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EVALUATING THE USE OF UNMANNED AERIAL SYSTEMS (UAS) FOR COLLECTING THEMATIC MAPPING ACCURACY ASSESSMENT REFERENCE DATA IN NEW ENGLAND FOREST COMMUNITIES

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EVALUATING THE USE OF UNMANNED AERIAL SYSTEMS (UAS) FOR COLLECTING THEMATIC MAPPING ACCURACY ASSESSMENT REFERENCE DATA IN NEW ENGLAND FOREST COMMUNITIES

BY

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THESIS

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FOREWORD

This work serves to connect fundamental principles in science and mathematics to the current apex of technology. In a world so in turmoil over alternative facts, scientific skepticism, accessible communication, and the role of automated platforms such as unmanned aerial systems, it is important to remain vigilant in our understanding of how we got to where we are. Knowing our current position allows us as a society to know where we can possibly go moving forward. This thesis serves not only a research exposition but also an information piece on the adoption of Unmanned Aerial Systems (UAS, UAV, RPAV, drone, etc.). At times this thesis will review basics, perhaps beyond the need of the scientific methods of the study; serving the purpose of connecting knowledge and thoughts necessary for those looking to integrate UAS into their own work. A great deal of this Master's degree research was spent investigating and confirming how UAS operate, both fundamentally as remote sensing platforms. In consideration with modern legality of the national airspace system (NAS) under the FAA. Being on the cutting edge of technology in this case has been eased by growing public acceptance of the platform however, there is still much work to be done in openly utilizing this platform for any project. Any qualitative or quantitative evaluation of Unmanned Aerial Systems, in this novel age, would not be complete without these considerations taken into account before even getting the system off the ground.

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ABSTRACT

EVALUATING THE USE OF UNMANNED AERIAL SYSTEMS (UAS) FOR COLLECTING THEMATIC MAPPING ACCURACY ASSESSMENT REFERENCE DATA IN NEW ENGLAND FOREST COMMUNITIES

by

BENJAMIN T. FRASER

University of New Hampshire, September, 2017

To overcome the main drivers of global environmental change, such as land use and land cover change, evolving technologies must be adopted to rapidly and accurately capture, process, analyze, and display a multitude of high resolution spatial variables. Remote sensing technologies continue to advance at an ever-increasing rate to meet end-user needs, now in the form of unmanned aerial systems (UAS or drones). UAS have bridged the gap left by satellite imagery, aerial photography, and even ground measurements in data collection potential for all matters of information. This new platform has already been deployed in many data collection scenarios, being modified to the needs of the end user. With modern remote sensing optics and computer technologies, thematic mapping of complex communities presents a wide variety of classification methods, including both pixel-based and object-based classifiers. One essential component of using the derived thematic data as decision-making information is first validating its accuracy. The process of assessing thematic accuracy over the years has come a long way, with site-specific multivariate analysis error matrices now being the premier evaluation mechanism. In order to perform any evaluation of certainty, or correctness, a comparison to a known standard must be made, this being reference data. Methods for reference data collection in

both pixel-based and object-based classification assessments are indeterminate, but can all become quite limiting due to their immense costs. This research project set out to evaluate if the new, low cost UAS platform could collect reference data for use in thematic mapping accuracy assessments. We also evaluated several collection process methods for their efficiency and effectiveness, as the use of UAS is still relatively unknown in its ability to acquire data in densely vegetated landscapes. Collected imagery was calibrated and stitched together by way of structure-from-motion (SfM), attempting calibration and configuration in both Agisoft PhotoScan and Pix4DMapper Pro to form orthomosaic models. Our results showed that flying heights below 100m above the focus area surface, while acquiring ultra-high-detailed imagery, only resulted in a maximum of 62% image calibration when generating spatial models. Flying at our legal maximum flying height of 120m above the surface (just below 400ft), we averaged 97.49% image calibration, and a gsd of 3.23cm/pixel over the 398 ha. sampled. Using a classification scheme based on judging the percent coniferous composition of the sampled units, our results during optimal UAS sampling showed a maximum of 71.43% overall accuracy and 85.71% overall accuracy, respectively, for pixel-based and object-based thematic accuracy assessments, in direct comparison to ground sampled locations. Other randomly sampled procedures for each approach achieved slightly less agreement with ground data classifications. Despite the minor drawbacks brought about by the complexity of the environment, the classification results demonstrated OBIA acquiring exceptional accuracy in reference data collection. Future expansion of the project across more study areas, and larger forest landscapes could uncover increased agreement and efficiency of the UAS platform.

INTRODUCTION

From the level of the terrestrial biosphere to the individual habitat patch, the effects of climate change and natural resource degradation can be linked to disastrous negative impacts. Patterns of biodiversity loss and habitat augmentation have become so severe that many have relabeled this era the Anthropocene (Kareiva and Marvier, 2011; McGill *et al*., 2015). Furthering this destructive disposition, swelling contentions between scientific principle, ecosystem conservation, and personal belief are driving the need for more definitive environmental solutions. Like many areas around the globe, forested areas in coastal New Hampshire have been harshly impacted by these disturbances. Each forest experiencing diminished functionality, area loss, and fragmentation of its critical habitat. Natural areas such as these provide countless ecosystem services which are directly linked to global welfare, including water quality regulation, wildlife habitat, air purification, and recreation (MacLean *et al*., 2012). Many fields of science now look to combat these harrowing impacts and conserve what remaining natural areas we have left. Modern conservationists are turning to adaptive management protocols and adopting novel ways of exploring current and future challenges.

Finding true measures for which to base models of complex systems is inherently difficult. Forested landscapes of New Hampshire, representative of the Northeastern United States, are especially indicative of this hardship, comprising a vast diversity of composition and structure (Justice *et al*., 2002). To understand these systems, we must find parameters which are readily assessable and characterize their elements. Land cover presents an opportunity for this, representing the fundamental constructs covering the surface (Burley, 1961; Anderson *et al*.,

1976). To collect land cover data at a scale sufficient for answering our questions of the

environment, remote sensing is used as a data enrichment tool (Field *et al.*, 1995; Ford, 2000;

Chapin *et al.*, 2002; Congalton and Green, 2009).

Thematic mapping of land cover characteristics fills the gaps in our ability to make

management decisions (Kerr and Ostrovsky, 2003; McRoberts and Tomppo, 2007).

Incorporating the context of spatial relations, through the use of remote sensing, gives a new

platform for measuring environmental phenomena at various scales (Sokal, 1974; Pugh, 1997;

Bolstad, 2012; Jensen, 2016). The continual technological advancement and adaptation of remote

sensing aims to match the complexity of the systems we use it to study (Hyyppa *et al.*, 2000),

most observably in spatial, spectral, and temporal resolutions. The methods for performing

thematic classifications have taken two primary forms with digital data. Originally, classification

algorithms distinguished individual pixels, labeling them based on trained or statistically

associative rulesets. These pixel-based classifications supported resolutions based on the

specifications of the sensor. More recently, image spatial and spectral resolutions, along with

improved computational power, have yielded object-based image analysis methods (Blaschke *et

al.*, 2000; Blaschke and Strobl, 2001; Blashcke, 2010; Kelcey and Lucieer, 2014). The creation

of image objects through segmentation incorporates additional types of information, potentially

furthering analyses (Robertson and King, 2011). To determine which approach is more

appropriate hinges on the specific needs of the project. The importance of this information,

however, always provokes the need for its accuracy just as much as its availability.

To test the validity of remote sensing systems for producing effective thematic maps of

complex forest communities, and therefore being implemented in management decisions, an

accuracy assessment must be performed on the resulting data product(s). Such processes ensure

the certainty of thematic mapping and work to uncover the sources of error in the classification. The obligation for verifying such expansive products has not always been a priority though, with both costs and intricate sources of error weighing heavily on the sampling designs (Congalton *et al*., 1993; Foody, 2002; Congalton and Green, 2009). Beginning with early forms of only visual inspection, the process of thematic mapping accuracy assessments has now evolved to site-specific statistical analysis of agreement (Biging and Congalton, 1989; Congalton, 1991; Congalton and Green, 2009). This process of validating the correctness of the remotely sensed data product requires having reference data that represents the actual conditions on the ground.

Reference data, used for either training the land cover classification or, independently, validating its results, comes from three major sources. These include: (1) ground sampling, (2) using remotely sensed data of a higher resolution, or (3) preexisting maps (Congalton and Green, 2009). Ground sampling stands out among these as the most established but is associated with an intrinsic greater cost. Although reference data exists as the standard of comparison for what is correct, there remains an unavoidable margin of subjectivity in all of these data sources, reasoning against the terminology of it as "truth". Professional fields such as forest mensuration or biometrics have been adopted by the geospatial sciences for their fundamental principles, to promote efficiency and minimize sources of uncertainty in collecting reference data. Forest mensuration is the foundation behind obtaining quantifiable information for forestry decision making (Husch *et al*., 1972; Kershaw *et al*., 2016). The need for information devoid of bias and inaccuracies in ecological and economical management has created precise procedures for the systematic accumulation of these observations and measurements (Husch *et al*., 1972), making an ideal standard for comparison. Methods such as implementing continuous forest inventory (CFI) for the simultaneous observations of large scale and long term trends are prevalent up to

the national level. Forestry techniques realize the infeasible nature of measuring every tree, instead inciting statistics for landscape estimations. Similarly, the overwhelming cost of accurate reference data collection with a suitable sample size results in considerable limitations (Harris and Ventura, 1995; Foody, 1999; Foody, 2002; Congalton and Green, 2009; Laliberte *et al*., 2010). In an effort to optimize the process of ground sampling MacLean *et al*., (2012) reformed previously set standards of thematic classification accuracy from Husch *et al*., (1972) for the minimum plot sampling requirements of forested landscape, based on statistical power and efficiency analysis. Even with these reevaluated benchmarks, the cost of going to the ground to collect reference data remains substantial.

Following a history of research and development parallel to manned aviation, unmanned aerial systems (UAS) have emerged at the forefront of remote sensing technologies in recent years with the advent of small-format, microprocessing computers (Marshall *et al*., 2016). These systems have evolved to make use of nearly every facet of modern technology, for the benefit of the user. With both fixed-wing and rotary-winged models, system configurations propose consumer desired versatility. Applications now include such things as low-cost 3D surveying (Westoby *et al*., 2012), coastal area management (Delacourt *et al*., 2009), wildlife monitoring (Jones *et al*., 2006), agricultural monitoring (Zhang and Kovacs, 2012), and rangeland imaging (Hardin and Jackson, 2014), bolstering the promise of flexibility, efficiency, and high-quality products. Real-time image analysis, rapid digital surface model (DSM) and planimetric model construction have the ability to capture extraordinary detail, even in complex environments more efficiently than other methods. Raising the question if this new platform could be instrumental for collecting highly accurate reference data in forest environments. Therefore, the goals of this research are:

1. **To evaluate if UAS are capable of efficiently and effectively collecting reference data for use in assessing the accuracy of thematic maps.**

   a. **Specifically, can UAS be used for collecting reference data for use in assessing thematic maps created from a pixel-based classification approach?**

   b. **Specifically, can UAS be used for collecting reference data for use in assessing thematic maps created from an object-based classification approach?**

BACKGROUND AND LITERATURE REVIEW

Troubled Ecosystems in the Anthropocene

The modern world is facing staggering rates of degradation in its natural systems. So much so that many scientists have deemed this a new ecological era, the Anthropocene or "Human epoch". Human caused patterns of disturbance have dominated trends in global biogeochemistry and biodiversity (Kareiva and Marvier, 2011; McGill *et al*., 2015). Much of the terrestrial biosphere is now affected by anthropogenic activities (Kerr and Ostrovsky, 2003), with virtually all projections estimating increases in magnitude. Compounding and perpetuating these effects, in a positive feedback loop, greenhouse gases are expected within the next century to cause the most rapid pace of climate change since the last deglaciation, approximately 18,000 years ago (Chapin *et al*., 2000). In the last four decades alone, fossil-fuel combustion and deforestation have contributed to half of the 30% increase in atmospheric CO_2 recorded for the

past three centuries (Chapin *et al*., 2000). The combined changes in biodiversity represent a pivotal challenge for ecologists, combining the efforts of sustainability, ethics, and policy (McGill *et al*., 2015), all clashing with public interests to predict the state of future natural resources.

Complex natural communities around the world are becoming functionally extinct, unable to perform their most basic of processes. Human led disturbances alter ecosystem resilience, leaving them further susceptible to irrevocable change (Chapin *et al*., 2000). Current datasets from around the world are producing interdisciplinary evidence of just how ubiquitous anthropogenic effects are becoming, altering virtually every remaining natural setting in existence (Redford, 1992).

Forests are ranked among the most the most exploited of natural environments, despite being well known for their sheer volume and diversity of resources which they provide the human society. The United Nations Food and Agriculture Administration (FAO) has estimated a net global loss of 7.3 million hectares of forest land per year between 2000 and 2005 (Kareiva and Marvier, 2011). Unregulated deforestation is a major cause for concern in many scientific disciplines, international economics, and levels of government. Deforestation is also an indirect means of defaunation, negatively influencing biodiversity (Redford, 1992). Loss of ecosystem function strains not only the biosphere but also pressures human economies. The term "ecosystem services" was formed to represent those good and services which are provided by the natural world, preserving human life (Kareiva and Marvier, 2011). These services, such as water quality regulation, wildlife habitat, nitrogen and carbon cycling, and primary production by forests and agriculture (Kareiva and Marvier, 2011; MacLean *et al*., 2012), represent vital

resources for mankind. They serve to classify and quantify the benefits given by earth's ecosystems; giving, in some circles, a way to defend their protection.

To understand and conserve natural environments, and therefore also their associated ecosystem services, ecologists must improve their ability to detect and predict changes all the while basing models on their knowledge of what is causing such impacts (Kerr and Ostrovsky, 2003). Many tools now exist to aid ecologists in assimilating mass amounts of heterogeneous data, at a range scales, and translating those data into useful information for conservation and management (Michener and Jones, 2012).

Land Cover Mapping from Remote Sensing

Tracking changes, disturbances, and repercussions requires a large amount of data in the form of variables which we can test and analyze. Capturing both biological composition and structure of complex environments is a challenging predicament. Further epitomizing these complex landscapes are forest stands in the Northeastern United States, which continually change (Justice *et al*., 2002). Understanding impacts all the way down to the level of the single tree requires an equally expansive indicator.

