the U.S. Forest Service Ecological Land Type phase (ELTp) approach to ecological classification. The most detailed type of ecological unit classification is an ELTp and requires ecological types based on physiographic and vegetation data collected through field inventory. Ecological type classification requires analysis and description of relationships among potential natural vegetation (PNV), soils, local climate or microclimate, geomorphology, surficial geology, bedrock geology, and/or hydrology (Winthers et al., 2005). The ecological type classification analysis is completed using plot inventory data, site level transect observations, and environmental data (Winthers et al., 2005). These final map units are then used in planning and conducting sustainable forestry operations.

It is most beneficial to overlay existing vegetation maps on ecological units generated by TEUI for the purposes of making sound land management decisions (Brohman et al., 2005). Existing vegetation classification maps describe current vegetation composition, structure, and patterns. However, TEUI provides ecological type classifications and defines land units, including the vegetation responses to disturbance processes and land use based on potential natural vegetation and physical site characteristics (Brohman et al., 2005).

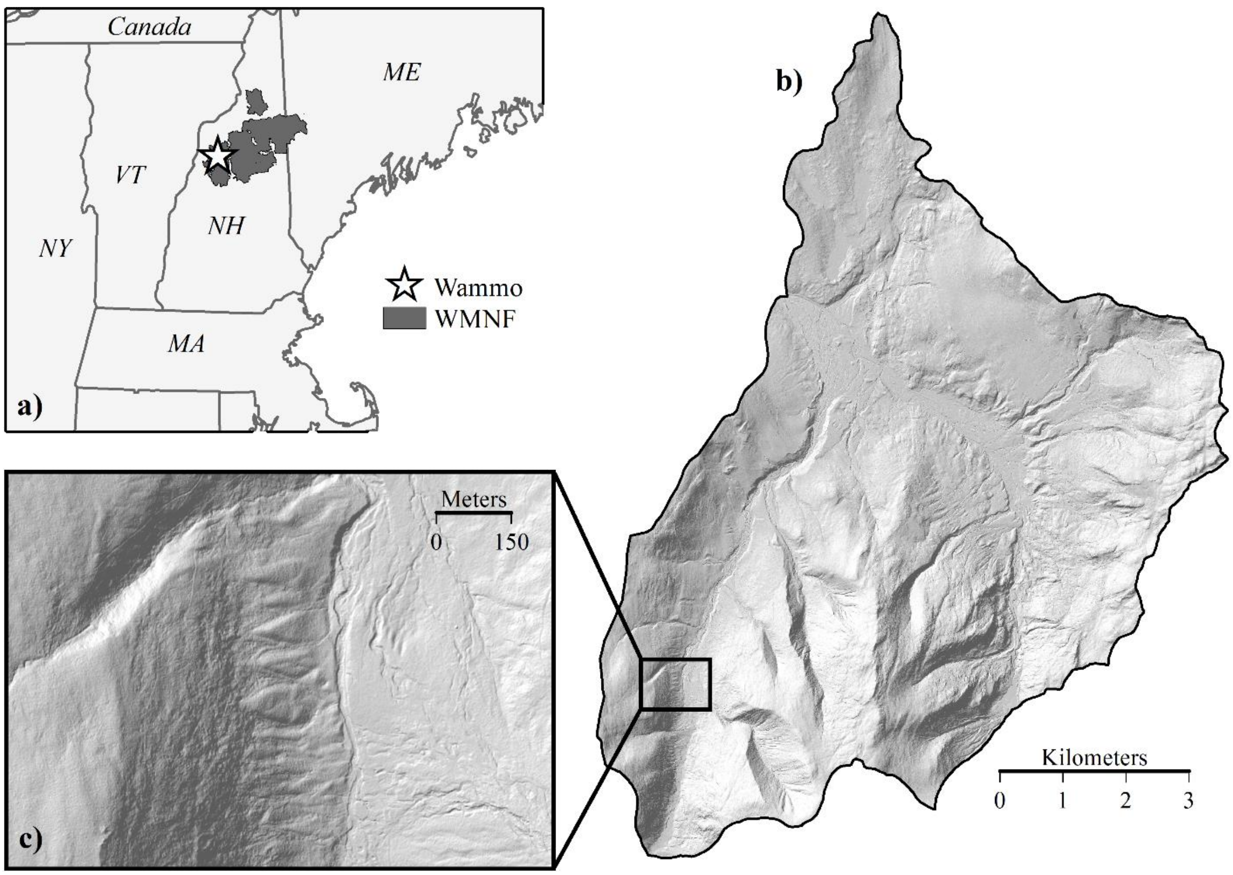
Land managers are able to evaluate ecological conditions when existing vegetation classification maps are combined with ecological type classifications and ecological unit maps to select appropriate land management practices based on ecosystem capability. Plot data is the basic premise underlying vegetation classification used to describe and recognize classifications (Jennings et al., 2004). Therefore, the objective of this chapter was to assess soil properties measured in the field and topographic metrics (e.g., slope, aspect, elevation and wetness) derived from LiDAR as predictors of understory species presence across a 17,010 acre watershed in western New Hampshire using multivariate statistical analysis.

3.2 Methods

3.2.1 Study site

The White Mountain National Forest (WMNF) covers approximately 800,000 acres located in north-central New Hampshire and adjacent western Maine shown (Figure 3.1). Specifically, the study area consisted of a single 17,010 acre watershed in the western New Hampshire portion of the WMNF called the Upper Wild Ammonoosuc (Wammo). The Wammo watershed was chosen because the WMNF had acquired LiDAR for the entire watershed by 2012 and the WMNF owns 16,245 acres of the watershed. The Wammo is also representative of most forest cover types, soils, and elevation gradients present within WMNF (McNab and Avers, 1994). The remaining 765 acres of private land in Wammo were not included in the plot inventory conducted in this project.

Figure 3.1: Inset map a) shows the White Mountain National Forest (WMNF) external boundaries in gray within the Northeastern US as well as the location of the Wammo study area marked by a five point star. Map b) shows a 1 meter shaded relief map derived from LiDAR within the 17,010 acre Wammo watershed. Inset map c) also shows a 1 meter shaded relief map within the Wammo watershed at a finer scale to highlight the notable differences in roughness.



The Wammo has an elevation gradient of 336 to 1,462 meters. Dominant vegetation types include northern hardwood, spruce-fir, and mixed-species forests (McNab and Avers, 1994). Annual precipitation averages 90-180 cm and total annual snowfall ranges from 250-400 cm (McNab and Avers, 1994). The soils tend to be Spodosols and are of the suborder either of

Aquods (wet), Cryod (cold), Humods (high organic matter), and Orthods (ordinary spodosols) (USDA, 2006). A NH Heritage code (Sperduto and Kimball, 2011) was assigned in the field to plots during data collection.

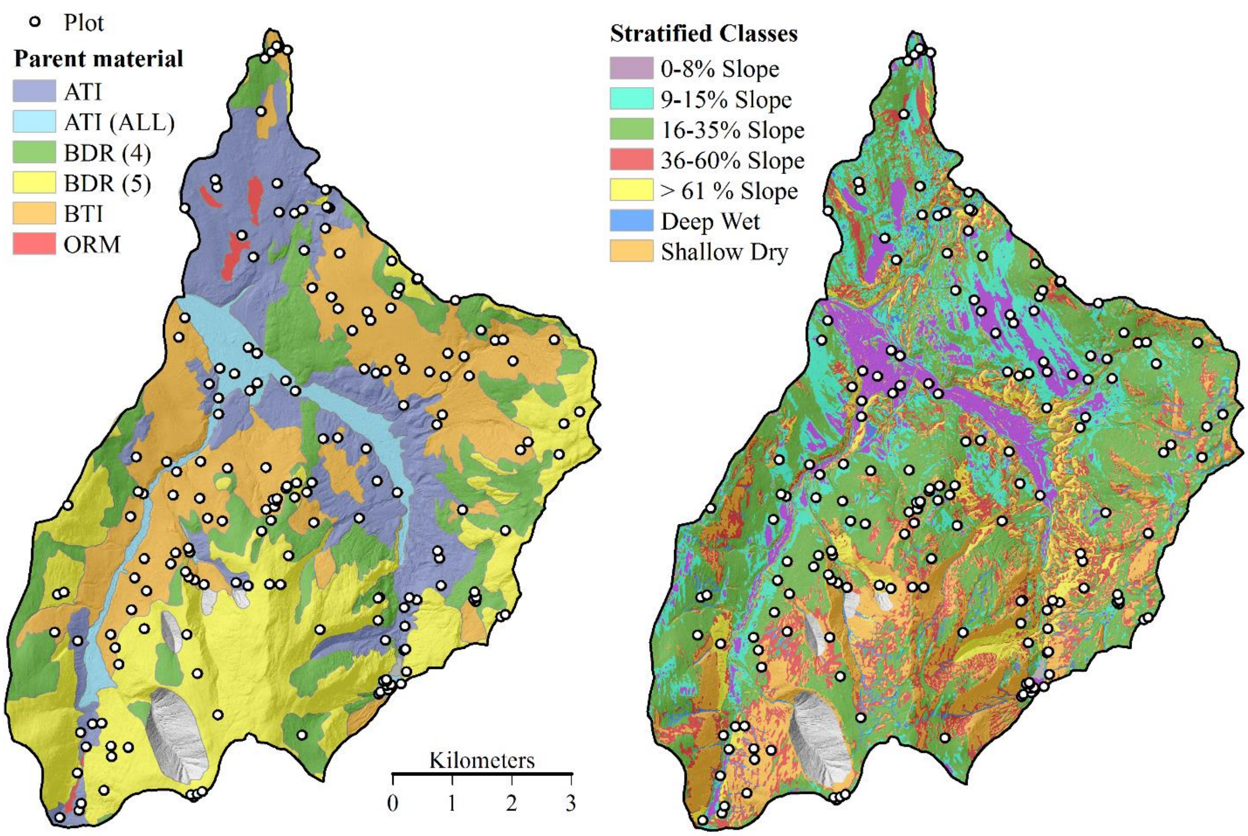
3.2.2 Sample design

Stratified random sampling was selected for distributing inventory plots across the Wammo. This method of sampling has been shown to reduce overall prediction error as points are uniformly allocated over the study area proportional to the distribution of soil types (Hengl et al., 2003). The topographic metrics that correspond to the important environmental variables driving vegetation patterns in the WMNF were used. It has also been reported that using a stratified random sampling approach can reduce costs and improves accuracy (Guisan et al., 2006). A total of 189 plots were randomly generated within strata based on parent material and topographic metrics (Figure 3.2). One hundred and seventy two of those plots had both vegetation and soils information recorded. All strata based on slope and drainage were first partitioned based on parent material. In addition, there were at least 8 plots per strata and strata were further divided by timber managed areas and non-timber managed areas. For example, this resulted in 63 plots in timber managed areas and 12 plots in non-timber managed areas within the basal till parent material. There were at least 10 plots per parent material and more than 12 plots in both timber and non-timber managed areas.

