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ERDC 6.2 Boreal Aspects of Ensured Maneuver (BAEM)

Estimating Forest Parameters Using Ground-Based Techniques with Implications for Airborne Data

Nancy E. Parker, Simone S. Whitecloud, Komi S. Messan,
Brian G. Quinn, Holly H. Vermeulen, Sally A. Shoop, and
Carissa F. Aoki

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Estimating Forest Parameters Using Ground-Based Techniques with Implications for Airborne Data

Nancy E. Parker, Simone S. Whitecloud, Komi S. Messan, Brian G. Quinn, Holly H. Vermeulen, and Sally A. Shoop

*Cold Regions Research and Engineering Laboratory
US Army Engineer Research and Development Center
72 Lyme Road
Hanover, NH 03755-1290*

Carissa F. Aoki

*Bates College
Environmental Studies
7 Andrews Road
Lewiston, ME 04240-6028*

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Abstract

Understanding forest structure and composition is critical to plan and execute troop and equipment movement in forested environments. This is especially important and challenging in denied (limited operational capability due to adversary control) areas. Existing mobility models do not adequately account for the heterogeneity (e.g., tree spacing, tree height, species, etc.) of forests. Knowledge of forest metrics over large scales has long posed a challenge within the forestry community. Previously, researchers have used ground-based and overhead remotely sensed data to attempt to quantify forest properties. But these methods have not produced the level of detail required for tactical mobility modeling.

Here we examine two of the forest properties critical to mobility (stem spacing and diameter) and review existing techniques to quantify these properties both in the field and remotely. From this review, we identify tree spacing as the key forest parameter that current methods cannot adequately estimate. To address this, we created two models using ground-based data to estimate tree spacing in forest plots. Using modeled relationships, it may be possible to extrapolate this critical forest parameter from aerial data. This report reviews past research, evaluates the ability to model forest density and tree spacing, and recommends a direction for future work.

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Contents

Abstract	ii
Figures and Tables.....	iv
Preface.....	v
Acronyms and Abbreviations.....	vi
1 Introduction.....	1
1.1 Background.....	1
1.2 Objectives.....	2
1.3 Approach.....	2
2 Forest Parameters Critical for Mobility.....	3
3 Approaches for Estimating Forest Parameters.....	4
3.1 Ground-based approaches.....	4
3.1.1 <i>Traditional field forestry methods</i>	4
3.1.2 <i>Digital image techniques</i>	6
3.1.3 <i>Terrestrial laser scanning (ground-based lidar)</i>	8
3.2 Remote methods.....	8
3.2.1 <i>Photogrammetry</i>	8
3.2.2 <i>Satellite imagery</i>	9
3.2.3 <i>Lidar</i>	11
3.2.4 <i>Synthetic-aperture radar</i>	12
4 Limitations in Existing Techniques.....	13
5 Model Formulation.....	14
5.1 Data.....	14
5.2 Establishing relational models.....	15
6 Results.....	20
7 Conclusions.....	23
8 Future Recommendations.....	24
8.1 Comparing ground-based and aerial data.....	24
8.2 Implications of tree distribution.....	24
8.3 Future work.....	25
References.....	26
Report Documentation Page	

Figures and Tables

Figures

1	Panchromatic satellite image (SAT, 1 m resolution) from a forested area in Enfield, New Hampshire, compared to an image collected from a camera mounted on a UAS (<i>inset</i> , 1 cm resolution).....	11
2	Example photos of “low” (<i>left</i>) versus “high” (<i>right</i>) density plots from the New Jersey Pine Barrens	14
3	Box plot for the mean differences between forest density and forest volume. The <i>a</i> 's indicate no statistical differences at $\alpha = 0.05$ with the F statistics $F_{3,20} = 1.68$ and $F_{3,20} = 1.25$ for the forests' relative density and volume, respectively	20
4	Estimate of tree density (RDC) for both datasets given the nearest neighbor distance (NND). The <i>black lines</i> are equation (4) RDC_p , and the <i>black points</i> are the data shown in Tables 3 and 4. R^2 represents the coefficient of determination, showing that equation (4), with only NND, is the better representation of the tree spacing.....	21
5	Contour plots of the density (RDC) of (a) Dataset 1 and (b) Dataset 2 given both the <i>DBH</i> and the <i>NND</i> (equation [5]). The <i>black diamonds</i> represent individual plots described in Tables 3 and 4. The <i>gray scale</i> represents the relative density estimated by equation (5). R^2 is the coefficient of determination showing that NND is the controlling factor in tree spacing and that the inclusion of BHD does not improve the prediction	21

Tables

1	Summary of techniques for characterization of forested environments.....	5
2	Pertinent forest parameters collect by Aoki et al. (2018). The second column lists those used in this study.....	15
3	Dataset 1 plot parameters measured in the field and estimated Curtis relative density (<i>RDC</i>). Data are from randomly selected plots from four forest types that were shown to be statistically identical in volume and density (Fig. 3), thus the data are pooled. None of the plots within Dataset 1 were infested by the southern pine beetle	17
4	Dataset 2 plot parameters measured in the field and estimated Curtis relative density (<i>RDC</i>). Forest type was grouped based on statistical similarity and so is not listed in the table. All plots within Dataset 2 were infested by the southern pine beetle.....	18
5	Equation (4) and (5) parameters values used in Figs. 4 and 5.....	19

Preface

This study was conducted for the Assistant Secretary of the Army for Acquisition, Logistics, and Technology under project number 465395, “Bo-real Aspects of Ensured Maneuver (BAEM),” which is part of the U.S. Army Engineer Research and Development Center (ERDC) 6.2 Remote Assessment of Infrastructure for Ensured Maneuver (RAFTER) Program managed by Ms. Danielle Whitlow.

The work was performed by the Biogeochemical Sciences Branch (CEERD-RRN), the Signature Physics Branch (CEERD-RRD), and the Engineering Resources Branch (CEERD-RRE) of the Research and Engineering Division (CEERD-RR), U.S. Army Engineer Research and Development Center, Cold Regions Research and Engineering Laboratory (ERDC-CRREL). At the time of publication, Dr. Justin Berman was Chief, CEERD-RRN; Dr. Andrew Niccolai was Chief, CEERD-RRD; and Mr. Jared Oren was Acting Chief, CEERD-RR. The Deputy Director of ERDC-CRREL was Mr. David B. Ringelberg, and the Director was Dr. Joseph L. Corriveau.

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COL Ivan P. Beckman was Commander of ERDC, and Dr. David W. Pittman was the Director.