Land cover, a descriptor of the physiographical characteristics of the surface environment in any of its capacities (Kerr and Ostrovsky, 2003), can be formed from a number of classification methods. Representing the actual features present in a landscape, land cover constitutes a fundamental relationship to the biological and ecological systems comprising environments (Anderson, 1976; Vitousek, 1994; Chapin *et al*., 2002; Foody, 2002; Jensen, 2016). Closely related to this, land use refers more intently to what people do on the surface, pertaining to the utility of its elements (Avery and Berlin, 1985; Jensen, 2016). A land cover type

could be labeled as grassland, giving significance only to the contents of the terrestrial surface. A land use classification for this same area would instead be pasture, insinuating livestock grazing; or recreation field, inferring anthropogenic activities. Increases in the intensity of land use can be significant, affecting key earth system functionality, and are predicted to have the largest impact on biodiversity by the year 2100 (Chapin *et al*., 2000; Lambin *et al*., 2001; Smith, 2002). McGill *et al*., (2015) reported that humans have already modified nearly 50% of the terrestrial land cover. In contrast to data on land use practices, data on land cover can be directly measured and changes quantified over time and space. To promote the progress of ecological studies, and inform critical decisions, we not only need more data surrounding such variables, it must also be justifiably accurate (Ford, 2000). Remote sensing is capable of collecting data of this manner for both cultivating and enriching data sets (Field *et al*., 1995; Congalton and Green, 2009).

Remote sensing is a highly versatile and readily available tool for collecting data beyond the scope of *in situ* observations, encompassing our ability to learn about an object, through a sensor, without coming into direct contact with it (Paine and Kiser, 2003; Jensen, 2016). The scale, range, and flexibility, of remotely sensed imagery justify its use as the leading source of both land cover and land use data (National Academy of Science, 1970; Anderson, 1976; McGargial and Cushman, 2002; Turner, 2005; Radoux *et al*., 2011; MacLean *et al*., 2012; Whitehead and Hugenholtz, 2014). Easily applicable to Geographic Information Systems and Science (GISS) due to its collection of spatially explicit data, remote sensing encompasses both our ability to measure, and our ability to visually analyze remote phenomena. Photogrammetry, or the math and science of remote sensing, has a rich history of numerically assessing remotely sensed features; while photointerpretation, more generally known as the art of remote sensing, specifies qualitative analysis of such features (Avery, 1977).

Most notably recognized as the indication of remote sensing's advancement, spatial, spectral, and temporal resolutions directly regulate the power of remote sensing for measuring aspects of nature. Spatial resolution is the digital imagery pixel size and represents the smallest divisible unit in a remotely sensed data product (Kerr and Ostrovsky, 2003; Paine and Kiser, 2003). Spectral resolution is characteristic of the wavelengths of light, or electromagnetic radiation, reflectance resolvable by the sensor employed. Lastly, temporal resolution is the revisit occurrence of the observations in question, ranging from several times a day to much broader scales. Recent advances in remote sensing have enabled data capture at resolutions that have matched a range of ecological processes (Turner *et al*., 2003), and at spatial and temporal extents which could not be met using field-based sampling methods. Multispectral and hyperspectral sensors now see well beyond that of the human visual capacity, while spatial resolutions have shrunk to sub-centimeter pixel sizes. All of this information can fill gaps for urgently needed surveying, at scales which more closely compare to anthropogenic changes in the environment (Kerr and Ostrovsky, 2003; Homer *et al*., 2012).

It is necessary to also recognize how remote sensing fits into the wider context of scientific discovery, working with geographic information systems (GIS) to command spatial data. GIS are an arrangement of computer hardware, software, and people used for entering, storing, manipulating, analyzing, and displaying geographic or spatial data (Congalton and Green, 1992). Working hand in hand, GIS and remote sensing provide the formation of qualitative and quantitative analysis of spatial data in the digital age. Geographic information science then ties together fundamentals from both disciplines, also amassing its own theories for how such unique data should be handled (Avery and Berlin, 1985; Goodchild, 1991; Goodchild, 1992; Longley *et al*., 2015). Much contention still emanates from the divergence and distinct

labeling of each field of study, as well as surrounding influences, due to how interdisciplinary each remains (Goodchild, 1992). The successful acquisition and assessment of remote sensing products however, necessitates guidance from all preceding disciplines.

Classifying land cover from remotely sensed imagery, more formerly known as thematic mapping, involves labeling objects or features in arranged groups on the basis of the relations among their characteristics (Sokal, 1974; Pugh, 1997; Bolstad, 2012; Jensen, 2016). This form of pattern recognition is an attempt to identify and describe natural, or artificial, systems based on expert knowledge. Thematic classification reflects both characteristics within the source imagery, and the motivations/objectives of the individual project (Sokal, 1974; Pugh, 1997). Once classified, individual units of data form patterns of discernible characteristics uncovering more complex processes and presenting more feasibly consumable information. This land cover information is needed to provide end-user guidance and products which can be directly incorporated into management plans and policies (Anderson, 1976; Civco *et al*., 2002). The strength of land cover classifications comes from the resolutions of the remote sensing platform, its compatibility with other data sources, image-processing procedures, classification algorithm choice, and time constraints (Lu and Weng, 2007). As part of the design for the project, the classification scheme addresses most of these concerns, using definitions for each class which are mutually exclusive, totally exhaustive, and hierarchical, ensuring that a comprehensive and repeatable outcome is formed in an objective manner (Anderson 1976; Jensen, 2016). Some projects have also used "fuzzy" classification procedures, in an attempt to avoid ill-fitting or overly subjective classifications, based on non-discrete results; however, acceptance of this methodology is not fully recognized. In the digital age, computer database management systems

are used heavily for the classification process, deriving statistical parameters for quantitative decision rules of pattern recognition (Avery and Berlin, 1985).

The most common, and simplest, form of thematic mapping in digital image processing classifies the individual pixels throughout the imagery. This procedure uses one of the many pixel-based classification (PBC) algorithms to harness the power of spectral data contained within each singular pixel, then assigns a class label based on the project's ruleset. Additionally, powerful ancillary information such as texture, terrain, and observable patterns can be used to form expert knowledge driven parameters for the classification algorithms (Haralick *et al*., 1974; Harris and Ventura, 1995; Lu and Weng, 2007; Caridade *et al*., 2008). Controlling the amount of detail contained within each minimum mapping unit is the resolution of the original remote sensing data source, or sensor platform (Anderson, 1976). As the pixel size decreases, therefore increasing spatial resolution, greater amounts of detail and data are collected (Figure 1). From a historical context, the line between low or coarse resolution and high-resolution imagery products has moved considerably, and in a subjective manner, with some sensors now producing high resolution imagery at sub-meter or sub-centimeter spatial resolution.
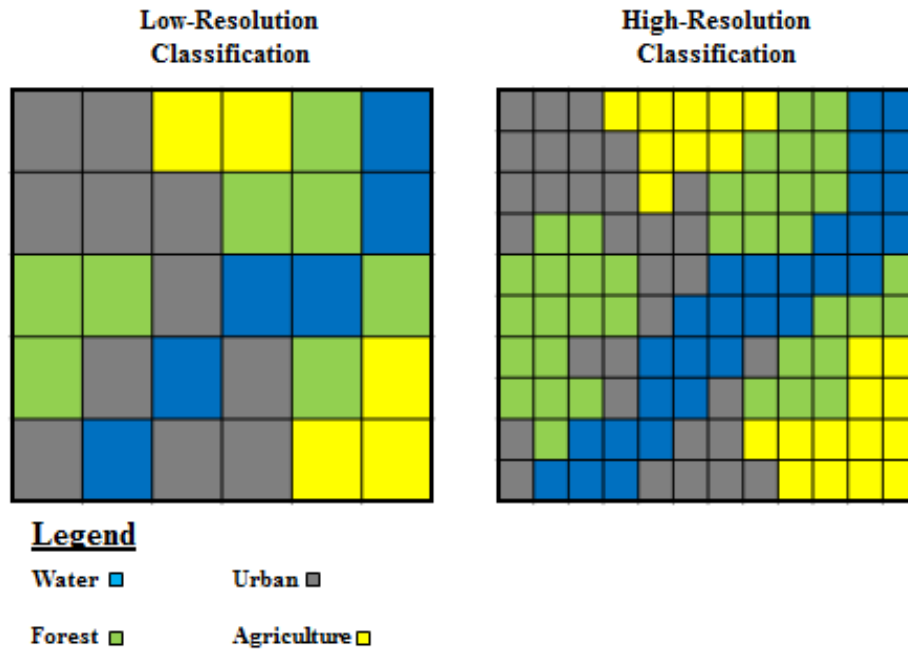
Figure 1. Pixel-based classification, spatial resolution detail incorporation.

The rules, algorithms, and methodologies for forming pixel-based land cover classifications have evolved just as rapidly as the technologies driving them (Lu and Weng, 2007). Still, modern high-resolution imagery has made the use of pixel-based thematic mapping largely inappropriate. Individual pixels can themselves be mixtures, they can be difficult to precisely locate, and in most cases, they are now smaller than the minimum mapping unit of the project design (Congalton and Green, 2009). These sources of error would only be compounded when using increasingly high-resolution imagery. To avoid misregistration errors between the remotely sensed data and the ground, it is more commonly found that 3x3 or 5x5 homogenous pixel clusters are used. Each pixel cluster still represents only a single sample, with the necessary size dependent on the positional accuracy of the data and the corresponding image resolution (Congalton and Green, 2009).

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With modern technology, users are now able to define more holistic units of analysis,

image objects. Capitalizing on the advancements of digital image processing, object-based image

analysis (OBIA) prescribes units designated as objects, polygons, areas, or in particular cases

extracted features, which can be identified within the imagery to incorporate additional data

parameters (Figure 2). OBIA bolsters the potential for analysis through this procedure of

increasing the content of each individual unit (Congalton and Green, 2009; Blashcke, 2010;

Radoux *et al*., 2011).

Image Object
Size: 19ha
Shape: 0.4
Class: Urban
Segmentation: 20
Compactness: 0.2
Smoothness: 0
Heterogeneity: 0.18
DN Average: 140
DN Std Dev: 7.3
Min: 103
Max: 185

Pixel
Spectral Reflectance: 17
Class: Urban

Legend

Water ☐   Urban ☐   Forest ☐   Agriculture ☐
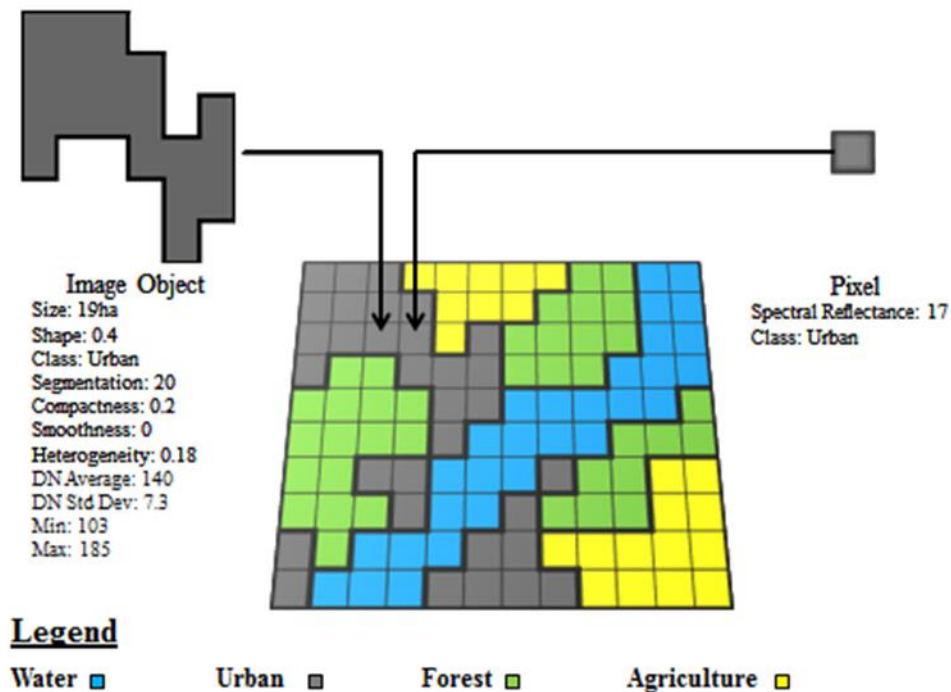
Figure 2. Object-Based Image Analysis data inclusion, in comparison to a single pixel
classification unit analysis.

At the heart of OBIA, segmentation sets the thresholds for internal variability and

maximum segment size. Depending on software functionality, algorithms set counter-balanced

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thresholds for spectral variability and area size to preserve units as homogenous in their heterogeneity (Definiens, 2007). Having more between object variability rather than within object variability is a defining trait of this method, giving it its additional power.

Among the benefits of OBIA, image objects reduce the noise of land cover classifications by lumping in alternatively classified areas, smaller than the desired threshold (Blaschke *et al.*, 2000; Blaschke and Strobl, 2001; Robertson and King, 2011). This can mean lumping in bare ground patches that peer through the canopy of forested area, or negating the presence of sporadic trees from large housing developments. This also aids in creating products which more closely represent the human perceptual ability, having computer vision match landscape classification characteristics in easily interpretable thematic layers (Figure 3) (Hay and Castilla, 2008; Robertson and King, 2011). Such products have the potential to create more accurate and repeatable results.

Figure 3. Computer Vision Interpretation Mimicry of the Human Ocular System, segmentation processed by Trimble eCognition Developer v9.2.0.

Determining which classification method, pixel or object-based, to employ hinges on the specific needs of the project, and the characteristics of the source imagery (Pugh, 1997; Lu and Weng, 2007). Varying levels of spatial detail and attribute complexity can be found even with contemporary technologies. Helping to guide this decision among approaches is the suitability of the land use and land cover information extracted from the resulting thematic layer (Civco *et al*., 2002; Foody, 2002; Lennartz and Congalton, 2004; Jensen, 2016).