3.2.3 Understory Sampling Protocol

The understory composition and structure were captured using a 10-meter radius plot. The scientific name along with the plant type code and sociability code (Sperduto and Kimball, 2011) were also captured.

Figure 3.2: The Wild Ammonoosuc (Wammo) watershed is outlined in black with the different parent material types represented by associated colors (on left). Wammo watershed also outlined in black with different stratified classes derived from LiDAR and the Soil Inference Engine represented by different colors (on right).



Ocular estimate of maximum height was recorded, to nearest 0.5 m if less than 2 m and to nearest meter if taller than 2 m and ocular estimate of percent cover, by the following categories, separately for 0-0.5m and 0.5m-5m. There were 252 understory species recorded across the 172 plots and 15 total NH Natural Communities were identified. Sperduto and Engstrom (1995) identified 12 sensitive indicator understory species that are important to locate across the WMNF and 10 of those species were found in a total of 28 plots across the Wammo watershed. In addition, the use of significant indicator species has been shown to aid in evaluating nutrient status to reduce the need for intensive soil sampling and interpretation (Horsley et al., 2008).

3.2.4 Soil Sampling and Chemistry

A soil pit was dug per field plot location and located within the plot. A full soil profile was characterized per NRCS standards. The NRCS standards include describing and sampling soil profiles based on genetic horizons and Munsell color, texture, structure, moist consistence, presence of redoximorphic features, rooting density, and coarse fragment content (Schoeneberger, 2012). Soil samples for chemistry analysis were collected from around the pit including the first 10 cm of the Oa horizon, the first 10 cm of the B horizon and the first 10 cm of the C horizon.

All soil samples were then air-dried, sieved to remove particles >2 mm, homogenized and split to generate a subsample for chemical analysis. Samples were measured for pH in 0.01 mol/L CaC_{l2} (Robarge and Fernandez, 1987). All samples were analyzed for carbon and nitrogen on a CN elemental analyzer (CE-Elantech Thermo FlashEA 1112 Series NC Soil Analyzer) using pulverized subsamples. Soil standards obtained from the North American Proficiency Testing program were used to standardize the instrument. Exchangeable cations were measured in an extract obtained from a mechanical vacuum extractor using 1 M NH_4OAc buffered at pH 4.8. Cation concentrations were measured with an Agilent inductively coupled plasma spectrometer (Agilent Technologies 700 Series ICP-OES) at the US Forest Service laboratory in Durham, NH. Reference samples of Oa and Bs horizons from Vermont were included in all analytical streams and yielded values of C, N, pH, and exchangeable cations comparable to the median values reported in an interlaboratory study (Ross et al., 2015).

3.2.5 Topographic Metrics

A 1 meter DEM was created from only LiDAR ground returns, coarsened to 5 meter through mean cell aggregation and filled using an algorithm that maintains the downslope gradient (Wang and Liu, 2006). A DEM resolution of 5 meter was selected because it was shown to strongly correlate with ground water fluctuations and land survey measurements (Gillin et al., 2015). Slope was calculated using maximum slope algorithm (Travis et al., 1975). Topographic wetness index (TWI) (Beven and Kirkby, 1979) was calculated with the upslope accumulated area (UAA) computed from a multiple flow direction algorithm and slope.

3.2.6 Statistical Analysis: NMDS

Nonmetric multidimensional scaling (NMDS) ordination (Kruskal, 1964) was used to investigate the relationship between soil properties and topographic metrics as environmental gradients associated with understory species. NMDS analysis works well with highly variable data to reveal significant relationships because NMDS avoids the assumption of linear relationships among variables (McCune et al., 2002). NMDS uses ranked distances to better align the relationship between distances measured in ordination space to distances in environmental space and is often the preferred method for ecological analyses (McCune et al., 2002). PC-ORD version 6.01 was used to calculate the ordinations based on the Wammo watershed understory species and environmental matrices (McCune and Mefford 2011). A binary presence–absence species matrix contained all species that were present in 172 plots which was a total of 252 species. An environmental matrix included variables of soil horizon thicknesses, soil chemistry, redox depth, elevation, slope, aspect, profile, and wetness index. To determine the appropriate number of dimensions needed, initial runs of NMDS in ‘‘autopilot’’ mode were used and three axes were chosen (McCune et al., 2002). “Clarke” stress values for ecological community data typically have values between 10 and 20 when successful (McCune et al., 2002). After the analysis was completed, a convex hull was used to display NH Natural Community types (Sperduto and Kimball, 2011) and parent material to assess whether understory species clustered within either categorical variables.

3.3 RESULTS

NMDS ordination explained 81.1% of the cumulative variation of understory species using soil chemistry and topographic metrics on three axes with a final stress value of 17.3 and a p-value of 0.04. 48.4% of variability was associated with axis 1 where elevation (r=0.646), pH (r=0.497) and carbon concentration (C) in the Oa horizon (r=0.483) were the strongest environmental variables correlated (Pearson) with understory vegetation (Table 3.1). Other variables strongly associated with axis1 were slope and nitrogen concentration (N) in the Oa horizon, exchangeable calcium concentration (Ca) in the B horizon, and the measured thickness of either the Oa or E horizons (Table 3.1). Understory species strongly positively correlated with axis 1 (Table 3.2) were hardwood species sugar maple (*Acer saccharum*, r=0.632), white ash (*Fraxinus Americana*, r=0.616) and beech (*Fagus*, r=0.532). Axes 2 accounted for 19.2 % of the variability. TWI had the strongest relationship (r=0.317) on Axis 2 followed by redox depth (r=0.209). Understory species strongly positively correlated with axis 2 were North American balsam fir (*Abies balsamea*, r = 0.493) and New England sedge (*Carex novae angliae*) (r=0.445). Axis 3 accounted for 13.1 % of the variability. N in the C horizon (r=0.333) and elevation (r=0.374) showed the strongest relationship to Axis 3 while C in the C horizon (r=0.289) and aluminum

(Al) in the B horizon (r=0.261) showed weaker influence. Understory species strongly positively correlated with axis 3 were northern beech fern (*Phegopteris connectilis*, r=0.458) and northern woodsorrel (*Oxalis montana*) (r=0.442). After the analysis was completed, the convex hulls associated with NH Natural Community types were displayed to assess whether understory species clustered within community types (Figure 3.3).

Table 3.1 Topographic Metrics and soil chemistry analyzed showing strongest correlations (Pearson) to understory species.

Variable	Axis 1	Axis 2	Axis 3
Oa horizon C	-0.483	0.145	0.214
Oa horizon N	-0.436	0.197	0.116
Oa horizon pH	0.497	-0.05	-0.053
Oa horizon Ca	0.106	0.168	0.127
B horizon Al	-0.14	0.041	0.261
B horizon Ca	0.321	-0.028	-0.027
C horizon C	-0.196	-0.119	-0.289
C horizon N	-0.14	-0.126	-0.333
C horizon Al	-0.205	0.049	-0.206
C horizon Mn	0.029	-0.179	-0.107
Redox depth	-0.113	0.209	0.092
Oa thickness	-0.397	-0.029	0.051
E thickness	-0.306	-0.147	0.002
TWI	0.264	-0.317	-0.213
Aspect	0.006	0.168	-0.12
Slope	-0.376	0.148	-0.125
Profile	-0.072	0.183	0.245
TPI (5m)	-0.013	0.111	0.234
Elevation (m)	-0.646	-0.156	-0.374

Figure 3.3: The soil and topographic metric variables are illustrated as lines in the ordination graphics, the direction of each line indicating the direction of gradient and the length indicating the strength of the correlation between variable, ordination and axis.