Acronyms and Abbreviations

3-D	Three-dimensional
ANOVA	Analysis of Variance
CRREL	Cold Regions Research and Engineering Laboratory
DBH	Diameter at Breast Height
DEM	Digital Elevation Model
EMT	Enhanced Thematic Mapper
ERDC	U.S. Army Engineer Research and Development Center
GEOBIA	Geographic Object-Based Image Analysis
GLAS	Geoscience Laser Altimeter System
HT	Dominant height
ICESat	Ice, Cloud, and Land Elevation Satellite
MD	Arithmetic Mean
MODIS	Moderate Resolution Imaging Spectroradiometer
NATO	North Atlantic Treaty Organization
NND	Distance to the Nearest Neighbor
NRMM	NATO Reference Mobility Model
PDE	Plotless Density Estimators
QMD	Quadratic Mean Diameter
RDC	Curtis's Relative Density
SAR	Synthetic-Aperture Radar
SBA	Stand Basal Area
TLS	Terrestrial Laser Scanner
TM	Thematic Mapper
UAS	Unmanned Aerial System
VAT	Variable Area Transect

1 Introduction

1.1 Background

Unimpeded mobility ensures warfighter safety and promotes mission success. The ability to predict, detect, and avoid obstructions is critical for assured mobility (Church 2007) but requires specialized tools for terrain analysis across a variety of environments. The North Atlantic Treaty Organization (NATO) Reference Mobility Model (NRMM) is a simulation tool to estimate how well a vehicle can move over terrain (Bradbury et al. 2016). Developed by the U.S. Army Tank Automotive Research, Development, and Engineering Center in the 1960s, it has been continuously updated since its conception—the most recent version being the NRMM 3.0. Currently, there is a plan to develop a Next Generation NRMM to address limitations of the current tool iteration, such as its reliance on in situ soil measurements, lack of capability for three-dimensional (3-D) analysis, and limitation to wheeled/tracked vehicles (Dasch and Jayakumar 2018).

The NRMM allows for a variety of input terrain data that can be changed based on the scenario. These include parameters like soil type, slope, surface roughness, and depth to bedrock. Forested areas, in particular, can be challenging to characterize, as they vary widely in terms of structure and composition. In the NRMM, vegetation is considered an obstacle and is input in terms of tree stem diameter and spacing (Haley 1979; Bradbury et al. 2016). The model uses average stem spacing, and trees are binned into nine size categories determined by the user (Haley 1979; Bullcock 1994). This type of input information is not readily available at the global scale and is particularly difficult to obtain in denied environments. Additionally, the NRMM does not account for vegetation that is heterogeneous across a landscape. Forested areas are treated as homogeneous in terms of vegetation density, size, and configuration. For these reasons, it is prudent that a more accurate and detailed set of vegetation input data be available for the NRMM.

Understanding forest characteristics, primarily tree spacing and forest density and stem diameter, is essential to both troop and vehicle mobility and maneuverability. Remotely estimating forest parameters has long been a challenge in forestry. Traditional forestry techniques involve intri-

cate and thorough field measurements carried out on-site. The level of detail and resolution acquired simply has not been reproduced using remote techniques. Forest measurements are labor intensive and introduce subjectivity (Hyyppä et al. 2000; Vastaranta et al. 2009, 2015). Establishing a method to collect these data remotely while retaining the high-resolution measurements and accuracy of on-the-ground methods is highly desirable.

1.2 Objectives

The objectives of this work are to examine the critical factors that affect mobility in forested environments and to identify the methods for quantifying them in the field and remotely.

1.3 Approach

To meet the above goals, we

1. identified critical factors that impact mobility;
2. reviewed existing techniques (manual and remote) to estimate these critical factors; and
3. developed two models to infer tree spacing, a key parameter that cannot be quantified through existing techniques.

Following this approach, our review establishes limitations to existing techniques for estimating key parameters in forests and from there provides a new, viable solution through mathematical modeling.

2 Forest Parameters Critical for Mobility

The complexity of forests directly impacts Soldiers' and vehicles' ability to move from one point to another. The homogenous nature of the land classes used in the NRMM input data does not capture the heterogeneity of tree growth within and among species and how that impacts mobility. To improve existing modeling and route-planning capabilities, one must consider several factors, ranging from the individual tree level to the entire forest. A tree obstructs troops and vehicles depending on where it stands. Beyond location, tree size (e.g., tree height and size of the trunk) can also influence mission success. The height to the first branch is of particular interest in mobility (S. Shoop, pers. comm.), given that it limits the height of vehicles capable of maneuvering through an area. Additionally, tree height in conjunction with diameter at breast height (DBH) can estimate tree volume. DBH is the standardized measurement foresters use to estimate tree size, defined as the diameter of a tree measured at 4.5 ft (~1.37 m).

Tree density (trees per unit area) is also important to consider, particularly in relation to tree size. For example, a forest with large trees but low density will be easier to move through than a dense forest with small trees. However, this example assumes that trees are evenly spaced, which is rare in the natural world. It is therefore critical to examine the spacing of trees within the forest. For example, two forest plots with the same density may be laid out differently (e.g., one could be evenly spaced while the other consists of clumps of trees, see section 3.1.1). The arrangement of trees directly impacts mobility—it would potentially be easier to avoid obstacles in the clumped forest rather than the evenly spaced forest. Finally, the identification of tree species can be very useful, as species type (when considered with tree age) is often linked to height, spacing, DBH, and density.

Different forest types will vary. The following section describes how these forest parameters are derived, both on the ground and remotely. While this report focuses on forests overall, it will be critical to investigate these parameters (and how to derive them) in various environments.

3 Approaches for Estimating Forest Parameters

This section identifies and reviews techniques for quantifying the factors critical for mobility, identified in section 2. For the purpose of this report, we have grouped the techniques in two categories: ground based (traditional forestry and digital images) and remote (aerial and space-borne). Table 1 summarizes these techniques and includes applicable references, measured parameters, the scale of applicability, and other important considerations.

3.1 Ground-based approaches

3.1.1 Traditional field forestry methods

Traditional forestry field techniques to calculate forest stand parameters include a multitude of measurements. Measurements are primarily at the individual tree or plot level and then scaled up to represent the whole stand.

Important parameters measured from individual trees include tree diameter, tree height, tree basal area (cross-sectional area at breast height), tree form (i.e., branching pattern), and tree volume (Reid and Stephen 1999). Measurements use simple instruments and include rigorous and careful data collection, making it a labor-intensive process.

Stand basal area (SBA) is an important parameter for estimating stand volume. Several methods estimate the SBA of a forest. These include summing the tree basal areas; using an optical method to assess basal area; or using the spacing factor method, which is simply the average distance between trees divided by the average stem diameter (Reid and Stephen 1999). SBA is then used to estimate stand volumes by using established relationships between plot area and tree height. Selection bias and measurement error are variable when taking SBA and other absolute measures of forest attributes, but they typically have much less effect compared to that of recording and omission errors (Williams and Baker 2010).

Table 1. Summary of techniques for characterization of forested environments.