Although OBIA approaches to thematic mapping still provide a wealth of unrealized potential, there are now new interests forming in the realm of high-resolution three-dimensional (3D) and digital planimetric modeling. These modeling designs reform our need for understanding core principles of remote sensing photogrammetry, such as how photographs originate with displacements in their features, and also perhaps distortions, barring them from being consumed as actual maps. Creating planimetric, or orthomosaic models, along with their associated 3D point-clouds, through structure from motion (SfM) utilizes significantly overlapping images and vast amounts of tie points for a low-cost, more inclusive output (Puschel *et al*., 2008; Remondino *et al*., 2012; Turner *et al*., 2012; Westoby *et al*., 2012; Fornstad *et al*., 2013; Haala *et al*., 2013; Mancini *et al*., 2013). These models, to perform adequately with the heightened resolution, require a sizeable endlap (latitudinal overlap) and sidelap (longitudinal overlap) among neighboring photos (Eisenbeiss and Zhang, 2006; Colomina and Molina, 2014). Unlike more traditional photographic rectification, which only accounts for tilt in the sensor, orthophotography by definition uses full geometric, differential, correction to adjust for tilt, topographic displacement, relief displacement, and even lens geometric distortions, using subsequent images (Avery, 1977; Avery and Berlin, 1985; Paine and Kiser, 2003). Aerial triangulation recognizes reoccurring features within overlapping images to calculate geometric

association and form a singular surface, as seen in Figure 4. These can be either automatically

generated, pixel-sized, tie points by way of computer vision, or manually registered ground

control points, which should both be dispersed throughout the area of interest.
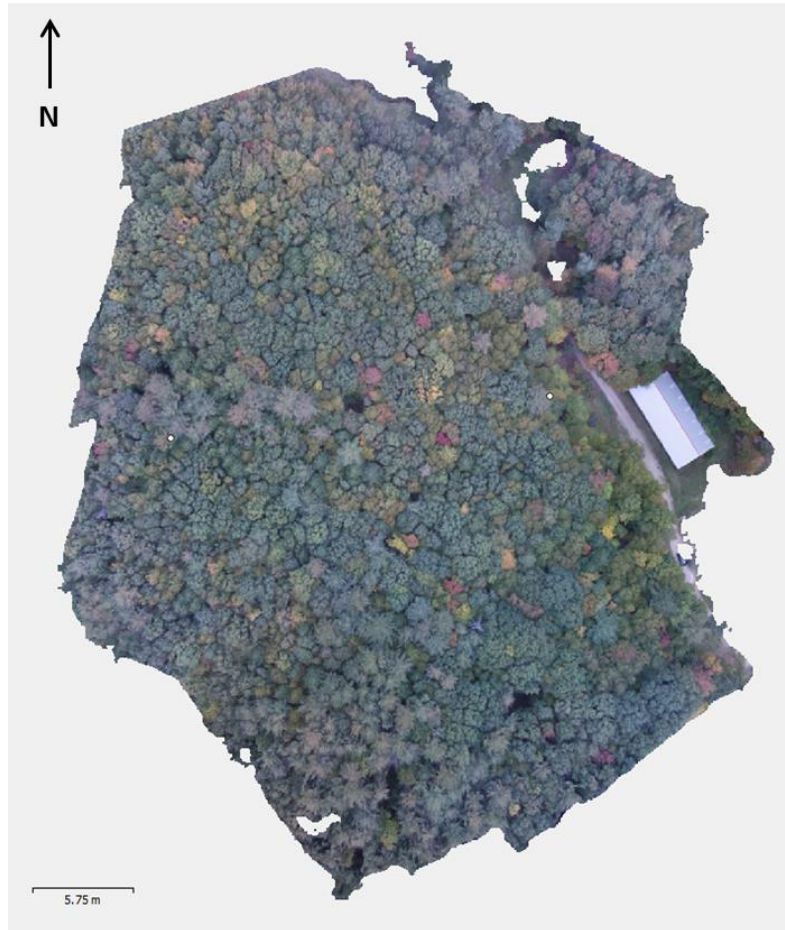
Figure 4. Forest Stand Orthomosaic Model Containing 106 Images, 94,696 tie points, and is
approximately 40x45m in size. Produced in Agisoft PhotoScan.

Apart from the automatic correction and calibration of the surface, the creation of more

holistic models such as these planimetric representations is quite ordinary. The fields of remote

sensing and photogrammetry specifically have been producing such geometrically correct

surface outputs for nearly 30 years now (Avery, 1977; Krzystek, 1991), for the benefit of many

disciplines. What is so revolutionary about these digital products are: their associated dense point

clouds, conceivably rivaling LiDAR or Terrestrial Laser Scanners (TLS), with on-demand

structure models deemed "PhoDAR" (Fritz *et al*., 2013); and the centimeter level ground

sampling distances uncovering a wealth of new context.

Accuracy, Uncertainty, and Efficiency Evaluations

The weight of decision making, poised on the conclusions drawn from remote sensing,

drives the urgency for validating data quality (Lunetta *et al*., 1991; Stehman and Czaplewski,

1998). Poor quality data often times misleads results, forming inaccurate conclusions which

weaken the foundation of conservation sciences and practices. Having ignorance of the focus

system, or how to properly create a project design for it will also lead to lower than desired

quality results. Data quality and validation procedures define potential sources of error within the

project assessment design. For remote sensing, this means uncovering sources of spatial data

error, which can be found at nearly every stage of the project (Lunetta et al., 1991; Thapa and

Bossler, 1992). Even more appropriately, this error can in some cases be thought of as confusion;

basing the sources of inaccuracy on more intrinsic properties of human observation (Congalton

et al., 1993; Congalton and Green, 2009). Thresholds of error or overall accuracy are an

individualized objective for each project, with many trade-offs and considerations for the user to

manage.

Spatial data accuracy is a combination of two distinct characteristics (Congalton and

Green, 2009). First, positional accuracy is the locational agreement between the remotely sensed

data and the ground position. Errors in location for remotely sensed data can be determined by

using known ground points of interest and applying geometry to determine the difference for its

respective output placement (Story and Congalton, 1986; Bolstad, 2005; Bolstad, 2012). This process calculates the discrepancy as the Root Mean Square Error (RMSE). Positional accuracy is a large component of photogrammetry, garnishing extensive standards such as the National Standard for Spatial Data Accuracy (NSSDA) (FGDC, 1998), the importance of which cannot be understated. As a much more complex metric of uncertainty, thematic accuracy compares specifically the labels, attributes, or characteristics of what is on the ground to the product of the spatial analysis (Pugh, 1997; Congalton and Green, 2009). Unlike positional accuracy, understanding thematic accuracy should not immediately impose that there is such strict, acceptable, standards of accuracy which are required for the results. Being that remote sensing classification for land cover mapping is such a large proportion of applications (Foody, 2002), and it derives such a purposeful outcome, the correctness of its product should be weighted accordingly.

In the early existence of remote sensing products quantitative evaluation of thematic accuracy was largely ignored due to the immense cost and infeasibility of validating entire mapping projects to any degree of precision. In this age, qualitative agreement between the features on the ground and the resulting product was deemed sufficient (Spurr, 1948; Katz, 1952; Congalton and Green, 2009). The cost of attainment, coarse resolution, and perceived dependability of these products made the most prevailing use as general landscape interpretation tools (Spurr, 1948; Spurr, 1952). In the attempt to bring merit and support for thematic mapping as a sensible scientific endeavor, the 1950s brought several prominent figures declaring the necessity for quantitatively assessing remote sensing accuracy beyond positional agreement (Spurr, 1948; Katz, 1952; Cowell, 1955; Congalton and Green, 2009). These initial notions of

accuracy standards fueled thoughts of methodological specifications; however, no affirmation was accomplished at this time.

At the onset of computer technologies, as is the case with many fields of analysis, early beliefs regarded digital products to be superior and without flaw. Flashy, automated systems, lived a period of profound growth with the main focus being capability. With the creation of ever more complex products, increased emphasis began to grow for the need to quantitatively assess data quality (Aronoff, 1982; Congalton, 1991; Congalton and Biging, 1992; Foody, 2002; Congalton and Green, 2009; Jensen, 2016). Although even today visual interpretation of results is still used in some projects, these measures often induce unwarranted uncertainty (Congalton and Biging, 1992). The use of this practice stems from the preceding belief that map makers are always right, and can be increasingly detrimental depending on the complexity of the project.

The quantitative assessment of thematic classification results is built on a solid foundation of statistical principles, comparing estimated to known, real values. Beginning as non-site specific assessments, total areas of map classes (e.g. Forest, Grass, or Developed) were compared between the thematic map and some reference material (i.e. county statistics or parcel map) to see to which level the two sources agree (Congalton, 1991; Foody, 2002). Using this method provided a very simplistic evaluation of the thematic accuracy, neglecting positional agreement in all regards, and withholding more comprehensive results of the classification. Quickly evolving to overcome previous uncertainty hazards, site-specific thematic accuracy assessments were formed to interject acknowledgement for the amount of specific locational conformity between the remotely sensed classification layer and what was on the ground (Congalton, 1991; Congalton and Green, 2009). Site-specific accuracy assessments provide overall agreement between the ground and the thematic layer. To facilitate this process of

assessing two data sources, and their relationship in a multivariate fashion, an error matrix, also

known as a contingency table (in statistics) or confusion matrix is used (Congalton and Mead,

1983; Story and Congalton, 1986; Congalton, 1991; Congalton and Green, 2009). The error

matrix presents individual categorical accuracies and relations among recorded inaccuracies

(Table 1) (Foody, 2002).

Table 1. Conventional error matrix example.

	Ground Sampled Reference Data			
	Water	Urban	Forest	User's Accuracy:
Water	34	9	8	66.67%
Thematic Map Layer — Urban	4	32	8	72.73%
Forest	6	2	27	77.14%
Producer's Accuracy:	77.73%	74.42%	62.79%	130

Overall Accuracy = 93/130   71.5% Accuracy

Unlike the regulated standards for positional accuracy (e.g., NSSDA), each thematic

mapping project must determine its own tolerance of uncertainty, and the type of uncertainty that

it can most justifiably accept. User's accuracy (Table 1), also known as error of commission,

evaluates the user's ability to produce a map which correctly classifies the characteristics of the

ground, in other words, if too many samples have been committed to a class (Congalton and

Green, 2009). Producer's accuracy, also known as error of omission, assesses if measured

locations have been viably captured for each class, alternatively if actual locations have been

20

omitted from the reference source (Story and Congalton, 1986). In most instances, errors of commission are preferred to their counterpart omission errors because, falsely allocating additional area to classes of interest generates less detriment than failing to locate critical features within the focus area (Congalton and Green, 2009; Cormier *et al*., 2013). For both producer's and user's accuracy there are notable tradeoffs in error between resolution, classification scheme complexity, and the overall objective, with regards to the emerging cost of the project. What can be even more important (in some cases) than the overall accuracy of the project, or either of the before mentioned errors, is the sources of error and how they affect the results in relation to the objective(s) (Congalton and Green, 2009).

Error matrices represent versatile quantitative assessments, capable of handling a myriad of data sample types, being that samples are comparable between the two sources. In PBC accuracy assessments this will be single pixels, belonging to a specific class. Identifying matching pixels between the thematic layer and reference source can lead to further error, however, with positional uncertainty causing misregistration. More commonly, homogenous pixel clusters, being either 3x3 or 5x5 depending on the spatial resolution, can be used to ensure proper registration of comparison units (Figure 5). For OBIA, multiple locations need to be assessed to ensure that the entire polygon, with its characteristics, is validated. Many reference sample units need to be taken throughout each individual polygon (Figure 5), for which their combined standard errors can be used as a level of agreement or uncertainty in the prevailing classification judgement (MacLean *et al*., 2012).
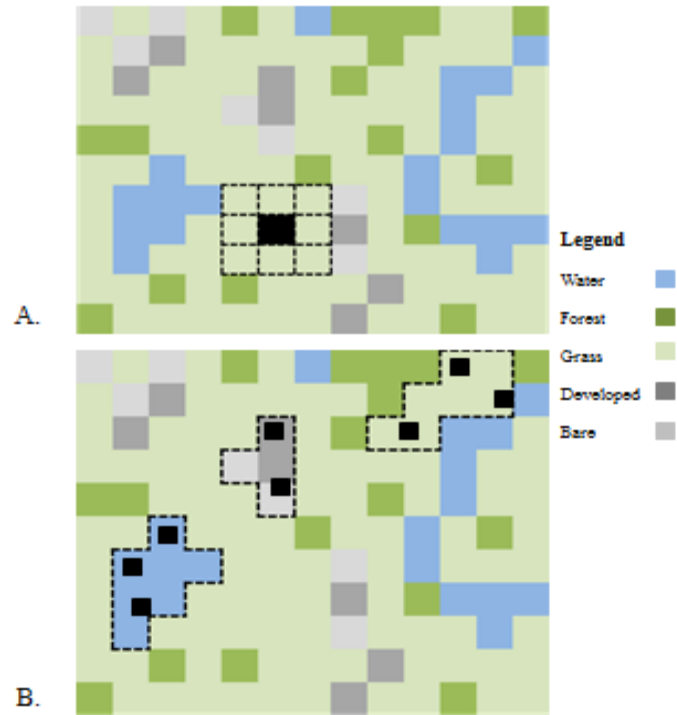
Figure 5. Reference Data Sample Units (in black) for (a) Pixel-based Classification and (b) Object-based Classification methodologies shown with black dots.

To ensure that the process of thematic mapping accuracy assessment is legitimized requires having reference data samples which, as alluded to before, can be used to validate reality (Foody, 2002; Congalton and Green, 2009). To form a basis for this "correct" material, statistical reasoning designs collection procedures for reference data; from either higher resolution remotely sensed data, ground sampling, or previously produced sources, to compare to the thematic layer. Reference data is used for two distinct purposes, depending on the classification algorithm used. First, it can be used to train the classifier, generating the decision tree ruleset which forms the model. Secondly, reference data is used as a validation source, to then test the model's accuracy. To remain statistically determinative, these two forms of reference data must remain independent throughout their collection and analysis. For spatial data, remaining independent prompts minimizing the influence of spatial phenomena. Spatial

autocorrelation is indicative of this phenomenon, conveying the influence which characteristics have on their condition in neighboring units (Cliff and Ord, 1973).

Although rightfully meticulous, methods of reference data collection are not absolute, and should not be understood as "truth". Unavoidable sources of error are present even during the assessment of accuracy. These inaccuracies can be assessed using the error matrix, deriving themselves from one of four possible sources: errors in the reference data itself, subjectivity or complexity of the classification scheme in relation to the observer(s), inability of the remote sensing data to capture the desired land cover classes, or lastly, direct errors in mapping (Congalton and Green, 2009). Even among collection procedures for reference data there are varying techniques including, relying solely on visual identification of the area, collecting GPS location confirmation, or collecting full-record, precisely positioned samples. Complexity or subjectivity in the classification scheme diminishes with proper definitions, but there will always be disagreement in interpretation of some land cover classes. Error in the collection of the remotely sensed data or its mapping can be marginalized with knowledge of the platform and sampling frame reasonable capabilities. One notable attempt to place a lower limit on the degree of accuracy required of thematic mapping accuracy assessment reference data is by Anderson *et al*., (1976). For our analyses, reference sample units generated from remotely sensing methods will match an acceptable error of 4-10% at a 95% confidence interval proposed by Fitzpatrick-Lins (1981). This threshold recognizes that such a "truth" finding process incurs minimal, yet inescapable uncertainty.