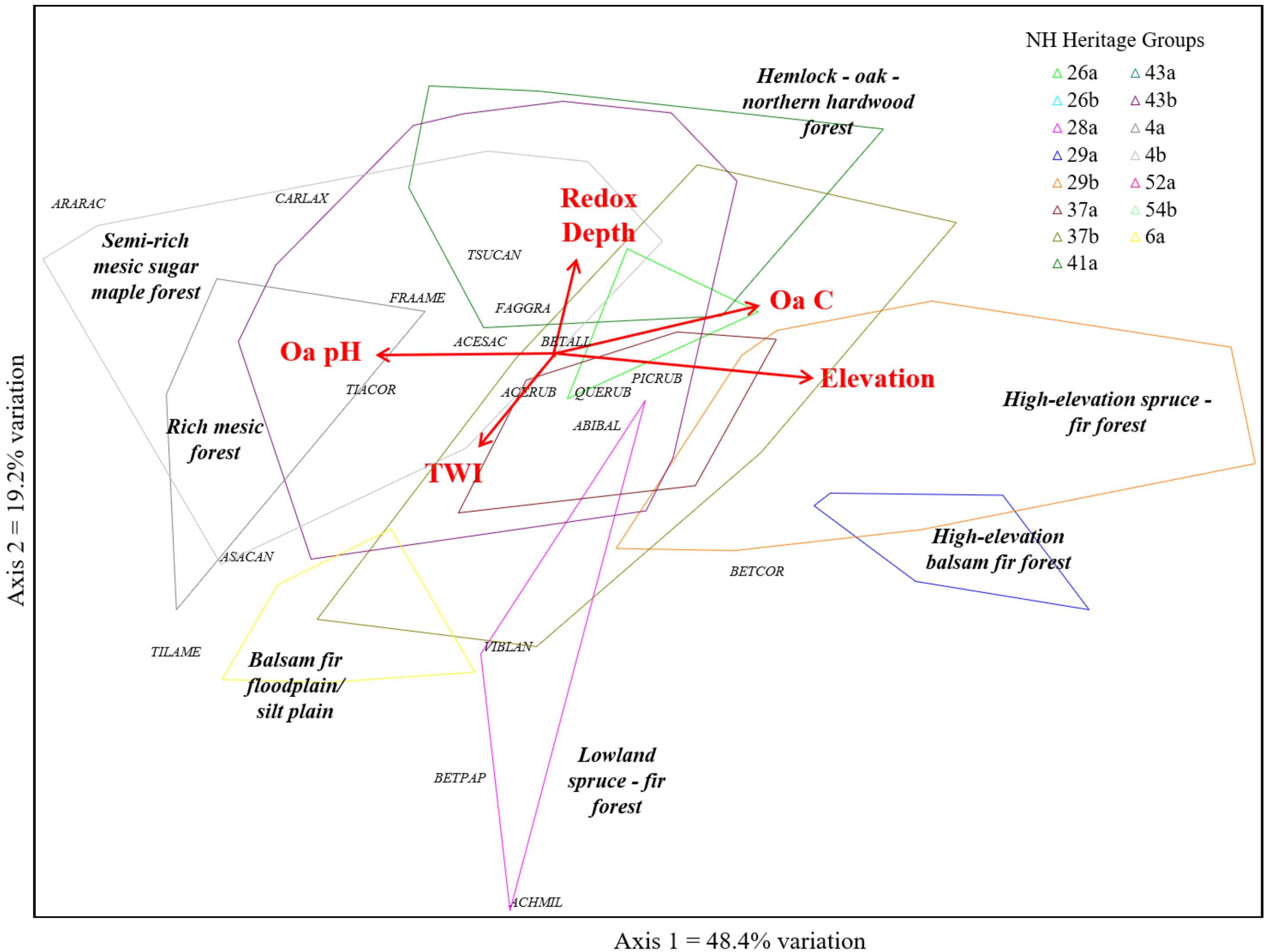


Figure 3.4: The soil and topographic metric variables are illustrated as lines in the ordination graphics, the direction of each line indicating the direction of gradient and the length indicating the strength of the correlation between variable, ordination and axis.

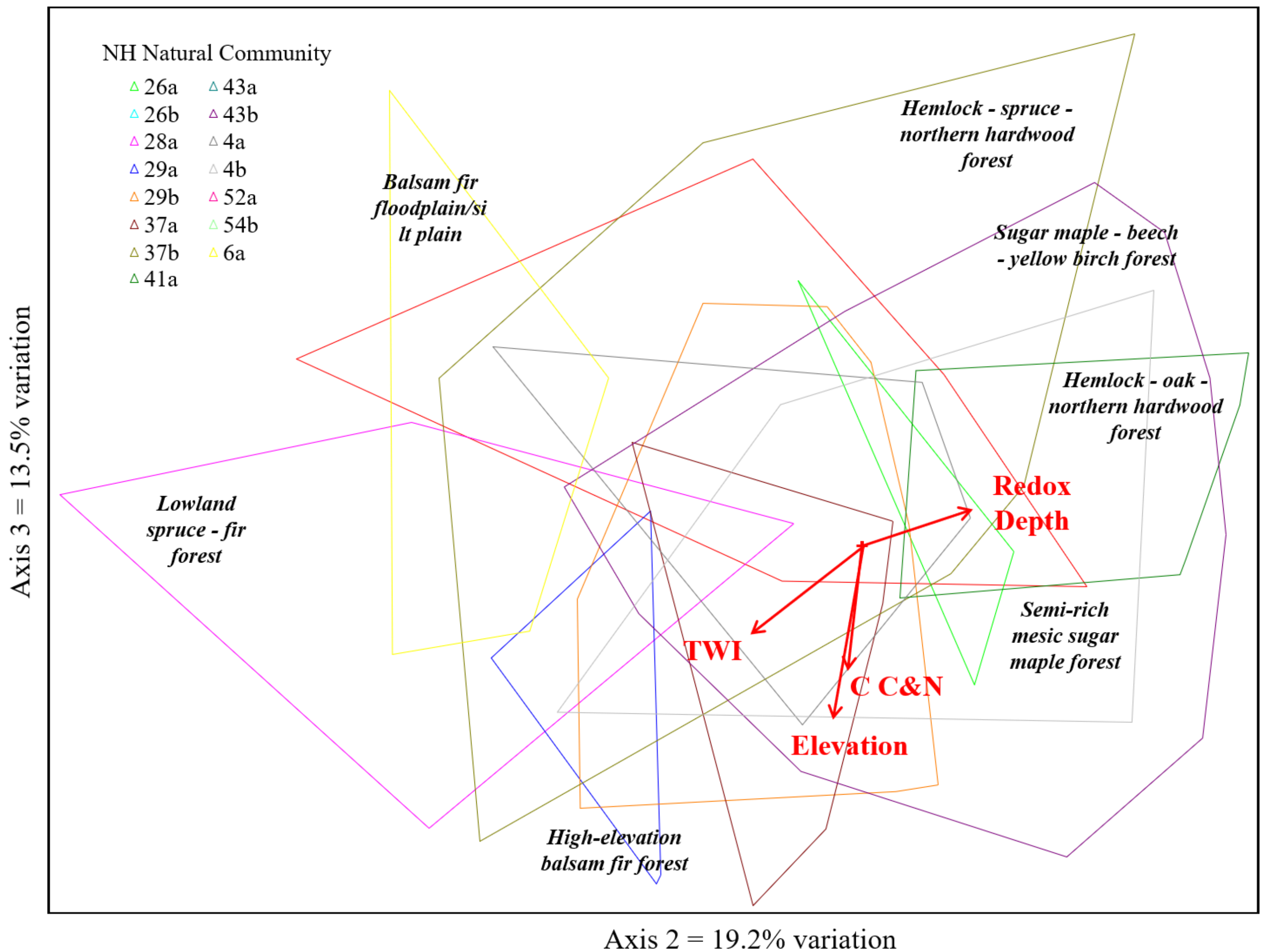


Table 3.2: NMDS results for correlations with the understory vegetation, with a three-dimensional ordination. Correlations are listed by r-values. Species are indicated by a 6 letter codes that corresponds to the first 3 letters of the genus and first 3 letters of the species. Scientific name and common name are shown too. (Appendix 1).

Species	Scientific name	Common name	Axis 1	Axis 2	Axis 3
ABIBAL	Abies balsamea	fir	-0.358	0.493	0.071
ACEPEN	Acer pensylvanicum	stripe maple	0.403	-0.162	0.114
ACERUB	Acer rubrum	Red maple	0.245	0.187	0.515
ACESAC	Acer saccharum	Sugar maple	0.632	-0.135	-0.047
ARITRI	Arisaema triphyllum	Jack in the pulpit	0.487	0.055	-0.097
ATHANG	Athyrium angustum	northern lady fern	0.414	0.186	-0.321
CARNOV	Carex novae angliae	New England sedge	0.121	0.445	0.161
COPTRI	Coptis trifolia	gold thread	-0.17	0.422	0.159
CORCAN	Cornus canadensis	dogwood	-0.103	0.427	0.241
DIPDIG	Diphasiastrum digitatum	fan clubmoss	0.143	0.084	0.313
FAGGRA	Fagus grandifolia	beech	0.532	-0.364	0.133
FRAAME	Fraxinus americana	ash	0.616	-0.078	0.204
HUPLUC	Huperzia lucidala	shining fir moss	0.093	-0.427	-0.305
LYCDEN	Lycopodium dendroideum	tree ground pine	0.131	0.083	0.352
LYCHIC	Lycopodium hickeyi	Hickey's tree club-moss	0.093	-0.041	0.323
MEDVIR	Medeola virginiana	Indian cucumber-root	0.22	-0.375	0.177
ONOSEN	Onoclea sensibilis	sensitive fern	0.413	0.168	-0.19
OXAMON	Oxalis montana	mountain woodsorrel	-0.135	0.078	-0.442
PHECON	Phegopteris connectilis	long beech fern	0.178	0.162	-0.458
SPIALB	Spiraea alba	white meadowsweet	0.266	0.493	0.26
THENOV	Thelypteris noveboracensis	New York fern	0.453	0.12	-0.292
TIACOR	Tiarella cordifolia	foamflower	0.494	0.166	-0.306
UVUSES	Uvularia sessilifolia	wild oats	0.565	-0.183	-0.053
VIOBLA	Viola blanda	sweet white violet	0.482	-0.128	-0.09
VIOROT	Viola rotundifolia	violet	0.405	-0.252	-0.295

3.4 DISCUSSION

The NH Natural Community types appeared to create distinct understory groups and contain understory species within those groups consistent with the NH Natural Community type definition. The pH of Oa horizon suggested a correlation with rich mesic and a semi-rich mesic forests. Based on existing knowledge of forest communities we would expect to have higher soil Oa pH versus the other direction in NMDS showing a high-elevation spruce or high-elevation balsam fir forest. The results also suggests TWI increases when redox depth is shallower. This is consistent with our understanding of redox depth as indication of water tables and higher TWI values would suggest surficial flowpath is more saturated. The NDMS results suggest TWI was greater with a Balsam fir floodpain/silt plain and a lowland spruce-fir forest rather than the redox depth occurring much lower in the soil profile of a hemlock-oak-northern hardwood forest. These species groupings are consistent with the NMDS results suggesting TWI was wetter and redox was higher in the profile within a Balsam fir floodpain/silt plain and a lowland spruce-fir forest.