Technique	Type	Reference(s)	Parameters Measured	Accuracy (relative)	Scale of Applicability	Considerations
Traditional field forestry measurements	Ground based	Reid and Stephen (1999)	Tree diameter, tree height, stand basal area (SBA), tree form, tree volume	High degree of accuracy is possible	Plot	Labor-intensive and require intricate sampling techniques, measurements can be subjective
Laser camera/image interpretation software	Ground based	Melkas et al. (2008); Vastaranta et al. (2009); Varjo et al. (2006)	Tree diameter and volume	Accuracies comparable to traditional methods	Plot	Manually intensive, only applicable at the plot scale
Laser-relascope	Ground based	Vastaranta et al. (2009)	Tree diameter	Less accurate than digital-camera-based methods	Plot	Manually intensive, only applicable at the plot scale
Lidar/TLS	Ground based	Vastaranta et al. (2009, 2015); Yang et al. (2016)	Tree location, tree height, tree diameter, stem curves	Highly accurate, comparable to traditional methods	Plot	Expensive, requires expertise for running equipment and processing data
Photogrammetry	Remote	Kovats (1997); Miller et al. (2000); Hapca et al. (2007)	Tree location, tree height, distance between trees	As accurate as, or superior to, traditional measurements	Plot or larger	More cost-effective than traditional or lidar methods
Satellite imagery	Remote	Hansen et al. (2003); Huang et al. (2001); Wagner et al. (2018); Mallinis et al. (2004); Ripple et al. (1991); Ardo (1992); Woodcock et al. (1994); Trotter et al. (1997); Ploton et al. (2012)	Percent tree cover, tree density, basal area, biomass, volume	High range of accuracies, dependent on imagery resolution	Landscape to global	Requires high-resolution imagery, may not generate high-resolution datasets, more applicable to homogenous forest types
Lidar	Remote	Yang et al. (2016); Brandtberg et al. (2003); Rahman et al. (2009); Dassot et al. (2011); Tweddale et al. (2014)	Tree location, tree height, crown width, crown base heights	Highly accurate, comparable to traditional methods	Plot to landscape	May have difficulty accurately capturing details at the branch level, dependent on leaf-on/leaf-off conditions
Spaceborne lidar	Remote	Nelson et al. (2009)	Tree volume and biomass	Within 10% of ground-based data	Landscape to global	High collection costs, large quantities of data
Synthetic-aperture radar (SAR)	Remote	Karjalainen et al. (2012); Holopainen et al. (2010)	Stem volume, basal area, tree diameter, canopy height	Less accurate than lidar	Plot	High collection costs, processing is challenging

Conversely, a number of plotless density estimators (PDE) use distance measurements in place of quadrats to estimate forest density. These estimators significantly reduce work associated with other traditional forestry techniques and can be applied in situations where it is difficult to create plots or where low impact is required (White et al. 2008). In a study comparing 24 different PDE, White et al. (2008) favored the variable area transect (VAT) method because of its robustness and ease of use. The VAT method applies a transect of fixed width and variable length, making the assumption that stems are randomly distributed.

However, ecological mathematicians do not agree whether trees are randomly dispersed across the landscape or clustered, this determination having implications for model development and selection (Cogbill et al. 2018). Cogbill et al. (2018) compared the four most common PDE (Cottam, Pollard, Morisita, and Shanks) by using simulated spatial patterns, 14 mapped modern stands, and historical public land surveys. While Pollard PDE is the most common method in the literature, it lacked accuracy for clustered spatial patterns, as did the Cottam. Cogbill et al. (2018) recommend the Morisita as an alternative when forests are clustered; but they note that it is sensitive to small sample sizes and, therefore, recommend using either the Pollard or the Cottam in conjunction with the Morisita PDE. It is critical to note that Cogbill et al. (2018) evaluated stand density and not actual distance between trees (see comments in section 8).

Though used for decades, traditional forestry methods are labor-intensive and require intricate sampling techniques. Additionally, the required measurements are made on-site. As a source of information for mobility models, these techniques are not ideal. Thus, many have explored the option of obtaining critical forest parameters through remote technologies.

3.1.2 Digital image techniques

Previous efforts have explored the option of extracting from terrestrial (landscape) photos distances between objects directly. This would allow distance estimates without actually being inside the forest and without the need for traditional field forestry techniques. In a previous effort to classify global vegetation types, the Army Engineer Research and Development Center's Cold Regions Research and Engineering Laboratory (ERDC-CRREL) developed the Global Natural Background Image Database, a collection of 1600 on-the-ground photos, many within or on the edge of forests (Parker et al. 2017). In an exploratory study, they used supervised

classification techniques to identify vegetation features but concluded that extracting quantitative metrics from terrestrial images was not possible without an embedded scale (Waldrop et al. 2018, Hart et al. 2018).

Thus, studies using terrestrial images to improve the accuracy of traditional forestry field methods have used a combination of digital cameras and laser distance measurement devices to collect forest measurements (Juujärvi et al. 1998; Melkas et al. 2008). Melkas et al. (2008) used a laser camera (digital camera with an integrated laser line generator) to gather tree diameters with a greater than 50% success rate. They used image interpretation software to extract diameter measurements (automatic method) with an option for manual adjustments (semiautomatic method). They found that the success rate averaged 57.4% across species when using the automatic method and 75.8% when using the semiautomatic method. Varjo et al. (2006) used only a digital camera and a reference marker stick and also used image interpretation software to estimate stem diameter and volume. Unfortunately, they found that accuracies depended on image quality, which varied with the weather and the time of day. However, their tree diameter and volume estimates were comparable to estimates using traditional techniques.

Vastaranta et al. (2009) compared several laser-based techniques, including the laser-camera, laser-relascope (a combination of a relascope and a dendrometer) and a Terrestrial Laser Scanner (TLS, described in section 3.2.3) for estimating forest parameters. They found that the laser-camera and TLS produced similar accuracies (8.3–8.5 mm) in measuring tree diameter and that the laser-relascope was slightly less accurate (14.3 mm). They concluded that hand-held laser-based systems are sufficient for measuring tree and stand characteristics and are more cost-effective. However, since this study (2009), TLS systems have advanced monumentally (see section 3.1.3).

Approaches using digital camera techniques overall have resulted in datasets that are comparable in accuracy to traditional methodologies. However, they remain manually intensive and require the measurements to be taken on-site. Therefore, measurements from these techniques cannot be obtained remotely and so do not meet our overall objective—to acquire measurements in denied areas.

3.1.3 Terrestrial laser scanning (ground-based lidar)

Lidar has been used extensively in forest monitoring and mapping due to its ability to estimate forest attributes from dense 3-D point clouds. Lidar systems can be ground based, aerial, or spaceborne.

Ground-based lidar methods include TLS and Mobile Laser Scanning, which enable forest mapping at the individual tree level beneath the canopy. A TLS consists of a scanner atop a tripod, measuring the 3-D locations of objects within reach (Vastaranta et al. 2015). It produces a dense point cloud from the surrounding trees. This point cloud can then be used to extract variables of interest. Yang et al. (2016) propose a method using TLS point-cloud data to isolate individual trees and to estimate structure metrics. They used TLS point clouds to collect information on tree location, DBH, and tree height.

One of the advantages of ground-based lidar, such as TLS, is that it can retrieve information at the ground level from within the forest. This information can be incredibly important for mission planning. For example, the forest understory might contain obstructions to mobility that cannot be detected remotely. Other considerations for route-planning include potential non-vegetative obstacles (e.g., rocks and landforms). However, ground-based lidar is not capable of collecting aerial remote measurements, which is the required to meet our objective. Alternatively, aerial lidar techniques do have the capability to collect many of the measurements critical for characterizing forests remotely (see section 3.2.3).

3.2 Remote methods

To reduce the high-cost, labor-intensive manual collection of forest attributes, many researchers have explored collecting these measurements remotely. Our objective, to characterize forest parameters in denied areas, requires remote methods. Here we outline the advantages and disadvantages of a number of remote approaches.

3.2.1 Photogrammetry

While ground-based techniques are useful, most forest inventory techniques have evolved to an aerial platform, including photogrammetry and aerial lidar. Photogrammetry is the science of extracting measurements

from photos. Its simplest application is to estimate the distance between points within a single image, but photogrammetric analysis can also create highly accurate 2- and 3-D models from overlapping images. Forest management, for example, has used photogrammetry to derive tree height (Kovats 1997; Miller et al. 2000) by either (1) reconstructing 3-D forest models or digital elevation models (DEMs) or (2) deriving elevation differences using overlapping photos calibrated to direct measurements from permanently established ground control points (Miller et al. 2000).