Statistically based ground sampling practices have gained widespread acceptance and innovation over the course of the last 100 years, promoting many of the practices that we adopt today for data collection. Natural forest areas exemplify an especially complex and vital resource

and challenge our ability to quantitatively or qualitatively analyze characteristics. The need for efficient and accurate sampling tools created the field of forest mensuration (Bates and Zon, 1922; Kershaw *et al*., 2016). Forest mensuration collects the most accurate and precise observations possible, using mathematical principles and field tested devices, to maximize efficiency (Spurr, 1952; Husch *et al*., 1972; Avery and Burkhart, 1983; Betchold and Patterson, 2005; Kershaw *et al*., 2016). For many decades now these methods have been the foundation for collecting accurate reference data, and general knowledge of forests, providing information devoid of excess bias, inaccuracies, and or confusion. These precise procedures for systematically accumulating observations and measurements have the ability to accurately represent complex communities (Husch *et al*., 1972). To then use forest mensuration to gather training and validation samples comes with the knowledge that such procedures have been rigorously tested, becoming a basis of understanding for the natural world.

Continuous forest inventory (CFI) plots are used by many large organizations to generate long term datasets for monitoring and managing forest landscapes. Many national agencies, in the United States and in Europe, have formed national forest inventories (e.g., Forest Inventory and Analysis (FIA) of the U.S. Forest Service) based on this systematic sampling design (Smith, 2002; Husch *et al*., 2003; Kershaw *et al*., 2016). Used to cover large expanses, CFI plots main purpose is to generalize long term trends, but, with their wealth of data, they can also dictate a prominent source of reference data for thematic accuracy assessments. Angle gauge sampling, a form of horizontal point sampling used in CFI plot networks, selects trees for measurement based on a probability proportional to their size (Kershaw *et al*., 2016). This size determinant probability, also known as a tree factor, creates an unbiased estimate for a basal area per unit area calculation (Kershaw *et al*., 2016).The network of samples uses strict and refined rulesets

for collecting data on the cross-sectional area of individual trees and their distributions as species classes which can be widely utilized (Husch *et al*., 1972; Kershaw *et al*., 2016). Such a system is also only as good as its coverage and resampling guidelines, being opposed by some groups due to its significant cost of use.

Even with efficiency being a primary concern in sampling, collecting a valid sample size of reference data units, in an appropriate fashion, is extremely costly; quickly becoming a project limitation (Dicks and Lo, 1990; Martin *et al*., 1998; Morisette *et al*., 2005; Radoux *et al*., 2011). For project budgets, reference data collection, or the assessment of accuracy, can constitute a large proportion of the overall funds (Congalton and Green, 2009). Due in part to the high cost of collecting validation samples, there is a tendency to neglect reporting accuracy results in modern science. Attaining more accurate, and at the same time cost effective conclusions, is especially imperative in today's world of limited natural resource conservation funding support. A further exacerbated illustration of this is modern forestry, with professionals charged with ever more demanding need for simultaneously making sustainable and profitable yield decisions.

Testing for the efficiency and statistical power of reference data sample units allows analysts to determine precisely how many observations are needed to correctly classify a given area. Using the bivariate normal distribution as the basis of general linear regression modeling the relationship between the classifications of the two data sources, the reference data and the remotely sensed product, can be determined (Quinn and Keough, 2002). The statistical power of each successive sample throughout the landscape can be established, for both pixel-based and object-based sampling, using their standard error in bootstrap resampling simulations (Snedecor and Cochran, 1980; Efron and Tibshirani, 1993; Mooney and Duval, 1993; Siciliano and Mola, 2000; MacLean *et al*., 2012). Bootstrap resampling uses averaging of simulated iterations to

calculate the standard deviation of the population for the classification results, based on specified parameters. From here, the declining return of accuracy for each successive removal of a reference sample unit can be used to find the relationship with sampling cost and efficiency (Thompson, 2002; MacLean *et al*., 2012). Understanding these factors, Husch *et al*., (2003) and MacLean *et al*., (2012) have proposed increasingly refined sampling minimums for collecting thematic mapping ground sampling data.

Unmanned Aerial Systems

Remote sensing continues to expand in the 21st century to meet the needs of the user. Now in a new frontier of high resolution and adaptable sensors, unmanned aerial systems (UAS) look to fill a niche role for the benefit of society. This newly prominent platform is technically defined only by its lack of an on-board operator (Finn and Wright, 2012; Wagner, 2015). The open-ended definition serves as a testament to the ubiquitous nature of the tool. The plethora of modifications popping up every new month brings with it a divided consensus of best suited terminology. Designations such as unmanned aerial system (UAS), unmanned aircraft system (UAS), unmanned aerial vehicle (UAV, unmanned aircraft (UA), remotely piloted aircraft (RPA), remotely operated aircraft (ROA), unmanned vehicle system (UVS), aerial robotics, and drone all have viable social and scientific perspectives (Colomina and Molina, 2014; Wagner, 2015; Marshall *et al*., 2016; Cummings *et al*., 2017). Distinction between titles comes from the respective understanding of the user and their approach to the system. For example, individuals in the conservation sciences often prefer the term UAV, while those with a military background commonly utilize RPAV (Colomina and Molina, 2014). Here in, I use as many others have already, that unmanned aerial systems (UAS) is the most fitting label because this platform

represents a culmination of components (Figure 6). Although not every UAS makes use of all of

the same components, the majority of systems can be expected to have some form or

modification of: (1) a launch and recovery system or flight mechanism, (2) a sensor payload, (3)

a communication data link, (4) the unmanned aircraft, (5) a command and control element, and

(6) the most important of all, the human (Everaerts *et al*., 2008; Eisenbeiss, 2009; Barnhart *et al*.,

2012; Colomina and Molina, 2014; Kakaes *et al*., 2015; Marshall *et al*., 2016; Cummings *et al*.,

2017). Launch and recovery systems are found predominantly with larger UAS, needing

additional components for their large masses. For smaller systems, these are more indicative of

their flight mechanism, needing little to no support for flight. The remote sensing payload

defines the primary utility for the UAS operation. With modern technologies this can be normal

color, multispectral, hyperspectral, and even LiDAR sensors. Additionally, multiple sensor

payloads can be deployed simultaneously, in some cases for first-person-view feeds, as

supplementary data acquisition. The communication datalink serves as the eyes for the UAS

pilot; this component interacts directly with the other components to transmit to the pilot and

controller current status of operations. The unmanned aircraft itself connects all of the other

pieces as the hardware nucleus of the UAS. Taking direct input of servo actions to dictate

actions, the command and control element of a UAS can either be a manual controller for

immediate operator control, or an autonomous control element, pre-programmed for the desired

mission plan. Lastly, all UAS do require some form of human input. This can range from pre-

programming actions and over watch in fully autonomous scenarios to real-time remote control

input, but should always be considered the most important component of the system (Marshall *et

al*., 2016).
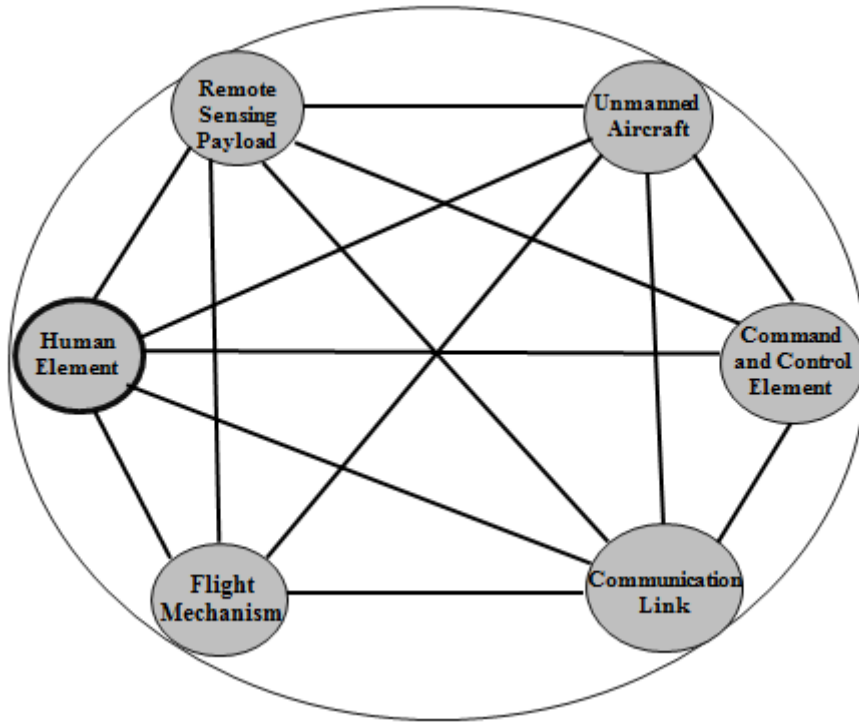
Figure 6. Core components of Unmanned Aerial Systems, all interconnected.

Apart from the actual naming of the UAS, a more preeminent classification may be whether it is a rotary-winged or fixed-wing aircraft. Each providing unique benefits and limitations for modern systems, the division between these two configurations regulates much of the structure of the core components. Rotary-winged UAS, having any number of horizontally rotating propellers, are best regarded for their vertical take-off and landing (VTOL) abilities. Their added maneuverability, and hovering capabilities (Avery, 1977) are only hindered by their lower altitude operation threshold, and on average shorter duration flight capacity (Barnhart *et al*., 2012). Fixed-wing UAS are coveted for their longer duration, therefore larger extent coverage, and their higher altitude flight threshold; but at a trade-off for their lack of focused coverage.

Naturally, any understanding or research into this recently emanating platform will unearth its rich heritage of military applications, with strides in the consumer market appearing only within the last decade. The history of UAS is very dependent on the interpretation of their true definition. Some accounts of UAS date back thousands of years to ancient Chinese emperors purposing of oil-lantern balloons for enemy surveillance (Barnhart *et al*., 2012; Marshall *et al*., 2016). More agreed upon accounts trace the origins back to early remote controlled torpedoes at the beginning of the 20th century. These contraptions evolved in parallel with manned aircraft technology, with innovators such as Elmer Sperry and his son Laurence Sperry devising autonomous guidance controls and the Wright Brothers pioneering aviation systems (Barnhart *et al*., 2012; Finn and Wright, 2012; Marshall *et al*., 2016). These early remote operations became ever more capable with the integration of the then recently invented radio transmitters from Nicola Tesla (Marshall *et al*., 2016).

Still maturing as "dangerous, dirty, and dull" contraptions (Barnhart *et al*., 2012) several attempts were made during the World Wars to have UAS match other weaponized machines. It is during this time that the British Royal Navy's unmanned reconnaissance drone coined the term drone (Marshall *et al*., 2016). The designation of drone reflects the behavioral ecology of bees, spurring several additional associated titles (Marshall *et al*., 2016). Following the war machine mentality for weaponized applications, interest shifted during the latter half of the 20th century to intelligence, reconnaissance, and surveillance (IRS) functions (Eisenbeiss, 2009; Barnhart *et al*., 2012; Marshall *et al*., 2016). This repurposing lent itself to the widespread goals of remote sensing, bringing to life public interest. Today's computer technology and micro-processing pushed the boundaries of each UAS component (Finn and Wright, 2012). The development of complex, scaled-down-stature computers in the mid-2000s formed an explosion in the consumer

market, making UAS available from $10 toy store configurations, to fully capable photogrammetric platforms with centimeter level mapping resolutions for roughly $1000 (European Commission, 2007; Cummings *et al*., 2017).

The proliferation of UAS, with their now achievable increased spatial and temporal resolutions has already been embraced by many scientific fields and applications. Operations such as emergency response (Choi *et al*., 2009), fire mapping (Hinkley and Zajkowski, 2011), structure characterization (Carvajal *et al*., 2012; Nex and Remondino, 2014), forest inventory (Puliti *et al*., 2015), precision agriculture (Zhang *et al*., 2012), general natural resource management (Horcher and Visser, 2004), or wildlife monitoring (Jones *et al*., 2006; Kakaes *et al*., 2015; Hodgson *et al*., 2016), have already expressed benefits of UAS, with many others reviewing the potential (Colomina and Molina, 2014; Whitehead and Hugenholtz, 2014; Cummings *et al*., 2017). This frontier expressed a scientific revolution, open to all those willing to be an early adopter for these new technologies. The widespread growth in capabilities and handling by the public did however form a major conflict of interest with the government and culture, forcing new regulations to cover the needs of worldwide privacy, security, safety, and understanding (European Commission, 2007; Hugenholtz, 2012; Whitehead and Hugenholtz, 2014; Marshall *et al*., 2016).

With any new technology there is of course a cause for question as to how it will inevitably affect society. All in their own right warranted, the major resisting factors to the advancement and adoption of UAS by more users are privacy, security, safety, and social understanding concerns (Dalamangkidis *et al*., 2008; Kakaes *et al*., 2015; Cummings *et al*., 2017). These major drivers are causing shifts in the worldwide acceptance of the platform, critically influencing remote sensing data acquisition in the broad intentions of science. Some

disciplines, such as natural resource conservation, are already experiencing considerable opposition do to their social acceptance, leaving no room for careless UAS operations to further denounce practices by the public. The shift towards approval is however already experiencing some notable progress. For example, there is a renewed connotation forming for the label of drones. With increased public awareness and interest, online searches for the word "drone" now return images of consumer grade models, while only a few years ago this would be populated only by weaponized, predator style models (Google, 2017).

To ensure the compliance of UAS operations, regulations and policy have been developed at local, state, national, and even international levels of government. This research was conducted in the U.S., therefore following the National Airspace System (NAS) guidelines. Although not the most liberal in its authorizations, major reforms are being founded, with the goals of appeasing both UAS and public stakeholders. All actions within the U.S. NAS are governed by the Federal Aviation Administration (FAA). Under recent FAA definition, UAS operations are broken down into three broad categories: public (governmental), civil (non-governmental), and model (hobby or recreational) (FAA, 2016a; FAA, 2016b; FAA, 2016c). These classifications were proposed to strictly limit sanctioned operation for the purpose of not exceeding a threshold of unnecessary risk within the NAS (Anand, 2007; Watts *et al*., 2012; FAA, 2015; FAA, 2016c). Up until recently, apart from these classifications, further regulations were not present to handle actual applications. This oversight caused noticeable issues, with improper or unsafe operations occurring across the country as the result of untrained pilots and further evolved systems. These conflicts opposed the overall goal of the FAA to administer safety standards for UAS which are at least as thorough as manned aircraft (Dalamagkidis *et al*., 2008).