The opposite was suggested for a hemlock-oak-northern hardwood forest where redox depth was lower in the soil profile and low TWI values indicates the site should be drier. In addition, the results suggested an elevation gradient that correlates well with the NH Natural Community groupings of high elevation spruce-fir forest and balsam fir forest. This is also consistent with Lee et al. (2005) results conducted on transects on the WMNF. It can also be suggested that an increase in elevation may result in soil Oa pH decrease. Although NH Natural Community groupings were distinct in the NMDS results for a few community types, there were several community types that had overlapping convex hulls. These overlapping community type convex hulls suggest that understory species in mid-elevation community types were not necessarily found together on a plot-level basis in the study watershed. Therefore, some other classification of understory species might be better suited for the understory species in this watershed.

NMDS results showed elevation, profile curvature, slope, aspect, and topographic wetness values derived from LiDAR correlated significantly to understory species. This suggests LiDAR-derived topographic metrics may be successful for predicting and locating ecological units based on the convex hulls displaying NH Natural Community types. However, the results also show physical and chemical soil properties explain significant understory species variation. In this study, physical and chemical soil properties were measured in the field, however more study needs to evaluate if soil properties can be modeled using topographic metrics (Fraser, 2019). Previous research at Hubbard Brook Experimental Forest in the WMNF, 16 kilometers southeast of Wammo watershed, had success predicting soils based on horizon sequences using LiDAR-derived topographic metrics (Gillin et al., 2015).

Finally, convex hulls were used to delineate parent material type associated by plot to assess whether understory species were correlated with parent material. The distribution of understory species in ordination space did not appear to cluster by parent material (Schoeneberger, 2012). The convex hulls of parent material were not distinct groups, whereas with the NH Natural Community types appeared to be more distinct. Lee et al. (2005), however, found elevation and parent material, grouped based on nutrient content, had strong influences to vegetation.

3.5 CONCLUSIONS

This study demonstrates the potential use of understory species as an indicator of ecological classification in the Wammo watershed. NMDS results also demonstrated LiDAR-derived topographic metrics and soil properties are important factors in explaining understory species variation. In addition, topographic metrics are potentially important predictors of NH Natural Community types. This conclusion was based on the apparent clustering of understory vegetation species (252 species) within NH Natural Community types. Parent material appeared to have little influence with understory species. Further research is needed to evaluate the use LiDAR-derived topographic metrics as model predictors for soil properties and ecological classification across Wammo and subsequently the WMNF.

CHAPTER 4

BUDGET COMPARISON OF TRADITIONAL ECOLOGICAL CLASSIFICATION TO STRATIFIED RANDOM APPROACH USING LiDAR AND SIE

ABSTRACT

Land managers need accurate ecological information to make sound decisions. Terrestrial Ecological Unit Inventory (TEUI) is a taxonomic land survey system that produces natural resource information that is a fundamental component of ecosystem management useful for forest planning by the U.S. Forest Service. The current cost of TEUI classification and mapping, however, is prohibitive based on current Forest Service TEUI requirements and budgets. New methods to complete TEUI classification and mapping used stratified random sampling based on LiDAR-derived topographic metrics rather than the traditional mapping transects to achieve the results at a reduced cost. The objectives of this chapter were to assess the cost of ecological classification by traditional methods outlined by the TEUI Inventory Manual compared to new methods based on stratified random sampling using LiDAR-derived topographic metrics. Traditional TEUI ecological mapping would require 630 plots across the study area compared to 189 plots used for stratified random sampling using LiDAR-derived topographic metrics across a 17,010 acre study watershed in the western portion of the White Mountain National Forest (WMNF). The number of plots calculated for stratified random sampling was predominately determined by the number of strata, the acres of timber-managed areas, and budget. In both approaches, the mapping of the plots averaged approximately $989.00 per plot including soil chemistry analysis from U.S. Forest Service Laboratory. This yielded a total cost of approximately $623,000 for the traditional TEUI inventory and mapping compared to approximately $187,000 for stratified random sampling using LiDAR-derived topographic

metrics. However, LiDAR technology is necessary to obtain results using the stratified random sampling approach. This technology comes at a cost of approximate $2.00 per acre for 1-meter nominal spacing with an average point spacing of 3 points per square meter, totaling approximately $34,000 across the 17,010 acre study watershed. The total cost to conduct the TEUI traditional method of mapping would have been approximately $623,000 in the study area, while the total cost to conduct stratified random sampling with additional LiDAR acquisition was approximately $221,000 across the study area. This chapter showed that stratified random sampling using LiDAR-derived topographic metrics costs approximately $402,000 less, including the additional LiDAR acquisition costs, than the traditional TEUI mapping approach. The advantages of stratified random sampling to establish ecological plots using LiDAR-derived topographic metrics establishes the possibility for the U.S. Forest Service to map ecological units at a feasible cost based on current budgets while increasing efficiency.

4.1 INTRODUCTION

Terrestrial Ecological Unit Inventory (TEUI) is a taxonomic land survey system that produces natural resource information implemented that is both a fundamental component of ecosystem management useful for forest planning by the US Forest Service (Winthers et al., 2005). The (TEUI) approach classifies and maps ecosystems based on biotic and abiotic factors that comprise the physical environment. Land managers should combine the existing vegetation classification and TEUI protocols to support good land management decisions (Brohman et al., 2005). Currently vegetation composition, structure, and patterns are the basis for existing vegetation classification maps (Brohman et al., 2005). In contrast, TEUI provides ecological classifications and defines land units by assessing the ecosystems response to disturbance processes and land management activities based on potential natural vegetation and physical site characteristics (Brohman et al., 2005).

Describing successional relationships and dynamics is an important component for predicting vegetation responses to various management scenarios or natural disturbance regimes (Brohman, et al., 2005). This requires describing and classifying the plant communities associated with an ecological type (Brohman et al., 2005). The Ecological Land Type Phase (ELTp) level is the most detailed of the classification of ecological units requiring ecological types of physiographic variables and vegetation data. Ecological type classification requires analysis and description of relationships among potential natural vegetation (PNV), soils, local climate or microclimate, geomorphology, surficial geology, bedrock geology, and/or hydrology (Winthers et al., 2005). This approach requires analysis on plot inventory data, site level transect observations, and environmental data (Winthers et al., 2005). The TEUI spatial unit delineation techniques typically use transect base field campaigns either by aerial photos and topographic maps or spatial data combined with Geographic Information Systems (GIS). Both approaches are inherently time consuming, field intensive, and require a large budget. Therefore, there is a significant need across the U.S. Forest Service for forest land management planning to develop more consistent, rapid, and cost-effective methods to delineate ecological Land Type Phase (ELTp) map units.

The TEUI Technical Guide (Winthers et al., 2005) outlined the requirement to interpret aerial photos for landform designation. This method has been used for decades by U.S. Forest Service, however there are challenges and problems when applying it across large survey areas. Gathering and viewing hundreds of photographs is both time consuming and the resolution of those photographs are not sufficient in areas of very dense vegetation. This method requires an expert observer to visually interpret photos which can lead to bias between users resulting in differing and contradiction delineation results. Finally, the traditional TEUI method requires a user to first draw proposed polygons on a photo and then later digitize them into spatial data to be used in a digital Geographic Information Systems program which can also contribute to inaccuracy results.

The TEUI Geospatial Toolkit (Toolkit), an ArcGIS tool, assists users in mapping and analyzing landscapes using geospatial data (USFS GTAC, 2008). The Toolkit allows the user to use geospatial data through Geographic Information Systems (GIS) to improve both mapping and landscape analysis. It also reduces the time required when using aerial photos. Data typically needed for use in the Toolkit include environmental and terrain layers such as soils, digital elevation models (DEMs), potential natural vegetation (PNV), and timber information. However it should be noted, widely available U.S. Geological Survey DEMs have a 10 meter spatial resolution. In comparison, LiDAR-derived DEMs often have a 1 meter resolution. Most U.S. Forest Service national forests have soil series maps produced by Natural Resource Conservation Service (NRCS), however the soil maps were generally produced in the 1960-1980s when surveys used aerial photographs and then digitized for GIS use. There are a number of U.S. Forest Service national forests across the country without a formal soil survey, including the White Mountain National Forest (WMNF). Because the WMNF did not have a soil survey, a hybrid system of ecological classification consisting of Ecological Land Types (ELT) was completed in the1970-1980s. The WMNF ELT map, used a combination of soil parent material and plot inventory data, along with hand drawn unit delineations, on black and white aerial imagery from 1956. The traditional plot inventory conducted in the 1970-1980s included transects and randomly generated field verifications. The ELT units were made digitally available in 2000 to land managers by digitizing the unit delineations in GIS.