Current aerial digital photogrammetric methods typically use specialized software to generate high-density point clouds through matching features between overlapping aerial photos. This technique relies on acquiring images of an area of interest from directly overhead in a grid pattern such that all features within the scene are captured from multiple angles. Point clouds can then be processed into measurable high-resolution data products, including georeferenced orthophotos, DEMs, and 3-D models. For example, high-resolution photos collected via a digital camera mounted on an UAS can be converted to orthophotos and DEMs, which can then be subjected to supervised classification techniques to automatically identify trees and their location. The resulting output is then used to estimate quantitative metrics, specifically the distance between trees, by using a distance matrix function. Alternatively, photogrammetric techniques have been applied horizontally at the tree level (Hapca et al. 2007). Hapca et al. (2007) demonstrate that 3-D stem profiles can be generated using two overlapping digital photos collected from a camera mounted on a tripod in the field. One of the limitations of the photogrammetric technique, and others detailed here, is the scale of application. These techniques are primarily useful at a small, plot-level scale. Satellite imagery covering larger areas has been used to estimate forest parameters on a larger landscape and even global scale.

3.2.2 Satellite imagery

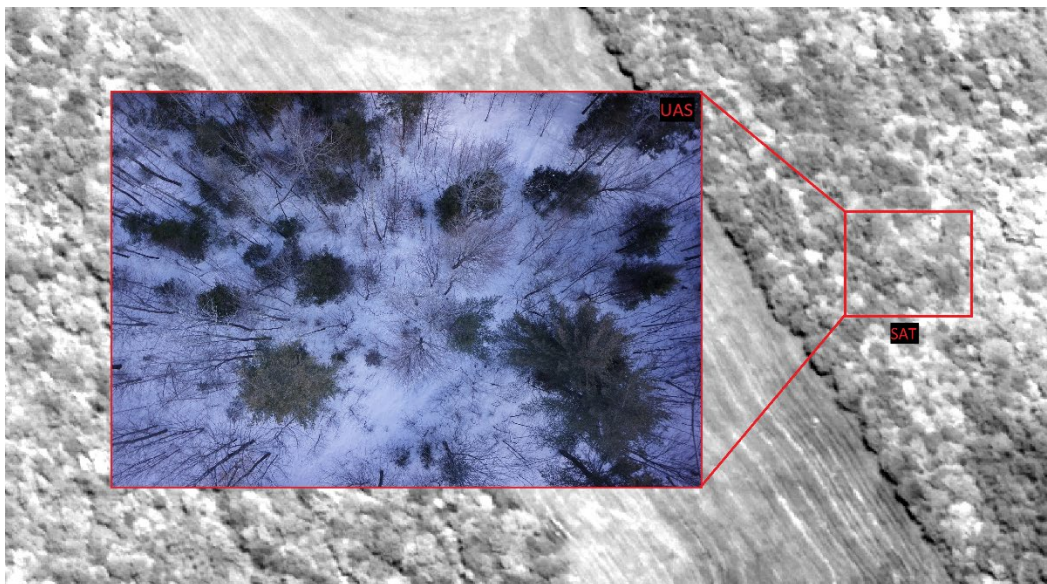
Satellite imagery provides information on larger scales and has become widely obtainable in high-resolution formats. On the global scale, satellite imagery has been used to estimate percent tree cover. Hansen et al. (2003) used Moderate Resolution Imaging Spectroradiometer (MODIS) 500 m data to generate a new global dataset of tree cover. They applied the continuous fields of vegetation cover algorithm to the MODIS datasets to classify vegetation within the pixels. Similarly, Huang et al. (2001) used high-resolution Landsat 7 ETM+ (Enhanced Thematic Mapper) images paired

with digital orthophoto quadrangles to establish relationships between tree canopy data and the satellite imagery. Recently, Wagner et al. (2018) used high-resolution WorldView-2 satellite images to detect individual tree crowns in tropical environments. They successfully detected 80% of the individual tree crowns in their study area and were even able to detect tree species.

Satellite imagery has also been used to estimate more specific forest parameters, such as tree density and basal area; but a study by Mallinis et al. (2004) concludes that, while using satellite imagery alone may be appropriate for homogeneous forests, heterogeneous environments are better surveyed using ground-based or aerial (photogrammetry) methods. Mallinis et al. (2004) evaluated the use of a single Landsat 5 TM (Thematic Mapper) image for estimating forest density, basal area, dry biomass, and volume. They found that the spatial resolution of the satellite imagery was not high enough to pull out the heterogeneity of the forest type they were interested in (Mediterranean). However, satellite imagery has been useful for determining forest volume for homogeneous forests elsewhere (Ripple et al. 1991; Ardo 1992; Woodcock et al. 1994; Trotter et al. 1997). Similarly, Ploton et al. (2012) were able to predict stand structure parameters for a tropical evergreen forest from Google Earth images (2×2 m resolution) with an error comparable to that using commercial IKONOS satellite images. Textural ordination, a method to characterize image texture, was applied to the images of 125 m by 125 m square plots to estimate parameters, including crown diameter, tree diameter, tree density, and aboveground biomass.

Vegetation indices such as Normalized Difference Vegetation Index and Perpendicular Vegetation Index are calculated from multispectral satellite images and have proven useful for estimating forest metrics from satellite imagery on large scales. Although satellite imagery has been useful to estimate landscape and global-scale forest parameters, it is rarely high-enough resolution to accurately identify parameters at the individual plot level. Figure 1 compares images collected from a satellite and a camera mounted on a UAS (inset). The superiority of the UAS-mounted camera in its ability to detect individual trees, and even some understory characteristics, is clear. Thus, to obtain accurate measurements, high-resolution orthophotos and lidar data are the preferred data sources.

Figure 1. Panchromatic satellite image (*SAT*, 1 m resolution) from a forested area in Enfield, New Hampshire, compared to an image collected from a camera mounted on a UAS (*inset*, 1 cm resolution).



3.2.3 Lidar

As discussed in section 3.1.3, ground-based lidar, or TLS, has many advantages for obtaining information beneath the forest canopy. Here we examine aerial lidar to obtain remote measurements of forest parameters. Though ground-truthing data is needed to calibrate models generated from lidar point clouds, a prominent advantage of the technology is that no other ground measurements are necessary for calibration. Aerial lidar data has been used to estimate many different forest parameters, including tree locations, heights, crown widths, and crown base heights (Yang et al. 2016). This has even expanded to the individual tree level (Brandtberg et al. 2003; Rahman et al. 2009). Aerial lidar does, however, have difficulty accurately capturing details at the branch level (Dassot et al. 2011).

Similar to the Vastaranta et al. (2015) study described in section 3.1.3, Tweddale et al. (2014) used aerial lidar to develop a model that estimated the location of individual trees and their height in an effort to reduce the need for field-based inventories for management of military installations. The Tweddale et al. (2014) model for finding tree stem locations combined aerial lidar and multispectral data to parameterize a forest growth model. Their assessment used variables like stem locations, tree height, DBH, and crown length. The model generated was accurate up to 98% of the time but varied based on tree species.