Furthering the three-part classification, current regulations now establish a small UAS (sUAS) definition for which size and flight restrictions are imposed. The major limitation of this specification being a weight restriction of roughly 25kg (55lbs), altitude restriction of approximately 121m (400ft), and high visibility only operation (FAA, 2017b). Each of these systems must be registered through FAA personal under their proposed classification so that they can be reported in case of incident or failure. Other UAS such as large format, high altitude, or long endurance platforms are currently beyond the scope of civil or hobbyist authorization. All regulated sUAS operations within the NAS, not of public or hobbyist control, previously required, prior to use, approval of a Certificate of Waiver or Authorization (CoA). Detailed guidelines of intended coverage, operator understanding, and safety mitigation tactics were subject to review by the Aviation Rulemaking Committee (ARC) of the FAA under this system (FAA, 2017a). Alternatively, section 333 exemptions to this process were also approved for minimal impact operations. As of August 29th, 2017, this process was recognized as tedious and not inclusive to its intended extent, establishing the Remote Pilot in Command (RPIC) license under 14 Code of Federal Regulations (CFR) Part 107 (FAA, 2017). Part 107 stipulates operational permission of sUAS with restricted flexibility for all those who gain a RPIC license. Each intended mission must have at least one primary overseer with the RPIC clearance. This license requires passing a biyearly, reoccurring aeronautical knowledge test (FAA, 2017b), which is administered by a certified flight instructor, much like authorization for manned aircraft aviation. Nearly all restrictions under this reformed policy can be waived through an approval process, allowing for controlled but necessary limits. The regulatory framework under the FAA is still highly unpolished, putting the goals of safety and knowledge first, and dampening the progress utility to operators.

At the state and local levels, supplementary guidelines are at the discretion of public opinion and lawmakers. Here in New Hampshire, house bill 602 looks to heighten registration and unlawful operation clauses (HB 602-FN, 2015). Looking at local levels, missions, especially routine and prolonged flights, must respect land owner permission and local authorities as to not incite concern.

The widespread acceptance and supportive regulations of UAS is promoted by the advances of their products. New products, with the aid of specialized or repurposed software, and computer vision, are further changing the way that we model the world. Orthomosaic models are being produced with small, point-and-shoot optics, with procedures designed to overcome sensor drawbacks. UAS photogrammetry is now being referenced in fields such as computer science, robotics and artificial intelligence, general photogrammetry, and remote sensing (Eisenbeiss, 2009; Cummings *et al*., 2017). Flight planning fundamentals call upon earlier manned mission planning protocols, with further reduced costs and flexibility. Multi-million dollar manned aircraft systems, and high-resolution satellite imagery scenes costing upwards of $20/ square km (WorldView-2, 2017) are now being repeatedly observed for a much lower cost of entry. Documented evidence for the shift towards inexpensive, on-demand options is popping up everywhere (Kakaes *et al*., 2015). The extremely high-resolution, flexible deployment, minimal cost, safety, and fast data acquisition of modern UAS makes them the ideal candidate for challenging ground, and alternative remote sensing platforms sampling (Eisenbeiss, 2009; Rango *et al*., 2009; Whitehead and Hugenholtz, 2014; Puliti *et al*., 2015).

As stated before, high-resolution remotely sensed data can be used as reference data for other data sources. Paramount to the utility of this process in ecological research and management is the standardization of outputs (Anderson, 1976). Aerial imagery has been used

since at least the 1950s to provide an ancillary source of validation data (Spurr, 1948; Spurr, 1952). This use has, over time, lead to skepticism over the appropriateness of photo interpretation derived reference data for thematic mapping accuracy assessments (Congalton and Green, 1992). While others have confirmed practices for accurately distinguishing composition from imagery (Martin *et al*., 1998). The photo interpretation potential of imagery has benefited with each increase in resolution, providing the ability for skilled professionals to identify individual species (Avery, 1977; Avery and Berlin, 1985) and then work up to deducing majority composition classes across samples. UAS derived orthomosaics enhance this process, associating three-dimensional (3D) texture and surfaces, with their readily formed high-resolution models. It is a question then if the UAS provide a potential platform for collecting thematic mapping accuracy assessment reference data of a necessary caliber, and if their operational efficiency supports their use over refined ground, or alternative sampling methods.

METHODS

Study Areas
This research was conducted using University of New Hampshire (UNH) woodland properties. Using properties owned and managed by the university gave several benefits including: comprehensive ground sampling measurements datasets (in the form of CFI plot networks), UAS operation permission, and study areas maintained for their research potential (UNH Woodlands and Natural Areas, 2017). The specific study areas chosen were selected for their complex species composition and structure, and for their spatial extent, to generate a statistically valid sample size for comparison. Of the over 1,200 hectares (ha.) (3,000 acres) of

woodland properties owned throughout the state, six locations were chosen within local

proximity of the main campus in Durham, New Hampshire (Figure 7).
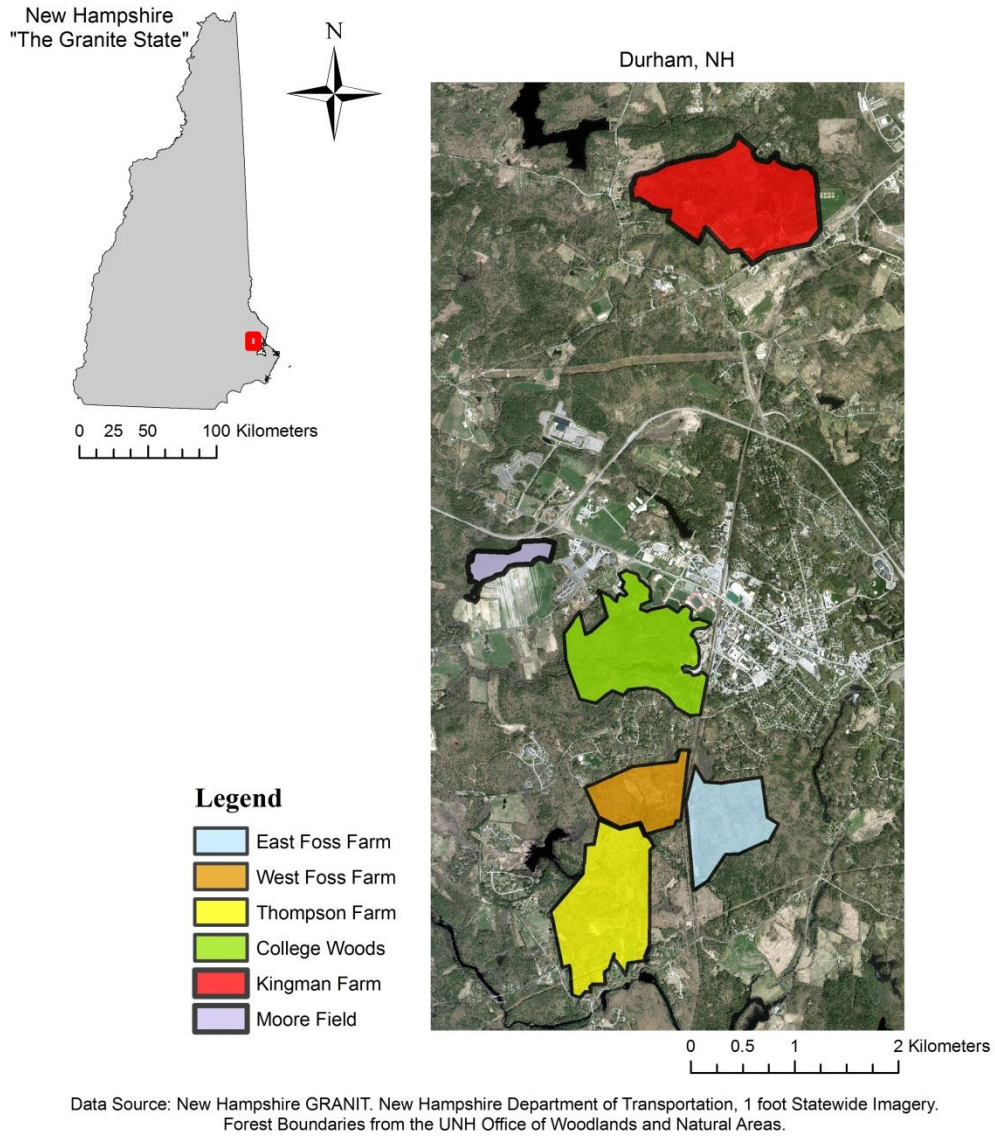
Figure 7. Estimated boundaries for focused study areas used in reference data collection and comparison.

These six forested properties comprise 522.85 ha. (1,292 acres) of total land, 377.57 ha. (933 ac.)

of which are considered forested land cover. For each property, the areal extent and CFI data

available is detailed in Table 2. The number of CFI plots shown in this table represent those

which have estimations of overstory species composition, measured as either count or measure

trees found during ground sampling.

Table 2. Focused woodland property attributes for the six study areas.

Location	Forest Area in hectares (Acres)	Total Area in hectares (Acres)	Forest Stands	CFI Plots
West Foss Farm	42.90 (106)	52.27 (144)	5	29
Thompson Farm	78.10 (193)	118.17 (292)	8	66
Moore Fields	17.00 (42)	47.76 (118)	4	15
Kingman Farm	94.70 (234)	135.17 (334)	8	91
East Foss Farm	51.80 (128)	62.32 (154)	10	55
College Woods	93.08 (230)	101.17 (250)	6	97
TOTAL:	377.57 (933)	522.85 (1,292)	41	353

West Foss Farm, located just south of campus in Durham, New Hampshire, contained a

total of 42.9 ha. of forested land cover. Characteristic of this property were its large central

grassland habitat, and its adjacent railroad tracks. Also present were low-laying powerlines, not

accompanied by a right-of-way. This property was last inventoried on the ground in 2014 with 29 CFI plots covering the area.

Thompson Farm was the southernmost study area. Identified by its large central farmland and adjacent wetland habitat, this large property was home to an above canopy AIRMAP tower in its southern region, utilized for ongoing climate change research. Having access to this tower provided additional visual coverage during missions, but also implemented a no-fly zone, for risk of collision which was not autonomously detected. For this property, 66 CFI plots were inventoried in 2013 to analyze the forested land cover of 78.1 ha.

Moore Fields represented the smallest study area chosen for observation. Just west of campus, this woodland also runs adjacent to a large agriculture field managed by the university. With only 15 CFI plots, inventoried in 2014, this 17.0 ha. (42ac) forest comprised fairly distinctive cover types.

Kingman Farm was home to both the NH Agricultural Experiment Station and the UNH Office of Woodlands and Natural Areas main residence. The northernmost study site, and the only one located outside of the college town, Kingman Farm is situated in Madbury, NH. Kingman was most well-known for its abundant agriculture fields, running the southern portion of the property. The forested land covering this property, comprised 91 CFI plots over nearly 95 ha, was inventoried in 2007 and again in 2017, during our field season.

East Foss Farm, sat southeast of the Durham campus. A mainly forested landscape, this property is notable for its actively managed early successional habitat. These habitats, as well as the sporadic wetlands, are not utilized in this study. The 55 CFI plots located systematically

throughout this property were last inventoried in 2014. East Foss farm has 51.8 ha. of forested land.

College Woods, with its associated natural area, was connected to the main portion of the UNH campus. Used as a primary source for educational opportunities to many departments, this area was highly characteristic of New England forest composition. Last inventoried in 2010, the 97 CFI plots located throughout this property incur the longest duration since last sampling. Altogether, College Woods contained an estimated 93.08 ha. of forested land cover.

Ground Reference Data

The extensive CFI ground sampling plot network used on the UNH woodland properties utilized methodologies for estimating landscape level characteristics. For each plot location, angle-wedge prism sampling was used to collect a number of biophysical measurements including: tree species composition, individual tree diameter at breast height (dbh), species count, and silvicultural code through horizontal point sampling (Kershaw *et al*., 2016). The ocular methodology employed by the prism to select individual trees created a variable radius plot. Selection for inclusion, and therefore measurement, was based on the basal area factor (BAF) of the prism chosen, relating a probability proportional to size selection potential to each individual tree (Kershaw *et al*., 2016). Size determinate inclusion zones codify each individual tree's basal area, or cross-sectional area at breast height (Husch *et al*., 1972). Such methods provide an efficient and elegant way of quantifying stand structure with minimized effort, sampling part of the population to represent the whole (Stage and Rennie, 1994; MacLean *et al*., 2012) because it can be directly related to metrics such as stand volume or overall biomass (Husch *et al*., 1972). Forest mensuration principles provide conditions for slight discrepancies in this methodology regarding hard to see trees (blocked line of sight), plot ground elevation

changes, and dual-stem individuals (Kershaw *et al*., 2016). For the New England region,

BAF $4.59m^2$ (or $20ft^2$) prisms are recommended (Ducey, 2001), and are used by the UNH

forest technicians. Any tree found by the prism to have basal area over the BAF $4.59m^2$

minimum sight threshold is counted as being representative of the basal area of the larger forest

stand, or part of the estimation sample. In addition to the single plot sampling methodology, the

integration of "Big BAF" sampling provides additional biometric characteristics. This selection

methodology is utilized at every plot location but with a BAF 75 probability of selection

(Kershaw *et al*., 2016). For trees within this greater magnitude (large dbh or close to the plot

center), tree height, bearing form the plot center, distance from the plot center, crown

dimensions, and number of silvicultural logs were also recorded, deeming them as "measure"

trees.

 CFI plots were sampled on a systematic grid with 1 plot per hectare (Figure 8). This

results in most management units, or unique forest stands, having a minimum size of 10 ha.

Resampling frequencies call for woodland properties being measured at a minimum every 10

years, with select areas being measured more on a needs-based rotation, depending on the

research agendas and management design.
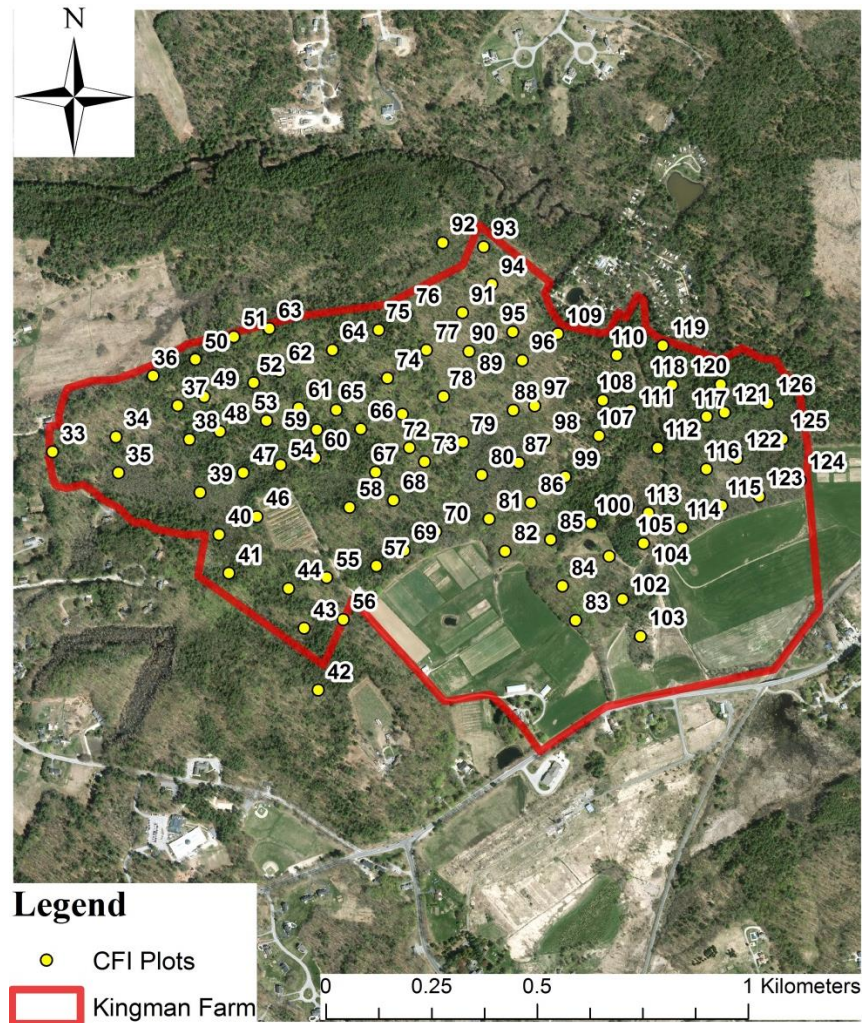
Figure 8. Kingman Farm systematic sampling grid arrangement of CFI plots. Plots 33-126 are present in this woodland.