Starting in the 1990s there was a large initiative in the U.S. Forest Service to map national forest landscapes using ecological classification. The WMNF was an early adopter of ecological classification as the 1986 Land Management Plan relied heavily on ecological units for land management planning. In 1990's, there was a dedicated line budget item from the Washington Office Headquarters of the Forest Service (WO) that directed money to national forests to meet the proposed target of mapped TEUI acres. However, the national budget starting in 2000's brought a change in land managers' focus and direction. The budget line item and target number of TEUI acres mapped was no longer included in budget direction from the WO as a high priority and several U.S. Forest Service Regional Offices (RO), including the Northeastern U.S. (R9) followed that direction. The current leadership direction from R9 requires individual national forests to use limited discretionary funds or obtain outside partnerships for implementing TEUI initiatives. Yet, the need for high quality ecological data remains in order to achieve maximum accuracy and efficiency.

In 2008**,** various new efforts to use Light Detection and Ranging (LiDAR) to increase efficiency and accuracy were explored by the WMNF. Ecosystem understanding has increased due to modeling and mapping made possible by LiDAR (Lefsky et al., 2002). Lefsky et al. (2002) LiDAR as "an alternative remote sensing technology that promises to both increase the accuracy of biophysical measurements and extend spatial analysis into the third (z) dimension (i.e., elevation)". High-resolution topographic maps and estimates of vegetation height, cover, and canopy structure can be made by LiDAR sensors penetrating the tree canopies to reach the ground. These maps advanced ecological understanding by making topography more visible which has influences on the structure, composition, and function of forest systems (Lefsky et al., 2002).

In 2012, a WMNF watershed study area in western New Hampshire called the Upper Wild Ammonoosuc (Wammo) was selected for study because it represented the full range of most forest types and soils found across the WMNF (Colter, 2019). Stratified random sampling was selected for distributing inventory plots across the Wammo because this method of sampling has been shown to reduce the overall prediction error since points are uniformly allocated over the study area proportional to the distribute plots (Hengl et al., 2003).

The objective of this chapter was to compare the cost of completing an ecological inventory using a traditional mapping method as outlined by the TEUI Technical Guide to new approaches using stratified random sampling based on LiDAR-derived topographic metrics as inputs in the Soil Inference Engine (SIE).

4.2 METHODS

4.2.1 Study Site

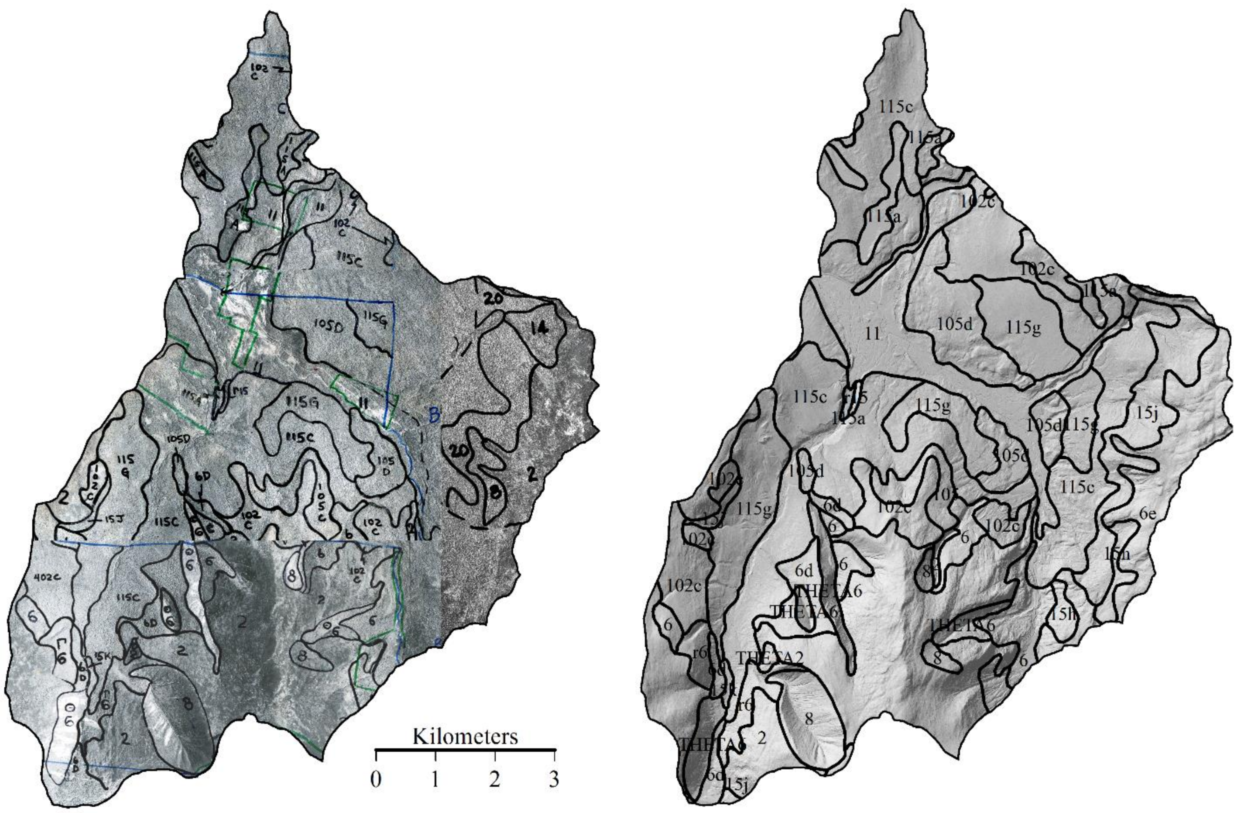
The White Mountain National Forest (WMNF) covers approximately 800,000 acres located in north-central New Hampshire and adjacent western Maine. Specifically, the study area for this project concentrated on a single 17,010 acre watershed in the western New Hampshire portion of the forest called the Upper Wild Ammonoosuc (Wammo) within the White Mountain National Forest (WMNF). The Wammo watershed has an elevation gradient of 336 to 1,462 meters. Dominant vegetation types include northern hardwood, spruce-fir, and mixed-species forests. Annual precipitation averages 90-180 cm and total annual snowfall ranges from 250-400 cm (McNab & Avers, 1994). The soils tend to be Spodosols and are of the suborder of either Aquods (wet), Cryod (cold), Humods (high organic matter), and Orthods (ordinary spodosols) (USDA, 2006).

4.2.2 TEUI Inventory and Mapping by Traditional Methods

Information for this chapter was obtained from the White Mountain National Forest Management Plans of 1986 and 2005, the current and past 20 years of national and R9 Forest Service budgets, as well as the past two decades of national and R9 land management objectives and reviewed for ecological classification. The Wammo study area was evaluated using traditional mapping methods outlined in the TEUI Technical Guide (Winthers et al. 2005) to estimate cost.

In order to estimate an accurate budget for the traditional method of Ecological Land Type Phase (ELTp) inventory and mapping, the watershed was partitioned using the current Ecological Land Type (ELT) layer which includes 21 total mapped ELT's (Figure 4.1). The TEUI Technical Guide manual requires a minimum of three transects across a proposed ELT with a minimum of 10 plots per transect in order to achieve accurate results. It was assumed, since accurate traditional mapping costs for the WMNF were unavailable, the plot inventory costs would be the same as the stratified random sampling using LiDAR-derived topographic metrics as the same inventory of vegetation and soil were required. It was also assumed the analysis of using aerial photos or the TEUI tool kit would require roughly the same amount of time as the SIE modeling and parent material analysis needed in the stratified random sampling using LiDAR-derived topographic metrics approach for the Wammo study area.

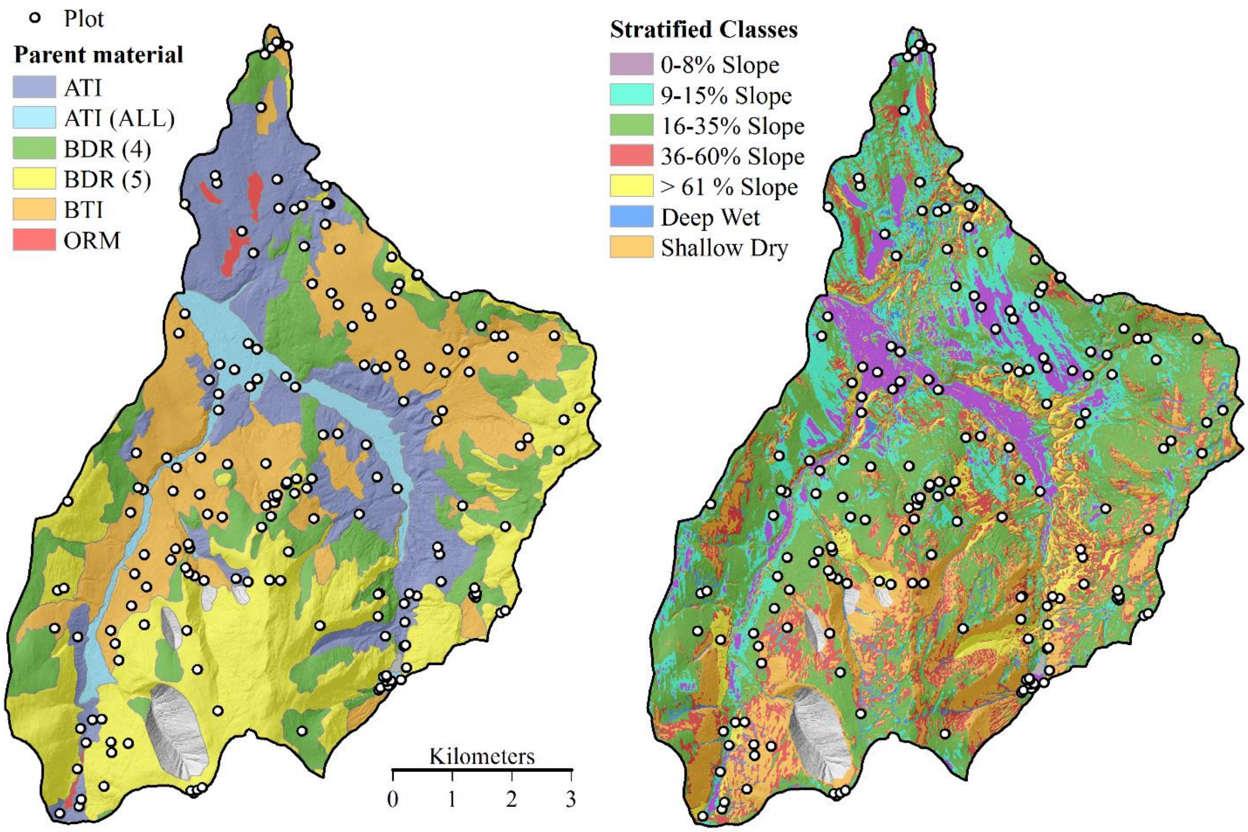
Figure 4.1: Georeferenced hand drawn Traditional Ecological Land Type delineations completed in 1998 of the Wammo study area using black and white aerial imagery from 1956 (on left). Digitized hand drawn Ecological Land Type delineations depicted on 1 meter LiDAR-derived shaded relief map (on right).