The first spaceborne lidar system was the Geoscience Laser Altimeter System (GLAS) carried on the Ice, Cloud, and Land Elevation Satellite (ICESat) (Wulder et al. 2012). Metrics generated from GLAS data allow for large-area estimates of forest parameters like volume, biomass, and carbon within 10% or less of ground-based systems (Boudreau et al. 2008; Nelson et al. 2009). The Nelson et al. (2009) study, for instance, found that volume estimates generated from GLAS observations were within 1.1% of their ground-based data. In addition, ICESat-II launched in September 2018 as a follow-up to the original system, with hopes of improving the accuracy even more. Although lidar has many applications for forest inventory, the primary drawbacks of these systems are the high collection costs, the large quantities of data, and the expertise needed to interpret and manipulate point-cloud datasets.

3.2.4 Synthetic-aperture radar

In more recent years, researchers have adopted synthetic-aperture radar (SAR) to estimate plot-level forest variables (Holopainen et al. 2010; Karjalainen et al. 2012). SAR, like other forms of radar, transmits pulses of radio waves, recording the echo of each pulse and producing a two-dimensional reconstruction of an object. SAR produces higher-resolution reconstructions than other types of radar because it uses the flight path of the platform to simulate an antenna rather than the traditional beam-scanning method. SAR images have been useful for forest inventory studies because image collection is not weather dependent—SAR can penetrate clouds—and can produce images over large areas in short periods of time (Karjalainen et al. 2012). Karjalainen et al. (2012) used TerraSAR-X stereo SAR images to extract elevation data. TerraSAR-X is a German satellite equipped to collect SAR images. The point clouds produced by the SAR images enabled estimation of forest variables. Using the nearest neighbor approach, they used field data as observations and features derived from the SAR images as predictors. Using this method, they found that forest variables (stem volume, mean basal area, mean DBH, and mean forest canopy height) were 14%–34% accurate. Though these percentages may appear low, they are quite impressive at the plot-level scale in the boreal forest environment, particularly for remote-sensing techniques (Karjalainen et al. 2012).

4 Limitations in Existing Techniques

In previous sections, we identified forest parameters important to include in the NRMM: tree location, size (diameter and height), tree density, spacing, and species. Section 3 reviewed existing capabilities and their ability to estimate and quantify these forest parameters, both on the ground and remotely. Additionally, we briefly explained each technique's limitations. Of the critical forest parameters we identified, the majority can be estimated with some level of confidence (Table 1). However, estimating tree spacing, or distance between trees, is not easy; and methods to do so have significant gaps.

Many remote methods are capable of estimating forest density (e.g., lidar, satellite imagery), but knowledge of trees per unit area does not necessarily indicate how trees are organized within a forest. For example, when comparing two areas of the same size (e.g., two forest plots), the same tree density could result in very different tree spacing. This is due to the organization of trees within a plot (e.g., clustered versus evenly spaced). Therefore, simply knowing forest density is not enough to make an informed decision regarding mobility. It is difficult to distinguish individual trees in satellite images (Figure 1), and that is likely why forest density is a commonly estimated parameter while spacing is not.

The NRMM allows estimates of tree stem spacing and diameter, but each stem size class is assigned a consistent average stem spacing (Haley 1979; Bullock 1994) and therefore assumes heterogeneity within size classes. This, however, is often not the case in reality—natural forests most often contain trees of differing ages and diameters. Plantations (planted forests) usually consist of trees with the same spacing and DBH. Therefore the NRMM should be updated to account for forests' natural variability in tree size and spacing.

To address this deficiency in existing methods, we identified the potential to extrapolate this information from aerial (e.g., photogrammetry and satellite-derived) data. To explore this method, we used a unique set of ground-based data to establish relationships between key forest characteristics. From there, we used these relationships to generate two models that can be used to relate ground-based data to aerial data. The following sections outline our methods, results, conclusions, and future recommendations.

5 Model Formulation

5.1 Data

We leveraged previously collected plot measurements from the work of Aoki et al. (2018) to develop the relational models. This data is unique in that it includes measurements of distance between trees, a metric that is typically not of interest to foresters (due to their primary interest in timber production and thus forest volume) and so is rarely included in traditional forestry measurements. Aoki et al. (2018) developed an innovative sampling method to quantify the distance between trees, which ranged from low to high density (Figure 2). In the summers of 2013 and 2014, Aoki et al. (2018) established 48 randomly selected plots, 50 × 100 m in size. The plots each contained three parallel 50 m transects spaced 50 m apart along which distance between trees was determined. At every 10 m, a focal pine tree was identified as the pine closest to the 10 m point along the transect. In some cases, the same tree was selected as the focal tree because it was the closest individual to two of the 10 m points. Distance to the nearest neighbor and second nearest neighbor from this focal pine was measured for both pine and hardwood neighbors. The dataset includes a wide range of additional measurements, including basal area, DBH, and tree height (Table 2), that were used to develop our models. For the purpose of this study and the simplicity of the models, we did not use tree crown base height. However, the addition of this parameter in future modeling efforts could further constrain mobility corridors based on tree height.

Figure 2. Example photos of “low” (*left*) versus “high” (*right*) density plots from the New Jersey Pine Barrens.



Table 2. Pertinent forest parameters collect by Aoki et al. (2018). The second column lists those used in this study.

Parameter Collected	Used in This Study
Diameter at Breast Height (DBH)	Yes
Tree height	Yes
Crown base height	No
Distance to the nearest neighbor (NND)	Yes
Stand basal area (SBA)	Yes

The plots are within the New Jersey Pine Barrens and are dominated by *Pinus rigida* (pine) but also contain broadleaf species (birch and aspen in the interior, oaks in the barrens) intermixed with conifers. For this study, we refer to two forest types within the upland habitat (conifer and mixed conifer/broadleaf) and two within the wetland habitat (conifer and mixed) of the Pine Barrens.

Following Aoki et al. (2018), we split the plots into two categories: *uninfested* and *infested* by the southern pine beetle, *Dendroctonus frontalis*. As we found no significant difference between the two, the uninfested plots were used as the first calibration dataset (e.g., Dataset 1), and the infested plots were used as the second calibration dataset (e.g., Dataset 2).

5.2 Establishing relational models

For this study, we were primarily concerned with estimating tree spacing, or distance between trees. To examine this parameter, we explored how changes in tree spacing affect overall calculations of forest density. To do so, we developed two models to predict forest density by using the aforementioned dataset collected by Aoki et al. (2018). Because the data for the four different habitats were not significantly different (see section 6), the data were pooled into one group. Plots spanned four forest types in both datasets. For Dataset 1, we divided plots evenly among forest types, while we pooled Dataset 2. We determined that the four forest types within Dataset 1 could be pooled by running a one-way analysis of variance (ANOVA) at $\alpha = 0.05$. We were able to confidently group the data accordingly after evaluating the data and establishing that it was not significantly different across forest type at the level of $p < 0.05$.

From the original Aoki et al. (2018) dataset, we used DBH; tree height, SBA; and NND, which is the measurement we used to describe “distance between trees.” The NND was determined through the focal pine method, described

in section 5.1. Aoki et al. (2018) details collection of these measurements. It is important to note that Aoki et al. (2018) made multiple estimations of SBA within each plot and so, for our model development, we assumed that the average of all SBA for an individual plot was the SBA for that plot.