CFI variable radius plots used the algorithm for basal area (see below) as a function for their probability proportional to size measurement of inclusion of individual trees (Kershaw *et al*., 2016). Basal area quantified both the distribution from the plot centers and cross-sectional area of each individually measured tree. Having such estimations of composition are useful to characterize forest stands and therefore landscapes using the relationships of distribution over area and size of the individuals' encountered (Husche *et al*., 1972; Kershaw *et al*., 2016). Species

composition, frequency, abundance, and distribution, are all generalized from this information, using majority rules.

$$BA = 0.00007854 * DBH^2$$

<div align="right">(1)</div>

From the raw data CFI observations, the count and measure trees (i.e., the dominant individuals within each stand chosen based on their size and location in reference to the plot centers) were used to derive a quantification of the percentage of coniferous species comprising the sample. This was facilitated by calculating the basal area of each tree, then classifying them as either deciduous or coniferous and finding the percentage composition of each class.. Rather than classifying down to a species level scheme, which in this case would leave 31 classes (See Appendix A), I adopted the conventional three forest classes of Deciduous, Coniferous, or Mixed from Justice *et al*., (2002) and MacLean *et al*., (2012) to more feasibly discern lkand cover classes. There is also a noticeable change in resources provided in contrasting deciduous and coniferous forests. To transform the original dataset, provided by the UNH Office of Woodlands and Natural Areas, first a qualitative analysis of the data took place. As these data were collected for general purpose research and management, unnecessary variables were present and had to be identified; these included measures such as saw log volume per individual. Next, the datasets for each woodlot were assimilated into R Studio, version 3.3.2 (2016), for cleaning and processing, namely removing missing values and standardizing values. All count and measure trees were separated out from those noted as regeneration because they would not be part of the dominant forest structure. Among the 353 CFI plots, a few were identified during this step as not containing any recorded trees due to the size threshold of variable plot sampling, these plots were removed from the analysis since they represented non-forest dominated land by definition (the difference between the number of plots counted in the management plans and the number

<div align="right">41</div>

referenced in Table 2). Standing dead trees were removed from the remaining plots, as a number

of years have passed since their measured occurrence, and because they provide unique, yet

differing resources to the forest ecosystem. Next, each remaining individual had its basal area

computed in centimeters squared and its deciduous or coniferous class association confirmed to

determine the percent coniferous composition based on basal area per unit area of each plot.

With the processed variables (Table 3), a simple decision tree was employed for assigning the

classification scheme ruleset to all remaining plots.

Table 3. Representative plot data to illustrate CFI classification variables used to derive plot

composition label (i.e. Plot Class).

PLOT	Total BA (cm2)	% Deciduous BA	% Coniferous BA	Plot Class	Latitude	Longitude	Date
33	1.240572	0.3148	0.6852	Con	43.17427933	-70.4964643482	July 2007
34	.024225	0.0	1.0	Con	43.1745851	-70.94452509	July 2007

The designed classification scheme here aims to match the complexity of previous studies

performed in this region, staying within a more basic hierarchy of forest land covers (Anderson,

1976). Adopting the conventional three forest classes of Deciduous, Coniferous, or Mixed from

Justice *et al*., (2002) and MacLean *et al*., (2012) was advised for this region due to the highly

variable forest composition even within minimal distances. For our research, the classification

scheme was partitioned into the same three categories, allowing for a direct comparison to the

findings of MacLean *et al*., (2012). Much like the national land cover dataset (NLCD), this

project recognized the hierarchical utility of the data. Looking at only forested landscapes during

our analysis, we focused on the Anderson (1976) definition of forest: areas with 10 percent or more aerial tree-crown density, capable of producing timber, and influencing either the climate or water regime. Then, the more specific class definitions were:

- "Coniferous", any land surface dominated by large forest vegetation species, and managed as such, comprising an overstory canopy with a greater than or equal to 65% basal area per unit area coniferous species composition.

- "Mixed", any land surface dominated by large forest vegetation species, and managed as such, comprising an overstory canopy, which is less than 65% and greater than 25% basal area per unit area coniferous species in composition.

- "Deciduous", any land surface dominated by large forest vegetation species, and managed as such, comprising an overstory canopy, which is less than or equal to 25% basal area per unit area coniferous species in composition (Figure 9).

Common coniferous species in New Hampshire include white pine (*Pinus strobus*), eastern hemlock (*Tsuga canadensis*), balsam fir (*Abies balsamea*), or black spruce (*Picea mariana*) (see appendix A for full breakdown of recorded species and classifications).
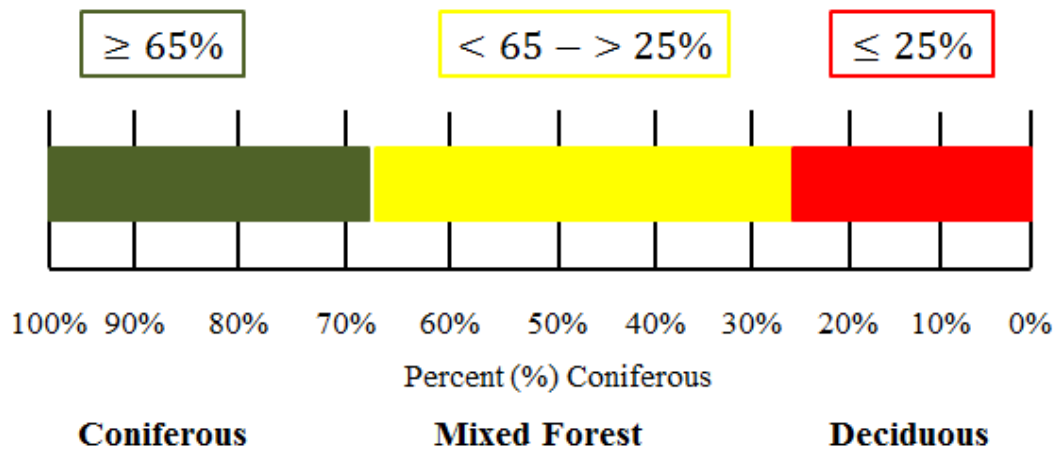
Figure 9. Sampling design classification scheme breakdown. Based on the percentage of coniferous species composition found within each sample.

Percent coniferous for each plot was factored to six decimal places in the "PlotClass" column (Table 3) unless whole integer values were obtained. Due to the collection materials, only a geographic coordinate system was confirmed for the CFI plot locations, in this case being the standard WGS-84.

To objectively assign forest stand boundaries for the management units of each woodland property, with adherence to our selected categories, the classified CFI plots were used to guide manual digitizing by fellow spatial analysis researcher Heather Grybas, in review with UNH woodlands manager Steve Eisenhaure. The processed systematic plot network formed, for the most part, recognizable divisions between management units of justifiable size while still managing the uniformity of the traditional New England landscape. Leaf-off, 2015, natural color, Department of Transportation (DOT) imagery with a 1-foot spatial resolution was used as a basemap during the digitizing process for visual, contextual understanding of boundaries between forest stands. Together more distinct edges between classes could be formed, working

down the hierarchical structure of the definitions. Non-managed forested areas within each of the woodlands were found using the management plans, and lack of CFI plots, all of which were digitized and ignored throughout the project. An example of these forest stand boundaries can be seen for Kingman Farm below in Figure 10, with the complete set for all of the study area properties in Appendix A.
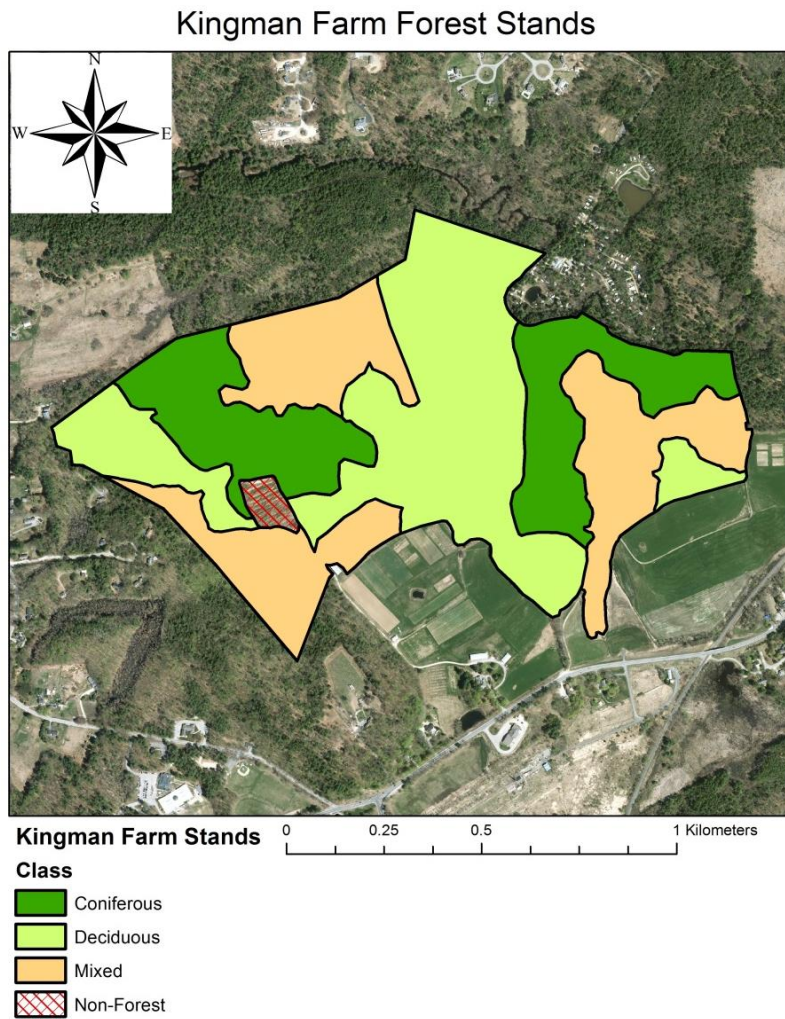
Figure 10. Forest stands for Kingman Farm, Madbury, NH. Based on ground sampling data.

UAS Image Sampling

        Two UAS were evaluated as primary sources for remotely sensed data acquisition during

this project, with an additional system used as a calibration and scouting unit. The first was an

Aeronavics Skyjib X-8 multirotor (octocopter) system (Figure 11). This rotary-winged platform

integrated DJI hardware including an A2 flight controller and inertial measurement unit (IMU), a

Mark-II iosD for real-time flight data capturing, and a LK24-BT (2.4Ghz) communication link.

For the remote sensing payload, a commonly used Zenmuse-Z15 gimbal and Panasonic Lumix

GH4 (12mm) camera are attached. Demanding two six-cell, 11.1-volt, 10,000mah Tattu batteries

to operate brings the take-off weight to approximately 19kgs (~42lbs), for a maximum flight

time of 8-10 minutes. In addition to the primary specified data collection system, an external

first-person-view (FPV) monitor was supported by the communication data-link during operation

on this UAS. Included with the DJI hardware is DJI Ground Station 4.0.11 for autonomous

mission control and monitoring. This software was circumvented following training missions for

the more ubiquitous Universal Ground Control Station (UGcs) version 2.10. DJI Ground Station

software was no longer supported and could not provide full functionality for the required spatial

data acquisition. Hardware limitations and project demands forced this system to only be used

during training missions.

Figure 11. Aeronavics Skyjib X-8 complete system configuration including: (1) eight-rotor flight mechanisms, (2) Panasonic GH4 payload, (3) two Tattu battery placements, (4) unmanned aircraft, (5) 2 manual command and control elements, one for aircraft, one for gimbal, and (6) Bluetooth communication data link for laptop. Also pictured are the FPV monitor (right, under drone) and UGcs mission planner (left).

The primary UAS used for data acquisition was the eBee Plus platform. The eBee Plus was an all-in-one fixed-wing aircraft from Parrot SenseFly. Integrated in this UAS (Figure 12) were a proprietary autonomous flight controller, communication data link, and IMU. For payloads, both a sensor optimized for drone applications (S.O.D.A) camera and parrot sequoia multi-spectral sensor were investigated. The SODA is a natural color, 20 megapixel payload, capable of a 2.9cm ground resolution at a 122m flying altitude (SenseFly, 2017b), specifically designed for sharp drone imagery collection/ photogrammetry. Alternatively, the parrot sequoia is a five sensor, multispectral payload. The combination of sensors on the sequoia included a

normal color (16 megapixels) optic, and a multispectral system with individual green, red, red

edge and near infrared sensors (SenseFly, 2017a). For a power supply, the eBee plus used a

single 3-cell, 11.1-volt, 4,900mah battery, capable of a maximum flight duration of 59 minutes

(SenseFly, 2017b). The total weight of the system came to approximately 1.1kg with either

payload. It was highly recommended that this system was only operated in pre-programmed

autonomous missions (an emergency manual controller is included) using the included,

proprietary eMotion3 mission planning software (version 3.2.4).

Figure 12. eBee Plus system configuration with (1) flight mechanism, (2a) SODA and (2b) sequoia payloads, (3) battery, (4) aircraft, (5) communication link, (6) ground control software and controller. Also pictured are the hardware and software manuals, in color (far left).