4.2.3 TEUI Inventory and Mapping using Stratified Random Sampling

Stratified random sampling was selected for distributing ELTp inventory plots across the Wammo study area. This method of sampling has been shown to reduce overall prediction error as points are uniformly allocated over the study area proportional to the distribution of plots (Hengl et al., 2003).

Figure 4.2: The Wild Ammonoosuc (Wammo) watershed is outlined in black with the different parent material types represented by associated colors (on left). Wammo watershed also outlined in black with different stratified classes derived from LiDAR and the Soil Inference Engine represented by different colors (on right).



The topographic metrics that correspond to important environmental variables driving vegetation patterns in the WMNF were used in an effort to reduce costs and improve accuracy. A total of 189 plots were randomly generated within strata. The number of plots calculated for stratified random sampling was predominately determined by the number of strata, the acres of timber-managed areas, and budget. One hundred and seventy two plots had both vegetation and soils information recorded (Figure 4.2). All strata based on slope and drainage were first partitioned based on parent material. In addition, there were at least 8 plots per strata and strata were further divided by timber managed areas and non-timber managed areas. For example, this resulted in 63 plots in timber managed areas and 12 plots in non-timber managed areas within the till parent material basal till. There were at least 10 plots per parent material (except BDR4 and ORM) and more than 12 plots in both timber and non-timber managed areas. Natural Resource and Conservation Service (NRCS) assisted in processing the LiDAR, conducted the Soil Inference Engine (SIE) modeling development, documentation, parent material mapping and GIS analysis at an approximate cost of $16,000.

4.2.4 Inventory Protocol Costs

The plot protocol per the TEUI Technical Guide (Winthers et al. 2005) requires that site information, overstory composition, understory composition, and soil descriptions be recorded at each plot. The cost of each plot inventory within the Wammo watershed study area was approximately $989.00. The information recorded per plot included location of plot (Trimble Pro XH), plot center monumented with a magnet for future inventory purposes, date of sampling, and site information regarding disturbance. Recorded plot information also included general notes that described overall plot surroundings, indicated as homogenous or heterogeneous, any departures in overall vegetation structure/composition near plot, their approximate distance/direction, apparent landform, and any other information of interest. In addition, the community type from New Hampshire Natural Heritage Bureau, key to natural communities, was visually evaluated and recorded by the field technicians (Sperduto and Kimball, 2011).

The overstory composition and structure was measured based on all woody stems greater than 2.5 cm diameter at breast height (DBH). Woody stems less than 2.5 cm DBH or shorter than breast height, and all herbaceous species, were treated as understory species. The understory composition and structure were recorded by the scientific name and captured using a 10 meter radius plot as a relevé. Ocular estimates of maximum height were recorded as well as ocular estimates of percent cover. In addition, a soil pit was dug at each field plot location and located within the plot. A full soil profile was characterized per NRCS standards. The NRCS standards include soil profile descriptions and samples based on genetic horizons and Munsell color (Schoeneberger, 2012). Soil samples for chemistry analysis included the first 10 cm of the Oa horizon, the first 10 cm of the B horizon and the first 10 cm of the C horizon. Field technicians later air-dried and sieved soil samples for lab analysis. Soil chemistry analysis, including pH, carbon, nitrogen, and cation concentrations, were also included in the $989.00 cost per plot.

The field crews consisted of 3 groups because each group worked on a different time scale needed to collect different types of information. The first group collected the plot information, monumented the plot, measured the overstory, entered the plot data and processed the soil samples for lab analysis. This two person group was contracted to University of New Hampshire (UNH) at a cost of approximately $60,000. The second group consisted of a single contract botanist hired to record the understory and herbaceous layer at a cost of approximately $21,000. NRCS was tasked as the third group, with digging the soil pit, recording the profile and collecting the soil samples at an approximate cost of $60,000. The soil samples were then analyzed by the Northern Research Station's soil lab in Durham, New Hampshire. This lab was selected instead of the NRCS soil lab in Lincoln, Nebraska because previous soils analyzed from the nearby Forest Service Hubbard Brook experimental forest were also analyzed by the Durham lab. This decision for lab analysis not only maintained regional consistency, but also ensured future comparison of soils would be possible. The cost of the lab analysis was approximately $30,000.

For the Wammo study project, all overstory inventory data was recorded in a Panasonic Toughbook in the field. However, per plot cost estimates of $989.00 include time for data entry typically required because some of the soils plot information was recorded by hand and then entered digitally.

4.3 RESULTS

4.3.1 Traditional TEUI and Mapping Expenses

Since the TEUI Technical Guide manual requires a minimum of three transects across a proposed ELT with a minimum of 10 plots per transect, this yielded a need for 630 plots across the 21 ELTs. Cost per plot was approximately $989.00 including plot location layout and soil lab analysis. Table 4.1 shows the total cost to conduct the traditional method of ELT mapping would have been approximately $623,000 for the total 630 required plots across the Wammo watershed.

4.3.2 Stratified Random Sampling by LiDAR-derived Topographic Metrics

The stratified random sampling using LiDAR-derived topographic metrics described in Table 1 showed a need for 189 plots in the watershed at a cost of approximately $989.00 per plot including topographic metric analysis and soil lab analysis. This yields a total cost of approximately $187,000 for 189 plots in a 17,010 acre watershed. However, LiDAR is needed in order to achieve these results at a cost of approximate $2.00 per acre for 1-meter nominal spacing with an average point spacing of 3 points per square meter. The watershed was 17,010 acres at a cost of $2.00 acre for LiDAR, totaling approximately $34,000. The total cost to conduct the sampling if LiDAR is not already available using stratified Random Sampling based on LiDAR-derived topographic metrics was approximately $221,000 for a 17,010 watershed.

Table 4.1: The number of plots needed, the cost per plot, LiDAR acquisition costs per acre, and the total cost between the two TEUI methods within the Wammo watershed.

TEUI Approach	Number of plots	Cost per plot	Cost	LiDAR per acre	Total cost
Traditional TEUI methods	630	$989.00	$623,000	$0.00	$623,000
Stratified by LiDAR and SIE	189	$989.00	$187,000	$2.00	$221,000

4.4 DISCUSSION

Land managers need accurate ecological information to make sound decisions as well as map ecological classifications, however the cost of traditional mapping methods are prohibitive based on current U.S. Forest Service direction and budgets. The goal of using stratified random sampling based on LiDAR-derived topographic metrics was to achieve the results of traditional ecological mapping at a significantly lower cost. This results from this chapter showed that stratified random sampling using LiDAR-derived topographic metrics costs approximately $402,000 less, including the additional LiDAR acquisition costs, than the traditional TEUI approach. The advantages of stratified random sampling to establish plots for TEUI using LiDAR-derived topographic metrics establishes the possibility for the U.S. Forest Service to map ecological units at a feasible cost based on current budgets while increasing efficiency.

However, designing a TEUI field campaign based on stratified random sampling using LiDAR-derived topographic metrics may not be appropriate for every U.S. Forest Service National Forest. First, LiDAR data is necessary for this process. As described above, LiDAR acquisition would be approximately $0.50-$2.00 per acre depending on the location and the objectives of the LiDAR acquisition. LiDAR can be used for other applications such as previous land use history. For example, on the WMNF LiDAR was used to delineate the location of rock walls and cellar holes, which is required by the WMNF Forest Management Plan (USDA, 2005). There is also a cost associated with having GIS and remote sensing expertise to run SIE and process LiDAR compared to more traditional ways of TEUI work. This cost was included in the cost per plot in this study as those skills were already available and measurable. However, if the user does not possess those skills, or does not have the ability to acquire them, there could be a measurable cost increase with hiring or contracting for additional spatial data processing.

Stratified random sampling based on LiDAR-derived topographic metrics was effective for the WMNF because traditional mapping methods were cost prohibitive. Additionally, LiDAR allowed for more accurate topographic maps and terrain derivatives of areas on the WMNF with significant elevation gradients compared to traditional methods using aerial photos. For geographical areas lacking steep elevation gradients or vegetation, the traditional mapping methods using the TEUI Tookit may be more cost effective.

The WMNF is one of the few national forests without a NRCS soil map. This created a unique opportunity for the WMNF to take advantage of a national initiative for soils mapping, creating a partnership to share field costs with other agencies. In this project, NRCS shared the field costs for soil sampling and profile descriptions, while the WMNF covered the vegetation measurement costs and the soil chemistry analysis. However, the total cost of analysis for each agency was shown in the cost per plot. Most national forests starting a TEUI project campaign would need to cover the costs for the soils collection or find partner agencies for cost-sharing. Inventory and sampling of the remaining 783,000 acres of the WMNF is necessary to complete the TEUI mapping efforts and to determine whether similar results in cost-savings and accuracy can be reproduced or improved in other watershed areas.