Our study calculated the stand density for each plot by using Curtis's Relative Density (*RDC*) (Curtis 1982):

$$RDC = \frac{SBA}{\sqrt{QMD}} \quad (1)$$

Relative stand density is an expression of an individual stand density relative to the standard condition (Curtis 1982). The *RDC* accounts for variability in trunk size by using the quadratic mean diameter (*QMD*), which includes the sample variance and the arithmetic mean:

$$QMD = \sqrt{\left(\frac{N-1}{N}\right)S_D^2 + MD^2}, \quad (2)$$

where

S_D^2 = the sample variance of the SBA,

N = the number of points from which SBA was estimated within a plot, and

MD = the arithmetic mean of the SBA.

For simplicity of the analysis, and because the trees in this study are all pines, we assumed that each tree has a conical form, and calculated tree volume using the formula for a circular cone's volume (i.e., $V = (h\pi r^2)/3$). Thus, stand volume for each plot (in cubic meters) was calculated using equation (3):

$$V = \frac{SBA \times HT}{3}, \quad (3)$$

where

SBA = Stand Basal Area and

HT = tree height.

Results of the calculated *QMD*, *RDC*, and *HT* are summarized in Table 3 for Dataset 1 and Table 4 for Dataset 2. The ANOVA test examined potential differences in stand density (*RDC*) and volume between the four forest types. To verify the validity of our results, we tested for normality and homogeneity of variance using the Kruskal-Wallis test and Levene test, respectively.

Table 3. Dataset 1 plot parameters measured in the field and estimated Curtis relative density (*RDC*). Data are from randomly selected plots from four forest types that were shown to be statistically identical in volume and density (Fig. 3), thus the data are pooled. None of the plots within Dataset 1 were infested by the southern pine beetle.

Plot ID	Forest type	<i>RDC</i>	Stand Volume (m ³)	<i>NVD</i> (m)	<i>HT</i> (m)
NUC1	Upland Conifer	4.528	142.719	3.260	17.267
NUC2	Upland Conifer	5.746	136.063	2.673	14.733
NUC3	Upland Conifer	5.768	184.874	2.867	18.300
SUC3	Upland Conifer	0.777	31.588	8.612	21.349
SUC5	Upland Conifer	2.483	111.198	4.687	21.367
SUC7	Upland Conifer	5.951	152.301	2.727	15.000
NMC1	Upland Mixed	3.412	84.187	3.460	15.000
NMC2	Upland Mixed	2.521	111.371	5.160	21.400
NMC3	Upland Mixed	5.529	144.876	2.580	16.133
SMC1	Upland Mixed	1.761	72.397	5.087	20.867
SMC6	Mixed Conifer	1.839	71.758	6.207	19.533
SMC7	Mixed Conifer	1.111	46.685	8.060	20.333
NWC1	Wetland Conifer	6.573	184.161	3.153	16.633
NWC2	Wetland Conifer	4.649	99.762	2.453	14.067
NWC3	Wetland Conifer	5.705	192.619	3.380	19.067
SWC1	Wetland Conifer	3.157	145.311	4.367	22.250
SWC3	Wetland Conifer	4.875	106.164	3.247	14.350
SWC7	Wetland Conifer	1.851	58.594	4.213	17.400
NWM1	Wetland Mixed	3.757	156.910	3.520	21.967
NWM2	Wetland Mixed	4.739	122.576	2.127	15.600
NWM3	Wetland Mixed	2.757	101.575	3.827	18.433
SWM2	Wetland Mixed	1.465	66.839	6.840	21.833
SWM3	Wetland Mixed	2.924	87.949	3.027	17.067
SWM7	Wetland Mixed	1.792	80.488	5.520	21.033

Table 4. Dataset 2 plot parameters measured in the field and estimated Curtis relative density (*RDC*). Forest type was grouped based on statistical similarity and so is not listed in the table. All plots within Dataset 2 were infested by the southern pine beetle.

Plot ID	<i>RDC</i>	Stand Volume (m ³)	<i>NND</i> (m)	<i>HT</i> (m)
116	4.514	195.162	3.393	22.633
160	4.441	194.055	3.847	23.333
178	4.040	120.385	3.180	18.433
204	2.678	86.012	5.213	16.367
234	4.118	112.708	2.787	15.667
269	3.320	109.616	3.280	17.467
349	2.574	86.149	4.000	19.633
382	4.321	215.793	2.967	24.733
s384	6.566	146.068	2.173	14.833
406	4.385	83.974	3.173	13.167
409	6.893	225.681	1.993	19.400
419	2.479	87.097	4.960	20.567
426	2.741	121.054	4.013	21.767
433	3.924	91.180	2.436	13.133
436	3.628	83.962	3.207	12.467
444	1.806	66.788	5.033	18.700
445	2.435	94.269	6.233	19.867
446	7.889	182.651	2.153	15.233
450	2.385	118.293	6.331	22.833
455	2.817	116.142	3.680	22.100
459	4.102	100.658	2.800	14.833
467	3.827	121.072	3.713	15.933
51	5.100	182.051	3.180	19.933
64	1.969	88.085	5.280	22.133

Using Dataset 1, we developed two models to estimate forest density. Dataset 2 was used to further tune the models and to compare against Dataset 1. The primary difference between the two models is the inclusion of DBH. Model development was based on the distribution of the data and prior modeling experience. The Density-NND Model (equation [4]) uses the average tree NND, and the Density-NND-DBH Model (equation [5]) uses NND and the DBH of the nearest neighbor. Both models predict density with NND data from photogrammetry. However, we created the Density-NND-DBH Model to anticipate incorporating lidar data, which remotely estimates both DBH and NND. We propose the following models:

$$\text{Density-NND Model: } RDC_p = \varphi + \frac{\theta + \gamma NND}{1 + NND^\lambda e^{-\lambda}} \quad (4)$$

$$\text{Density-NND-DBH Model: } RDC_p = \left(\frac{\theta + DBH}{\theta_{max} + DBH^2} \right) \beta e^{-\lambda NND} \quad (5)$$

where

RDC = Curtis's Relative Density,
 NND = distance to the nearest neighbor,
 DBH = diameter at breast height,

and the remaining parameters are defined below and in Table 5.

The Density-NND Model depicts the existing relationship between NND in meters and the unitless density, RDC_p , where the subscript p indicates that these are predicted values calculated from the model, as opposed to those calculated from the original plot data, RDC . The Density-NND-DBH Model takes into account both NND and DBH . The addition of DBH adds a third dimension to the density metric, where diameter of the trunk at breast height is included instead of the two-dimensional basal area alone. The parameters $\varphi + \theta \geq 0$ in the Density-NND Model represent the maximum density possible, which occurs when the average $NND = 0$ or the trees are growing directly adjacent to one another. Here, $\theta \geq 0$ represents the upper limit of RDC when $NND = 0$ in the Density-NND-DBH Model with $DBH \rightarrow 0$. We note, however, that $DBH = 0$ is indicative of an empty plot; that is, there are no trees on the plot. θ_{max} is a half-saturation constant; and β is a scaling parameter of how the magnitude of tree distance to NND affects the density of each plot. γ measures the initial rate of increase at low NND , and λ captures the decline of the relative density per increase in NND . Using the data presented in section 5.1, we selected optimal values (i.e., values that best fit to the data) of the parameters (Table 5) for the models using the Basin-hopping algorithm described in Wales and Doye (1997).