The final UAS system operated was a DJI Phantom 2 Vision+. A small rotary-winged (quadcopter) system, the Phantom series now represents a highly praised model in the consumer market. The Phantom 2 Vision+ came with a singular manual controller, and operates a Wi-Fi communication link to connect a smartphone device for gimbal and camera manipulation. An internal IMU collected minimal GPS and sensor orientation data throughout missions. This model of Phantoms offered the first version of an integrated normal color camera, boasting 14 megapixels (DJI, 2017). A 5200mah, 11.1-volt, single battery was used to provide a 15-20-minute flight time with a total weight of 1.2kg (DJI, 2017). The Phantom 2 Vision+ (Figure 13) was used primarily as a calibration and scouting platform due to its ease of use, but was not used to collect data analyzed in this project.
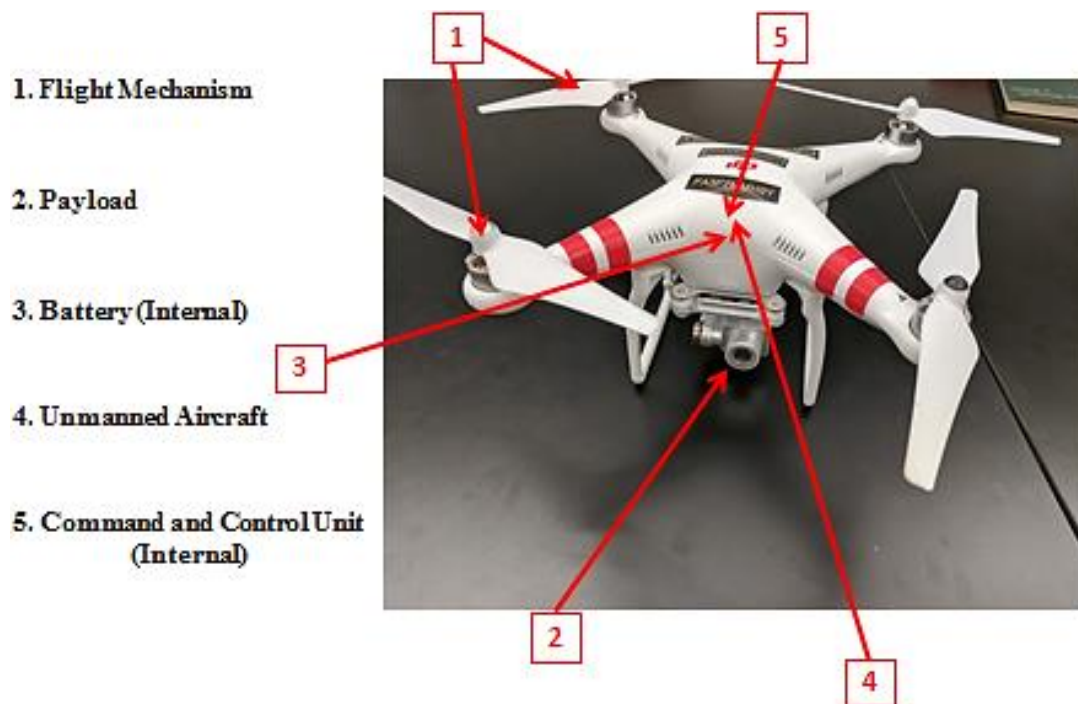
Figure 13. Phantom 2 Vision + UAS Configuration.

Reference data collected by the UAS platforms was designed to match the characteristics of the classification outcome derived by the CFI plot-based ground data network. Having a new protocol which formed incompatible products to the ground data collection would relinquish the utility of the UAS data. For each of the woodland properties, proper notification was used for access and research permission by the appropriate parties (see table of access permissions in Appendix B). Flight planning was set up to capture the maximum possible area of each woodland property, while still flying only within the property boundaries. For larger properties (such as Kingman Farm) this meant breaking the property into up to four separate missions, to be merged later during processing of the imagery (Figure 14).
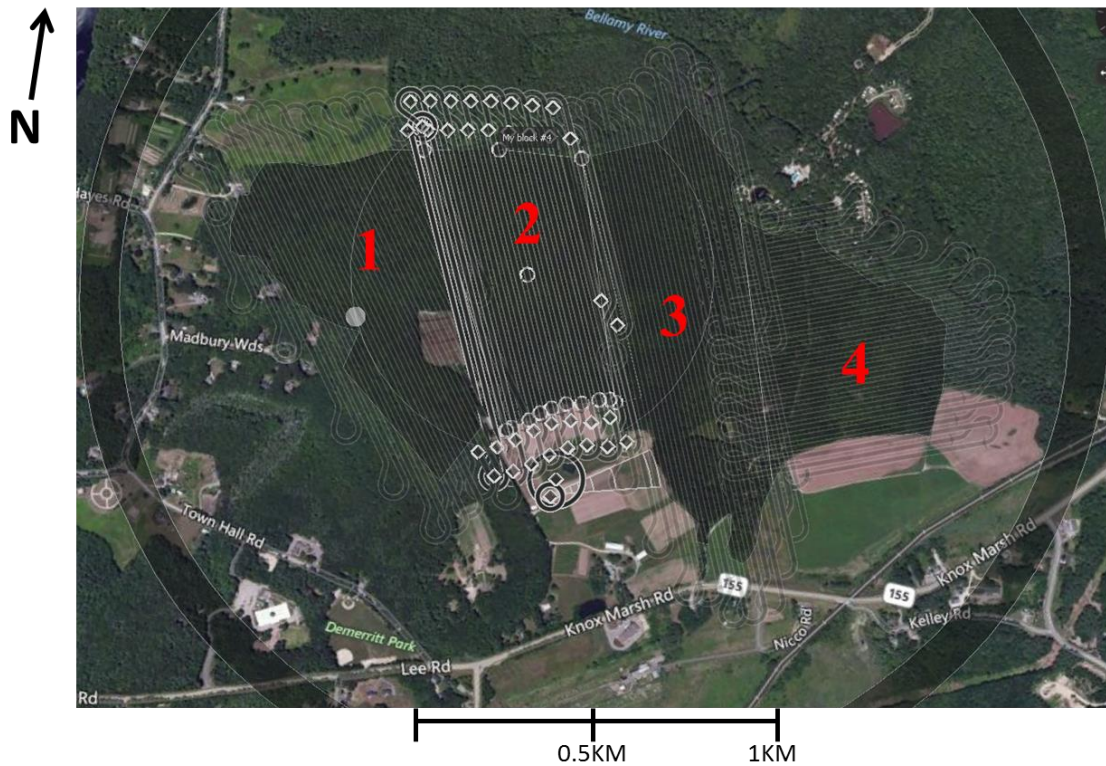
Figure 14. Kingman Farm flight planning mission blocks, eMotion3 flight planning software from Parrott SenseFly.

Images, once collected, could have their spatial location joined to them, avoiding the need to restrict flights to individual forest stands (sample units) during mission planning. Prior day weather forecasting was used as the most accurate estimate of precipitation and wind speed. These weather condition estimations were reviewed through the National Weather Service (NWS) and serval drone flight mapping services. Although our systems could fly in winds over 20m/s, it would have severely diminished their image quality and battery life. Instead, wind speeds in excess of 12m/s were not used for operation as a safety and accuracy precaution. It was highly recommended that for autonomous missions, flight lines are also set up perpendicular to the wind. Having perpendicular wind angles would cause flight speed and image spacing regularity, severely increasing accuracy and image matching capabilities (eMotion3, 2017). It was also desirable to have a near vertical sun angle during image acquisition and consistent sun exposure. Cloudy days and near dawn or dusk flights were avoided as to not cause irregular shadows or excess darkness in the imagery. Although individual images would not be influenced greatly, model generation could have been impacted at various stages. To summarize the mission planning information and retain notes on the progress understanding the systems, a checklist and flight log was organized (seen in Appendix D). Many mission planning software programs now include these records by default and even record some of the desired information as part of the flight data file (.EXIF data), never downplaying the importance of having excess records.

For the assessment of sampling efficiency, several flying heights above canopy were included in the initial imagery collection planning. Originally this entailed 25m, 50m, and 100m above the average canopy height. However, as test missions were flown these were adjusted as necessary. Any missions below 50m quickly lost line-of-sight (a legal requirement) and

communication link. The desire to find the minimum effective flying height above the forest

canopy in the pursuance of high spatial resolution while maintaining radio communication

resulted in analyzing heights of 50m, 100m, and 120m above the forest canopy. The cap set here

(120m above surface or canopy) was based on the restriction of the Part 107 regulations, stating

sUAS operations are limited to a 400ft ceiling above surfaces (FAA, 2017b). The canopy height

model was provided by NH GRANIT, as was the DOT basemap imagery. Additionally, a state-

wide LiDAR (.las) dataset, with its original two points per meter squared was made coarser, and

had outliers removed. The final LiDAR input was brought to two points for every ten square

meters, resulting in a much smoother flying height for UAS mission planning. To keep a

constant ground sampling distance (gsd), or model pixel size, image acquisition flying height had

to match the surface of the forest canopy. Having three flying heights would test the levels of

detail derived (Figure 15) and the processing efficiency of varying numbers of images.

**Figure 15.** Flying heights above canopy detail comparison for UAS imagery collection.

Following flight sessions, the images had to be linked to the spatial data collected by the

UASs IMUs and global navigation satellite systems (GNSS). For both the Skyjib, and eBee plus

platforms, this was done by attaching the internally stored .bbx (or .dat) formatted text file to the

folder containing the raw images captured for that specific mission block. The Phantom 2 Vision+ performed this process automatically during image acquisition. During mission block flight, every sensor with the exception of the parrot sequoia had an external SD card for storing the captured images. The sequoia, as standardly configured, had both an internal and external storage location. Having both data storage options provided the possibility for on-the-fly changing of preference. For the eBee, the mission planner is able to post-flight process the flight log file and the images to match the servo action of camera triggering to the specific image to facilitate the creation of any number of outputs. For the Skyjib, the .dat file had to be rewritten to match required text formatting of the selected processing software such as eMotion3. Once reformatted, the spatial data could then be linked to the individual images. All systems were backed-up in multiple digital storage locations after daily flight sessions so that successive operations would not lead to the loss of data for any reason and to alleviate any data storage limitations.

Generating spatial models from heavily overlapping successive images once structured flight planning to achieve image overlaps necessary for transcribing photographic detail to previously available planimetric maps (Avery and Berlin, 1985). This degree of overlap was purposed to match the horizontal positioning of common features in successive captures, using the historically low quality sensors (Avery and Berlin, 1985). To generate planimetric models from the exceedingly high spatial resolution UAS imagery, it is recommended to require at least a 65% forward and sidelap (Pix4D, 2017). This higher percentage of overlap forms the basis for computer vision SfM modeling (Westoby *et al*., 2012; Mancini *et al*., 2013). Low altitude flights, with high levels of detail, make image matching of specific tie points through aerial triangulation (Figure 16) very difficult. Even minimal distortions from shadows, from the wind,

from the drone, or even from the features of interest, can disrupt the automatic tie point

agreement. Images which do not establish at least three tie points are not calibrated or

assimilated into model processing.
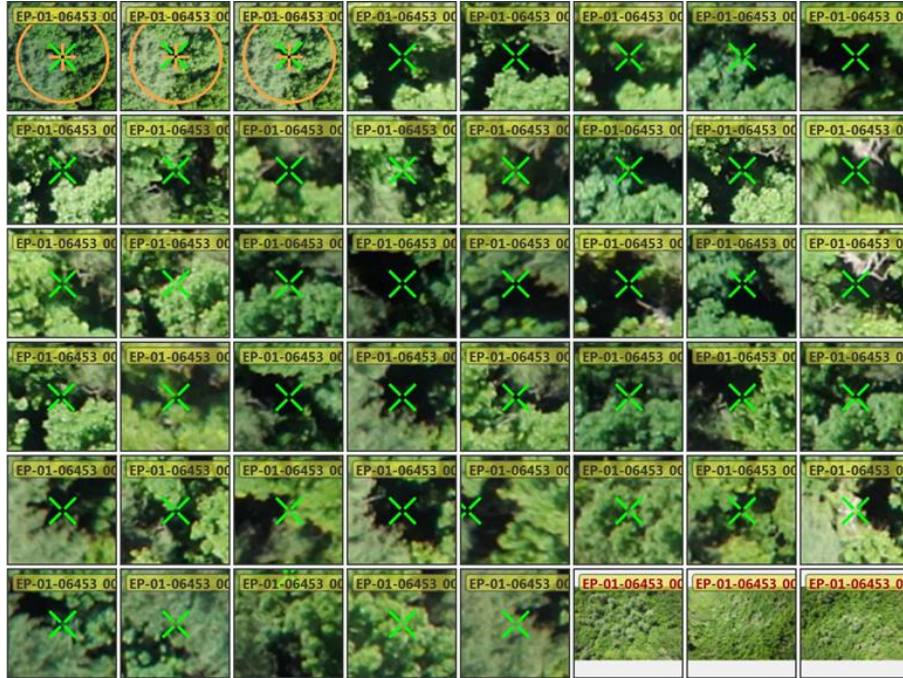
Figure 16. Tie point Image Matches between images with overlap, shown by green crosshairs.
Image matching produced in Pix4Dmapper Pro.

For complex environments, such as highly vegetated forests, point cloud and orthomosaic

models are recommended to have images with 85% forward and 70-75% side overlap (Pix4D,

2017b). These overlaps result in thousands of matches between images in an ideal scenario

(Figure 17). Manual tie points can also be selected from within the imagery to improve

matching, using either distinctive features in the landscape or prerecorded ground control points.

To mitigate the complications of the high-resolution imagery error, image scales within the

processing software are set for these tie point matches to further aid their calibration (Pix4D,

2017a). If tie points cannot be found between an image and any other, it will be automatically

disabled during model processing, resulting in a lower overall image calibration percentage.
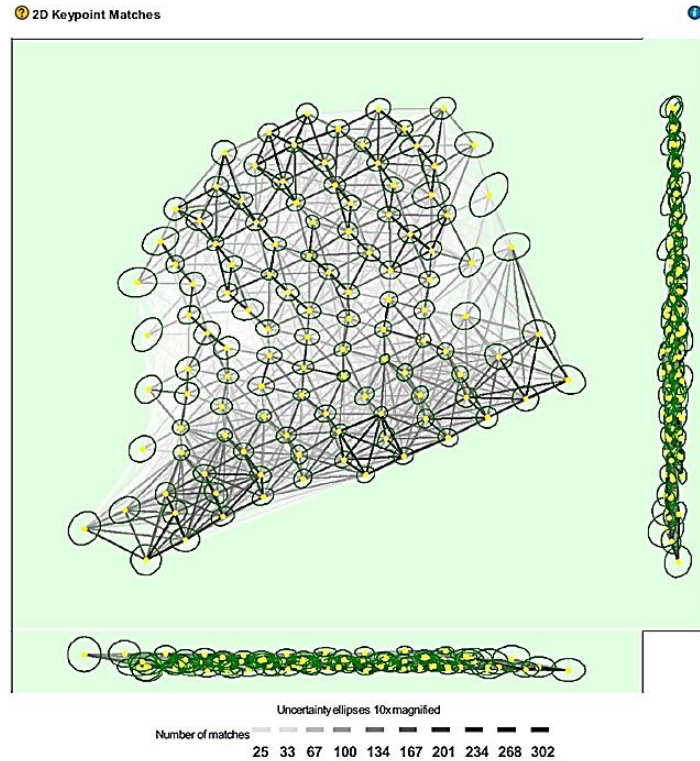
Figure 17. Keypoint (tie point) matches for UAS aerial imagery in orthomosaic generation. Connecting lines show the number of matches between overlapping images, with darker lines showing a greater number of automatic matches. Green circles show geolocation uncertainty of images. Processed in Pix4Dmapper Pro.