4.5. CONCLUSIONS

The chapter concludes that stratified random sampling based on LiDAR-derived topographic metrics can reduce costs and increase efficiency for the U.S. Forest Service WMNF to map ecological units compared to the current traditional mapping methods. It is important for national forests seeking to start future TEUI projects to establish the objectives and the available resources before deciding if stratified random sampling best tool to use for TEUI mapping.

CHAPTER 5

CONCLUSIONS

5.1 INTRODUCTION

Land managers need ecological classification to assess and describe resource conditions, vegetation conditions, outcomes resulting from various management prescription scenarios, and communicate environmental effects of land management planning alternatives. The U.S. Forest Service's approach to ecological classification relies heavily on field data collection and verification of map unit delineations that is time-consuming and costly. However, there is a need to incorporate more ecological classification into the land management plans. Traditional mapping methods for ecological classification far exceed the capacity of the U.S. Forest Service's current budget. In order to justify new ecological classification mapping approaches, there needs to be significant evidence that new approaches will reduce costs and improve efficiency. The results from chapter 2 illustrated stratified random sampling based on LiDAR-derived topographic metrics as Soil Inference Engine data inputs was sufficient in capturing the environmental gradients required by the U.S. Forest Service ecological classification requirements. Additionally, 10 New Hampshire Natural sensitive indicator species were located and recorded in 16% of plots stratified by topographic metrics and parent material. This suggests and supports the new approach to ecological classification on the White Mountain National Forest (WMNF) as likely improving the accuracy and efficiency in delineating ecological units and locating the presence of nutrient rich areas.

The results from nonmetric multidimensional scaling (NMDS) in chapter 3 showed how soil properties and topographic metrics as environmental gradients correlated with understory species in ordination space. NMDS ordination explained 81.1% of the cumulative variation of understory species in three dimensions using soil properties and topographic metrics with a final stress value of 17.3 and a p-value of 0.04. NMDS results also suggested that understory species clustered distinctly within New Hampshire Natural Community types. These results support the idea that LiDAR-derived topographic metrics could assist in determining where community types are positioned across a landscape. Additional NMDS analysis also showed either soil chemistry or topographic metrics explained nearly equal amounts of cumulative understory species variation. The results from this objective highlights the use of topographic metrics as predictors of understory vegetation and likely community types which could be validated in other WMNF watersheds.

Finally, the primary challenge for ecological classification is reducing the cost of traditional unit mapping. Therefore, chapter 4 was to compare the cost of completing an ecological survey under TEUI using the traditional method as outlined by the TEUI Technical Guide to new approaches using stratified random sampling based on LiDAR-derived topographic metrics as inputs in the Soil Inference Engine. In both approaches, the mapping of the plots averaged approximately $989.00 per plot including soil chemistry analysis from U.S. Forest Service Laboratory. This yielded a total cost of approximately $623,000 for the traditional TEUI efforts compared to approximately $221,000 including the LiDAR acquisition required for stratified random sampling using topographic metrics and parent material. This chapter showed that stratified random sampling using LiDAR-derived topographic metrics reduced costs by approximately $402,000, including the additional LiDAR acquisition costs, than the traditional TEUI approach.

5.2 BROADER IMPLICATIONS

Additional research is needed to understand the application of stratified random sampling for the purposes of ELT/ELTp inventory and mapping across other WMNF watersheds. Since the results from chapter 2 suggested the stratified random sampling approach was successful in partitioning the watershed across significant environmental gradients and located sensitive indicator species of enrichment, it appears the same results would be achieved in other WMNF watersheds with similar soil types, elevation gradients, and forest cover types. The mean and standard deviation of topographic metrics within each New Hampshire Natural Community type suggests topographic metrics were adequate predictors for high-elevation and flood-plain areas but did not appear to be as distinct in mid-elevation, slightly sloping community types in well-drained soils. The results also suggest the sampling approach was successful in distributing plots across numerous soil series within and outside timber managed areas. The methods presented in chapter 2 greatly improved the accuracy, efficiency, and geographic extent of applying stratified random sampling based on LiDAR-derived topographic metrics beyond the study area. Finally, the study design outlined in objective 1 can also serve the U.S. Forest Service in their efforts to create ecological classification maps across the Northeastern U.S.

The results from chapter 3 warrant further investigation to evaluate the use of LiDAR-derived topographic metrics as model predictors for various soil properties and ecological classification across the Upper Wild Ammonoosuc (Wammo) watershed and subsequently the WMNF. NMDS results demonstrated LiDAR-derived topographic metrics and soil properties are important factors in explaining understory species variation. In addition, topographic metrics are potentially important predictors of NH Natural Community types. However, the results also show physical and chemical soil properties explain significant understory species variation. In this study, physical and chemical soil properties were measured in the field, however more study needs to evaluate if soil properties can be modeled using topographic metrics. Previous research at Hubbard Brook Experimental Forest in the WMNF, 16 kilometers southeast of Wammo watershed, had success predicting soils based on horizon sequences using LiDAR-derived topographic metrics (Gillin et al., 2015). Additional research could use the Wammo watershed inventory soils data to assess the accuracy of predicting soils based on horizon sequences using topographic metrics. Finally, additional research is needed to evaluate how well understory species matches the overstory vegetation present to consider whether existing vegetation represents potential natural vegetation.

Chapter 4 evaluated the new stratified random sampling approach in reducing costs for ecological classification compared to traditional mapping methods. Further investigations are warranted for U.S. Forest Service national forests seeking to start TEUI projects to establish the objectives and the available resources to determine if stratified random sampling and topographic metrics are the best tools to use for ecological mapping. As the WMNF continues ecological classification across the remaining 793,000 acres, it will be important to evaluate if the number of plots per watershed can be reduced from 172 using analysis of watersheds similar to Wammo watershed. Finally, additional LiDAR-derived topographic metrics may refine the inventory process, increase prediction accuracy, and ultimately reduce the cost of mapping ecological units even more.

LIST OF REFERENCES

Abrams, M.D., Sprugel, D.G. and Dickmann, D.I., 1985. Multiple successional pathways on recently disturbed jack pine sites in Michigan. *Forest Ecology and Management*, *10*(1-2), pp.31-48.

Attiwill, P.M., 1994. The disturbance of forest ecosystems: the ecological basis for conservative management. Forest Ecology and management, 63(2-3), pp.247-300.

Austin, M.P. and Heyligers, P.C., 1991. New approach to vegetation survey design: gradsect sampling. Nature conservation: cost effective biological surveys and data analysis, 5, pp.31-36.

Bailey, R.G., Jensen, M.E., Cleland, D.T. and Bourgeron, P.S., 1994. Design and use of ecological mapping units. Ecosystem management: principles and applications, 1, pp.95-106.

Bergeron, Y., Leduc, A., Harvey, B.D. and Gauthier, S., 2002. Natural fire regime: a guide for sustainable management of the Canadian boreal forest. Silva fennica, 36(1), pp.81-95.

Beven, K.J. and Kirkby, M.J., 1979. A physically based, variable contributing area model of basin hydrology/Un modèle à base physique de zone d'appel variable de l'hydrologie du bassin versant. Hydrological Sciences Journal, 24(1), pp.43-69.

Bourgeron, P.S., Humphries, H.C., DeVelice, R.L. and Jensen, M.E., 1994. Ecological theory in relation to landscape and ecosystem characterization. Jensen, ME, Bourgeron, PS (Eds), 2, pp.58-72.

Brohman, R.J., Bryant, L.D., Tart, D., Williams, C.K., Brewer, C.K., DiBenedetto, J.P., Schwind, B., Crowe, E., Girard, M.M., Gordon, H. and Sleavin, K., 2005. Existing vegetation classification and mapping technical guide: version 1.0. Gen. Tech. Rep. WO–67. US Department of Agriculture, Forest Service, Ecosystem Management Coordination Staff.

Brubaker, L.B., 1987. Forest disturbance and tree-ring analysis. In: Jacoby, G.C.; Hornbeck, J.W., comps. Proceedings of the international symposium on ecological aspects of tree-ring analysis. 17-21 August 1986. Tarrytown, NY. Washington, DC: U.S. Department of Energy. 101-118.

Carvell, K.L., 1986, May. Effect of past history on present stand composition and condition. In Proceedings, guidelines for managing immature Appalachian hardwood stands (pp. 28-30).

Cissel, J.H., Swanson, F.J. and Weisberg, P.J., 1999. Landscape management using historical fire regimes: Blue River, Oregon. Ecological applications, 9(4), pp.1217-1231.

Cleland, D.T., Avers, P.E., McNab, W.H., Jensen, M.E., Bailey, R.G., King, T. and Russell, W.E., 1997. National hierarchical framework of ecological units. Ecosystem management applications for sustainable forest and wildlife resources, 20, pp.181-200.

Colter, R.A., 2019. Ecological classification across the White Mountain National Forest using LiDAR (Doctoral dissertation, University of New Hampshire).

Cook, J.E., 1996. Implications of modern successional theory for habitat typing: a review. Forest Science, 42(1), pp.67-75.

Ellenberg, D. and Mueller-Dombois, D., 1974. Aims and methods of vegetation ecology. New York: Wiley.

Engstrom, R.T., Gilbert, S., Hunter Jr, M.L., Merriwether, D., Nowacki, G.J. and Spencer, P., 1999. Practical applications of disturbance ecology to natural resource management. Ecological stewardship: a common reference for ecosystem management, 2, pp.313-330.