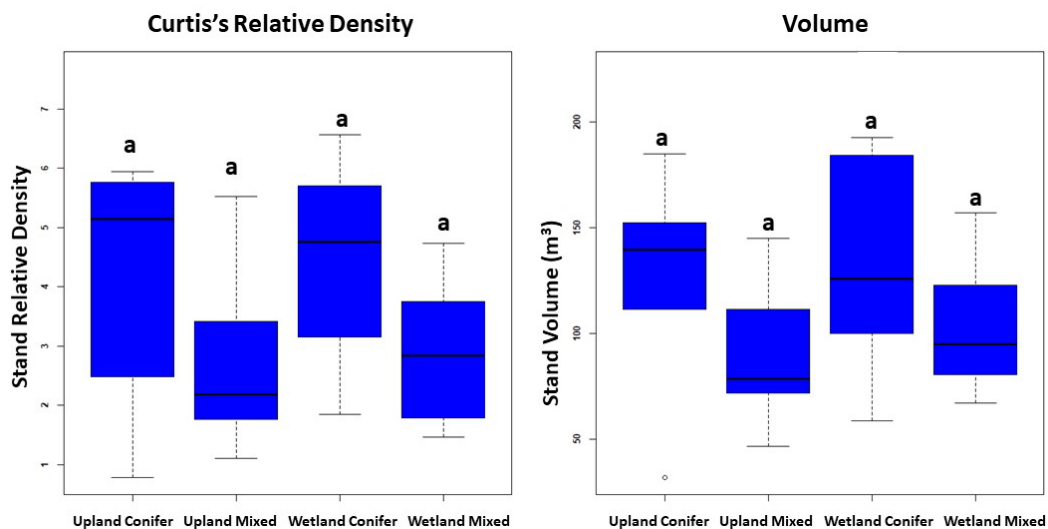
Table 5. Equation (4) and (5) parameters values used in Figs. 4 and 5.

Models	Dataset 1						Dataset 2					
	φ	θ	γ	λ	β	θ_{max}	φ	θ	γ	λ	β	θ_{max}
Equation (4)	1.1	-11	7.6	5.4	-	-	19	2.9	-12	1.4	-	-
Equation (5)	-	-0.1	-	0.3	590	1e-6	-	-1.4e+4	-	33.7	-18	145

6 Results

A one-way ANOVA was used to test the statistically significant difference between the relative densities (calculated using equation [1]) of the four forest types described in section 5.1. The ANOVA test did not show differences in relative density or volume (calculated using equation [3]) among the forest types in Dataset 1 at $\alpha = 0.05$ (Figure 3), indicating the homogeneity of tree density in wetland and upland forests in the New Jersey Pine Barrens. Our analysis provided results regarding the volumetric area, taking into account the 3-D space. However, we leave further analysis of the volumetric studies for future studies.

Figure 3. Box plot for the mean differences between forest density and forest volume. The *a*'s indicate no statistical differences at $\alpha = 0.05$ with the F statistics $F_{3,20} = 1.68$ and $F_{3,20} = 1.25$ for the forests' relative density and volume, respectively.



It is important to note that the results from the models are presented in different formats to account for the effects of solely *NND* (the Density-NND Model, Figure 4) versus the coupled effects of *NND* and *DBH* (the Density-NND-DBH Model, Figure 5).

Both Models can successfully described the relationship of forest density relative to forest parameters. We judge this success by the fact that both models were developed using Dataset 1 and also describe the relationship of density to *NND* and *DBH* Dataset 2. Additionally, the models reflect patterns observed in natural environments.

The Density-NND Model indicates that plot density decreases with increasing *NND*, which, when applied to a natural system, means that the forest is less dense when the trees are farther apart (Figures 4a and 4b).

Figure 4. Estimate of tree density (RDC) for both datasets given the nearest neighbor distance (NND). The *black lines* are equation (4) RDC_p , and the *black points* are the data shown in Tables 3 and 4. R^2 represents the coefficient of determination, showing that equation (4), with only NND, is the better representation of the tree spacing.

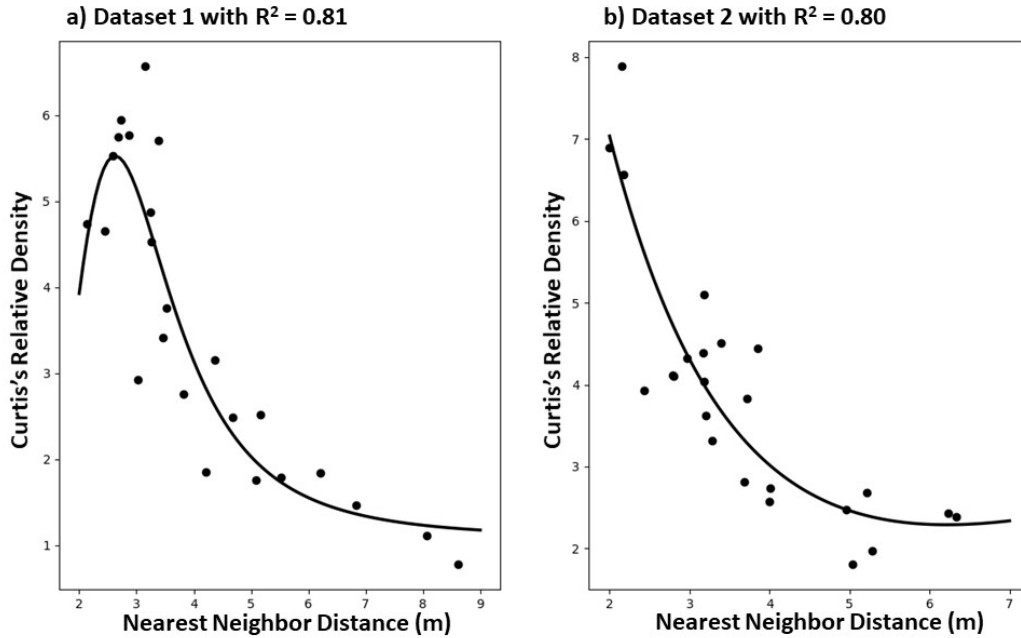
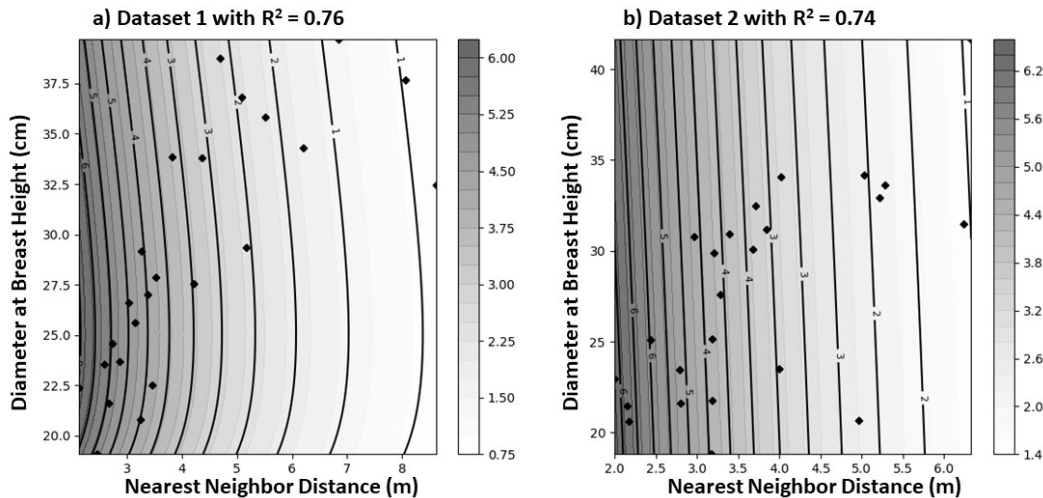


Figure 5. Contour plots of the density (RDC) of (a) Dataset 1 and (b) Dataset 2 given both the *DBH* and the *NND* (equation [5]). The *black diamonds* represent individual plots described in Tables 3 and 4. The *gray scale* represents the relative density estimated by equation (5). R^2 is the coefficient of determination showing that NND is the controlling factor in tree spacing and that the inclusion of BHD does not improve the prediction.



The Density-NND-DBH Model (equation [5]) takes into account both the *DBH* and the *NND*. Figures 5a and 5b present the contour plots of plot density for both Dataset 1 and Dataset 2, respectively. These plots were developed using the optimum parameters that were selected for the forest plots (Table 5).

Figure 5 shows that, independently of the *DBH*, the forest density follows a trend similar to that depicted in Figure 4, where density decreases with increasing distance between neighboring trees. Such a result highlights that *NND* is a more important parameter for modelling forest density and that *DBH* does not significantly affect forest density for this forest type. This is reflected in the lower R^2 value of the more complicated Density-NND-DBH Model. However, since both *DBH* and *NND* are known controlling factors for vehicle movement in vegetated areas, both must be considered when assessing vehicle mobility, and therefore further research is needed to determine how to assess these parameters remotely. Tables 3 to 5 summarize the parameters used in the models and the estimated relative density and stand volume.

7 Conclusions

Our study examined two major factors that are critical to plan and execute troop and equipment movement in forested environments. Although existing techniques can approximate spacing and diameter based on gross forest type, there is no existing method to accurately estimate tree spacing or stem diameter remotely. To address this issue, we used ground truth data to construct two mathematical models that use average NND and DBH to estimate forest stand density, a parameter commonly reported in forest management. Through this exercise, we captured the importance of tree spacing in the overall calculation of stand density.

The results highlight that forest density estimates are independent of the DBH measurements. Although preliminary, these results provide a basis for modeling relationships between ground-based and aerial (e.g., lidar and photogrammetry) data and should be explored in the future. It is noteworthy that with lidar capabilities, other forest metrics, such as DBH or plant species, could be captured. Equation (5) was developed specifically to accommodate the additional data of DBH. However, equation (5) output demonstrated that NND is a better predictor of forest density than NND and DBH combined, reflected in the lower R^2 value of the more complicated model. Both models constitute a basis for more complex studies that account for topography; forest density; stem diameter; bow height; and other parameters important to mobility, acoustics, and climate effects.

8 Future Recommendations

8.1 Comparing ground-based and aerial data

While the methods developed by Aoki et al. (2018) estimate tree distance in forest stands with regard to insect infestation, we are not certain it is the best method for modeling mobility from aerial surveys. One factor to consider is how to compare ground and aerial techniques to validate the accuracy of aerial-derived distance estimation. In future studies, we recommend using the same sampling method for both data sources and emphasize the importance of considering the requirements of machine learning for analyzing aerial data in sampling-methods development. Ideally, a follow-on to this project would involve collecting ground-truth data with a method that includes aerial sampling considerations, which could then be compared to methods of Aoki et al. (2018). This would help to determine which method best describes the distance between trees.

Additional challenges of combining and comparing ground and aerial data collection will need to be anticipated and resolved. While conifers tend to grow with one main trunk, pests such as the white pine weevil (*Pissodes strobi*) induce trunk splitting, resulting in what could look like multiple crowns from above. Additionally, forests prone to ice events will have trees that bend under the weight of ice, yielding a crown that is potentially several meters away from the tree base. Such disfigurements will confound the distance between trunks when measured aerially. Aerial data collection will also not identify ground obstacles, such as fallen trees, large boulders, or small topographic features (e.g., embankments). Ideally, a future model would account for the likelihood of such ground obstacles and tree deformations given the glacial and ecological history of a given habitat.

Because the objective of this study was to develop methods to compare ground-based to aerial data, these are important issues that future studies must consider.

8.2 Implications of tree distribution

One critical component to evaluate regarding collection and analysis is whether trees are randomly scattered or clustered. This has huge implications when determining the sampling method used for both ground-based and aerial data. Future work must also determine the relationship between

tree density per unit area and the distance between trees and whether PDE accurately estimate tree distances. This includes whether to measure from a random point, which is what most ecological methods use for determining density, or from a randomly selected tree. At this point, we feel that it is most prudent to measure from a specific tree as we are ultimately interested in distance between trees as well as density. Additional considerations include (1) the size of the plot and how far that plot information can be extrapolated to a stand of trees or a forest, (2) how many samples to take within the plot (from either a random point or a random tree), and (3) how many nearest neighbors to measure. It is also necessary to determine if and how the basal area and DBH of the tree fits into the model. Finally, it is critical to consider how to fit minimum distance into the model.

8.3 Future work

The initial results reported here hold promise for the future of remotely estimating mobility in forests. A next logical step in model development will be to test the models using aerial data, as stated above. The models could then be modified following an evaluation of additional sampling methods, both ground based and aerial. Once the model development for a single forest type is refined, it will be critical to test the methodology for other forest types (e.g., boreal, tropical, broadleaf, etc.) in different climates. Finally, it would be interesting to test the applicability of model results to other applications, such as estimating the influence of forests on infrasound and acoustic wave propagation, both topics of interest for the U.S. military.

Following these proposed recommendations will allow for a better assessment of the ability to model critical forest parameters using data collected remotely. This study has established the complexities of modeling forests, particularly when considering troop and equipment movement in denied areas. We believe the steps outlined here provide a path forward for advancing mobility modeling technologies and better preparing our troops for combat.

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14. ABSTRACT

Understanding forest structure and composition is critical to plan and execute troop and equipment movement in forested environments. This is especially important and challenging in denied (limited operational capability due to adversary control) areas. Existing mobility models do not adequately account for the heterogeneity (e.g., tree spacing, tree height, species, etc.) of forests. Knowledge of forest metrics over large scales has long posed a challenge within the forestry community. Previously, researchers have used ground-based and overhead remotely sensed data to attempt to quantify forest properties. But these methods have not produced the level of detail required for tactical mobility modeling.

Here we examine two of the forest properties critical to mobility (stem spacing and diameter) and review existing techniques to quantify these properties both in the field and remotely. From this review, we identify tree spacing as the key forest parameter that current methods cannot adequately estimate. To address this, we created two models using ground-based data to estimate tree spacing in forest plots. Using modeled relationships, it may be possible to extrapolate this critical forest parameter from aerial data. This report reviews past research, evaluates the ability to model forest density and tree spacing, and recommends a direction for future work.

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