Fraser, O., 2019. Quantifying rates of change in forest growth and soil chemistry across the White Mountain National Forest (Doctoral dissertation, University of New Hampshire).

Foster, C.H., 1998. Stepping back to look forward a history of the Massachusetts forest (No. 574.52642 S7).

Gilliam, Frank S., 2007. The Ecological Significance of the Herbaceous Layer in Temperate Forest Ecosystems, BioScience, 57(10), pp 845–858.

Gillin, C.P., Bailey, S.W., McGuire, K.J. and Prisley, S.P., 2015. Evaluation of LiDAR-derived DEMs through terrain analysis and field comparison. Photogrammetric Engineering & Remote Sensing, 81(5), pp.387-396.

Gillison, A.N., 1985. Transects or Gradsects in. Journal ol Environmental Managemenl, 20, pp.103-127.

Guisan, A., Broennimann, O., Engler, R., Vust, M., Yoccoz, N.G., Lehmann, A. and Zimmermann, N.E., 2006. Using niche-based models to improve the sampling of rare species. Conservation biology, 20(2), pp.501-511.

Kricher, J.C., 1998. A field guide to Eastern forests, North America (Vol. 37). Houghton Mifflin Harcourt.

Hengl, T., Rossiter, D.G. and Stein, A., 2003. Soil sampling strategies for spatial prediction by correlation with auxiliary maps. Soil Research, 41(8), pp.1403-1422.

Horsley, S.B., Bailey, S.W., Ristau, T.E., Long, R.P. and Hallett, R.A., 2008. Linking environmental gradients, species composition, and vegetation indicators of sugar maple health in the northeastern United States. Canadian Journal of Forest Research, 38(7), pp.1761-1774.

Jennings, M., Loucks, O., Glenn-Lewin, D., Peet, R., Faber-Langendoen, D., Grossman, D., Damman, A., Barbour, M., Pfister, R., Walker, M. and Talbot, S., 2004. Guidelines for describing associations and alliances of the US National Vegetation Classification. The Ecological Society of America Vegetation Classification Panel, 46.

Kimball, A.J., Witham, J.W., Rudnicky, J.L., White, A.S. and Hunter Jr, M.L., 1995. Harvest-created and natural canopy gaps in an oak-pine forest in Maine. Bulletin of the Torrey Botanical Club, pp.115-123.

Leak, W.B., 1982. Habitat mapping and interpretation in New England. Res. Pap. NE-496. Broomall, PA: US Department of Agriculture, Forest Service, Northeastern Forest Experiment Station. 28p, 496.

Lee, T.D., Barrett, J.P. and Hartman, B., 2005. Elevation, substrate, and the potential for climate-induced tree migration in the White Mountains, New Hampshire, USA. Forest ecology and management, 212(1-3), pp.75-91.

Lefsky, M.A., Cohen, W.B., Parker, G.G. and Harding, D.J., 2002. Lidar remote sensing for ecosystem studies: Lidar, an emerging remote sensing technology that directly measures the three-dimensional distribution of plant canopies, can accurately estimate vegetation structural attributes and should be of particular interest to forest, landscape, and global ecologists. BioScience, 52(1), pp.19-30.

Major, J., 1969. Chapter II Historical Development of the Ecosystem Concept. The ecosystem concept in natural resource management, p.9.

McCune, B., Grace, J.B. and Urban, D.L., 2002. Analysis of ecological communities (Vol. 28). Gleneden Beach, OR: MjM software design.

McCune, B. and Mefford, M.J., 2011. PC-ORD: multivariate analysis of ecological data; Version 6 for Windows;[User's Guide]. MjM software design.

McKay, J., 2008. Using a knowledge-based system to test the transferability of a soil-landscape model in northeastern Vermont (Doctoral dissertation, University of Florida).

McNab, W.H. and Avers, P.E., 1994. Ecological subregions of the United States, section descriptions.

Mueller-Dombois, D., 1965. Eco-geographic criteria for mapping forest habitats in southeastern Manitoba. The Forestry Chronicle, 41(2), pp.188-206.

Nowacki, G., 2003. Twins from separate mothers–soil scientists and ecologists. P. 1-2 *in* R. Davis and C. Talbot (eds.), 2003 National Cooperative Soil Survey Conference Proceedings, Committee 2: Ecological Interpretations & Principles, June 16-20, 2003, Plymouth, MA. USDA National Resources Conservation Service Supplemental Report [https://www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/16/nrcs143_016890.pdf]

Nowacki, G. and Sorokine, A., 2003. The limitations of applying single-resource taxonomies to ecological partonomies. P. 17-19 *in* R. Davis and C. Talbot (eds.), 2003 National Cooperative Soil Survey Conference Proceedings, Committee 2: Ecological Interpretations & Principles, June 16-20, 2003, Plymouth, MA. USDA National Resources Conservation Service Supplemental Report [https://www.nrcs.usda.gov/Internet/FSE_DOCUMENTS/16/nrcs143_016890.pdf]

Nowacki, G.J. and Abrams, M.D., 2008. The demise of fire and "mesophication" of forests in the eastern United States. *BioScience*, *58*(2), pp.123-138.

Nowacki, G.J. and Kramer, M.G., 1998. The effects of wind disturbance on temperate rain forest structure and dynamics of southeast Alaska. Portland, USA: US Department of Agriculture, Forest Service, Pacific Northwest Research Station.

Picket, S.T. and White, P.S., 1985. The ecology of natural disturbance and patch dynamics. Orlando (FL): Academic.

Reice, S.R., 2003. The silver lining: the benefits of natural disasters. Princeton University Press.

Robarge, W.P. and Fernandez, I.J., 1987. Quality assurance methods manual for laboratory analytical techniques. US Environmental Protection Agency, US Department of Agriculture, Forest Service.

Ross, D.S., Bailey, S.W., Briggs, R.D., Curry, J., Fernandez, I.J., Fredriksen, G., Goodale, C.L., Hazlett, P.W., Heine, P.R., Johnson, C.E. and Larson, J.T., 2015. Inter-laboratory variation in the chemical analysis of acidic forest soil reference samples from eastern North America. Ecosphere, 6(5), pp.1-22.

Rowe, J.S., 1980. The common denominator of land classification in Canada: an ecological approach to mapping. The Forestry Chronicle, 56(1), pp.19-20.

Seymour, R.S. and White, A.S., 2002. Natural disturbance regimes in northeastern North America—evaluating silvicultural systems using natural scales and frequencies. Forest Ecology and Management, 155(1-3), pp.357-367.

Shi, X., 2013. ArcSIE user’s guide. Available in:< http://www. arcsie. com/index. htm> Acessed on: Jun, 4.

Schoeneberger, P.J., Wysocki, D.A. and Benham, E.C. eds., 2012. Field book for describing and sampling soils. Government Printing Office.

Sperduto, D.D. and Engstrom, B., 1995. An Ecological Inventory of the White Mountain National Forest in New Hampshire–Fourth Year Summary Report. NH Natural Heritage Inventory, Department of Resources & Economic Development, Concord, NH.

Sperduto, D.D. and Kimball, B., 2011. Nature of New Hampshire. University of New Hampshire Press.

Swetnam, T.W., Allen, C.D. and Betancourt, J.L., 1999. Applied historical ecology: using the past to manage for the future. Ecological applications, 9(4), pp.1189-1206.

Tansley, A.G., 1935. The use and abuse of vegetational concepts and terms. Ecology, 16(3), pp.284-307.

Travis, M.R., Elsner, G.H., Iverson, W.D. and Johnson, C.G., 1975. VIEWIT: computation of seen areas, slope, and aspect for land-use planning. Gen. Tech. Rep. PSW-GTR-11. Berkeley, CA: Pacific Southwest Research Station, Forest Service, US Department of Agriculture: 70 p, 11.

Urban, D.L. and O'Neill, R.V., Shugart jr, HH, 1987. Landscape ecology. A hierarchical perspective can help scientist understand spatial patterns. Bioscience, 37, pp.119-127.

USDA Soil Conservation Service. 1994. Soil climate regimes of the United States. Lincoln, NE: National Soil Survey Center. 22 p.

USDA Forest Service. 2005. White Mountain National Forest: Land and Resource Management Plan. http://www.fs.fed.us/r9/forests/ white mountain/ (accessed 20 May 2018).

USDA, Soil Survey Division. 2006. Soil taxonomy: a basic system of soil classification for making and interpreting soil surveys. Natural Resources Conservation Service Agriculture Handbook 436. Washington, DC:

USDA Forest Service. 2008. TEUI-Geospatial Toolkit: An Operational Ecosystem Inventory Application. Presented at: 3rd Global Workshop on Digital Soil Mapping Utah State University-Logan, UT September 30-October 3, 2008.

Walker, D., Stelfox, J.B., Wasel, S. and Hebert, D., 1995, October. Natural disturbance regimes as templates for boreal forest harvest. In Bats and forests symposium (pp. 19-21).

Wang, L. and Liu, H., 2006. An efficient method for identifying and filling surface depressions in digital elevation models for hydrologic analysis and modelling. International Journal of Geographical Information Science, 20(2), pp.193-213.

Whitney, G.G., 1996. From coastal wilderness to fruited plain: a history of environmental change in temperate North America from 1500 to the present. Cambridge University Press.

Winthers, E., Fallon, D., Haglund, J., DeMeo, T., Nowacki, G., Tart, D., Ferwerda, M., Robertson, G., Gallegos, A., Rorick, A. and Cleland, D.T., 2005. Terrestrial ecological unit inventory technical guide. Gen. Tech. Rep. WO-GTR-68. Washington, DC: US Department of Agriculture, Forest Service, Washington Office, Ecosystem Management Coordination Staff. 245 p., 68.