At the leading edge of UAS photogrammetry and modeling, the software packages

Agisoft PhotoScan (Agisoft) and Pix4Dmapper Pro (Pix4D) have become the dominant players.

Both programs have been used during this project, with varying results across study areas.

Previous questioning of other users (ASPRS conference in spring 2017) and use during test

missions provided comparable results across outputs, with the only consistent, observable

difference being the usability preference. The increased core functionality (image input options) and added statistics provided during initial processing in relation to image quality, stitching completeness, and model accuracy, favored Pix4D for most locations during initial testing. Agisoft was also run for a large portion of analyses to evaluate its processing products.

In determining the efficiency of processing such large area models, at such a fine scale, Moore Field was used to assess if high density and high accuracy processing was necessary in our analysis, or whether moderate level parameters could create appropriate products. Altogether, eight orthomosaic models would be generated in the final data source comparison analysis. Thompson Farm was split into North and South due to forest stand locations. College Woods was split into East and West due to its heavy processing loads. High accuracy photo alignment and calibration, and medium dense cloud formation were set as the batch processing parameters; all other options in the standardized workflow of Agisoft remained unchanged.

Classification Unit Sampling

Both PBC and OBIA thematic mapping accuracy assessment reference data samples collected from the UAS were derived from the resulting woodland property orthomosaics. These samples, in their use as validation data were analyzed over all of the woodland properties other than West Foss Farm (which was used for training samples). Mission blocks (individual flight plans), were processed together to make holistic property models. For the PBC reference data sampling, 90x90m areas were positioned within each forest stand, using an internal buffer, for two analysis methods. In the first, UAS samples were positioned near the center of cover type area to simulate the collection of reference data for more routine sampling protocols (Congalton and Green, 2009), without prior plot level ground data context for the areas. To more directly

compare the classification of the UAS reference data samples to labeling based on the CFI plots,

a second method of PBC reference data collection placed the UAS samples directly over known

CFI plots and compared the classification of each for the forest area. From the selected 90x90m

areas, representing a pixel cluster, the center 30x30m area serves as the effective area, being

visually interpreted to classify the sample and used as a representation of the overall

homogenous area (Figure 18). This effective area serves two purposes: first, it avoids

misregistration errors for matching the reference data to the thematic map, and secondly, it

ensures that the area that is classified truly fits within the boundaries of the given stand

(Congalton and Green, 2009). Although the UAS has a positional accuracy of within ten meters,

the thematic layer can have a greater, varying, degree of positional uncertainty. Accounting for

such a large margin of error negates the necessity of verifying each sample's locational

agreement. Sample units of 30x30m squares also created equivalency among the samples

collected at the varying flying heights. Of the 41-total forest stands found at the six properties,

some could not be analyzed using this 90x90m area due to their linear or narrow arrangement.
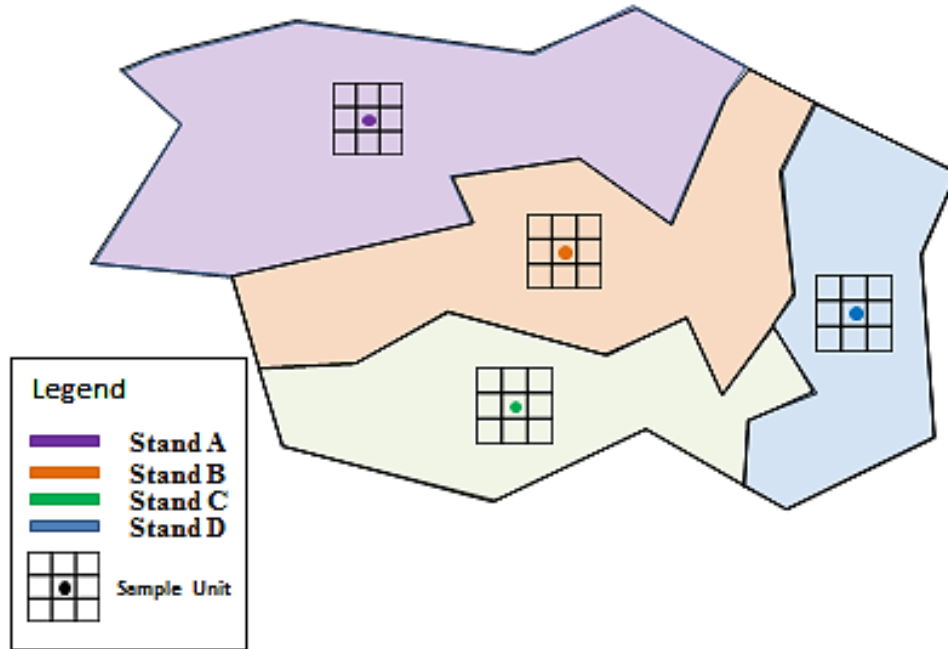
Figure 18. Pixel-based classification reference data sample units.

For object-based image analysis, reference data sample units must be able to label classes

at the image object structure level. The goal here was to have a greater amount of external

variation rather than internal for image object formation (i.e., between objects/forest stands is

more variable that within objects/forest stands) (Congalton and Green, 2009). These thematic

objects, the forest stands, require multiple samples each to accurately represent their

heterogeneity (Congalton and Green, 2009; MacLean *et al*., 2012). To retain conformity between

the flying heights, the comparison samples were again a standardized size. Like the PBC

samples, a 30x30m effective area for interpretation was used. For the OBIA approach there were

also two collection methods for the location of reference sample units. First, independent, non-

overlapping, orthomosaic samples were randomly distributed throughout each of the forest

stands (Figure 19). Sample units followed a stratified random sampling approach. Sample size

(n) during collection was the maximum allowable without inducing spatial bias (i.e.,

autocorrelation), resulting in 268 units. Using the stratified random sampling approach would assess if UAS products were viable to photo interpret forest stand classification in complex communities as reference data. For the second method, UAS reference samples were directly compared to the classification of the individual CFI plots and their overall polygon decision. Forest stands were internally buffered 21.215m (half the hypotenuse of the 30x30m square sample), with remaining, interior CFI plots being used as sampling locations for the UAS orthomosaic sections. Among the five analyzed woodlands, 202 sample units were appropriate for this method. This secondary analysis assessed whether we can directly compare the classification of forest stands by looking at the ground sampling plot against the UAS reference data classification. The majority agreement of the UAS sample units within each of the forest stands was used to derive a classification for the object area using both methods. In the case of a non-clear majority split among the sample units for the classification, the decision followed the ruleset shown in table 4 for majority composition. The decision for majority agreement in forest stand classification was supported by the inability to further breakdown UAS orthomosaic sample units into a discrete averaged percent coniferous composition estimates. Overall forest stand classifications instead relied on the judgment of the three-class decision for each orthomosaic sample unit.
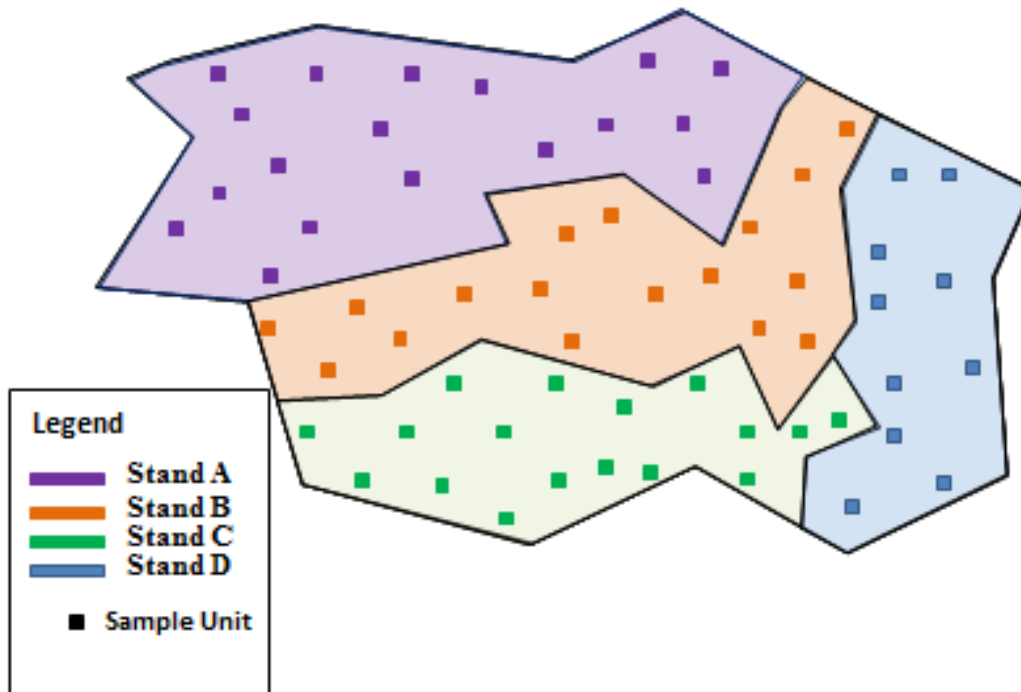
Figure 19. OBIA stratified random sampling units for each example forest stand, image object.

Table 4. Decision ruleset for classification of split decision polygons during OBIA.

Split 1	Split 2	Resulting Classification
Coniferous	Mixed	Coniferous
Deciduous	Mixed	Deciduous
Coniferous	Deciduous	Mixed

Image Analysis

Collected orthomosaic samples for both classification comparison methods required diligent interpretation to derive compositional cover type identification. Remote sensing photo interpretation harnesses a confluence of evidence from within the image, relying greatly on the mind for generalizing features (Avery, 1977; Avery and Berlin, 1985). The confluence of

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evidence in remotely sensed imagery can include image or feature characteristics such as site, shape, shadow, tone, pattern, size, and/or texture (Avery, 1977). Photographic identification of forest vegetation species is concerned with recognizing key characteristics of morphology and spatial distribution patterns (Avery, 1977). These characteristics, being visually unique down to the species level for experts, can be generalized more readily at the level of deciduous and coniferous type classes (Figure 20). Deciduous species being more soft, rounded, or billowy in shape, while coniferous species have jagged branching and pointed crowns (these are generalizations of types and not always indicative). To provide a more sound judgement for the fit of each sample within the three class classification scheme, a photo interpretation key for the separation of each classification scheme category was generated (see Appendix C).

Figure 20. Image examples of Coniferous and Deciduous species.

To construct the photo interpretation classification keys, or training samples, the basal area per unit area class composition of known CFI plots were found for each distinction. Orthomosaic 90x90m samples of 100%, 66%, 26%, and 0% coniferous composition were distinguished using their computed basal area compositions (Appendix C). These keys represent the distinction between thematic classes. The center 30x30m cell serves as guides for later visual estimation of coniferous composition. These key training samples were not reused during comparison to ground data and were all taken from West Foss Farm, which then was not used during the analysis of data source agreement. Samples analyzed for agreement with the ground data were performed using a blind interpretation process, so that locational knowledge bias did not influence classification judgement.

Accuracy Assessment
Both PBC and OBIA thematic mapping reference data accuracy assessments used site specific error matrices. For each of the four proposed methods, UAS orthomosaic sample units were interpreted to adhere to the classification scheme, and to be comparable with the ground sampled, forest stand delineations created by spatial data analyst Heather Grybas (Table 5).

Table 5. Error matrix example for UAS sampling reference data.

PBC / OBIA 120m above canopy	Ground Data		
	Coniferous	Mixed Forests	Deciduous
UAS Reference Data Coniferous			
Mixed Forest			User's Accuracy Totals
Deciduous			
	Producer's Accuracy Totals		Total Samples
	Overall Accuracy		

Site specific accuracy assessments were generated for each of the six woodland properties. Overall accuracies were evaluated alongside producer's and user's accuracies to form a comprehensive analysis of the agreement and uncertainty.

Effectiveness of Comparison

Statistical analysis differed slightly between pixel-based and object-based classification methods due to their inherent sampling natures and products. Both methods needed to determine the effectiveness/efficiency of the UAS orthomosaic samples, in comparison to the ground sample data, in classifying the complex forest environments. Following the use of the decision tree for classification, pixel-based methods, could be directly compared to ground sampling for

both the photo interpretation potential method and the direct comparison to the CFI plot method.
For OBIA reference data, sample size (n) plays a significant role in the threshold of accuracy and
power of each additional sample used to label each unique object/forest stand. MacLean *et al*.,
(2012) in their revised efficiency model for ground sampling plots in thematic mapping, based
on Husch *et al*., (2003), looked at thresholds of ≤1%, ≤2%, and ≤4% standard error (SE) per
change in sample size (Table 6). These thresholds represent common, but not definitive accuracy
results for each forest cover type.

Table 6. Optimized prism sampling protocol for meeting error thresholds, proposed by MacLean
et al., (2012).

	$\Delta SE/\Delta n \leq 1\%$	$\Delta SE/\Delta n \leq 2\%$	$\Delta SE/\Delta n \leq 4\%$
Maximum	8	5	3
Minimum	3	2	2
Deciduous Avg.	5	4	3
Mixed Avg.	6	4	3
Coniferous Avg.	6	4	3
Overall Avg.	6	4	3

Bootstrap analysis was used here to determine the mean of all possible combinations of
sample units, within each forest stand, for a given random sample size (Mooney and Duval,
1993; MacLean *et al*., 2012); 1,000 iterations were run to ensure statistical validity and
convergence of the mean. The standard deviation of the bootstrap estimates for each sample
classification within the larger polygon will, by this method, be the standard error of the mean
for all estimates for percent coniferous (MacLean *et al*., 2012). To contrast the findings of

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MacLean et al., (2012), regression analysis determined change in accuracy per successive UAS OBIA reference data sample size reduction (Quinn and Keough, 2002). Calculating the bootstrap estimations allowed us to devise a relation between error and the efficiency of the orthomosaic samples. For our methods however, UAS samples were photo interpreted for this classification, not providing a distinct percent coniferous composition of each resulting sample. Instead, bootstrapping was used to find the mean classification result of 1,000 iteration estimations (Fox and Weisberg, 2010). Only polygons with at least 10 samples were valid for this analysis. Determining if minimum sampling requirements proposed by MacLean *et al*., (2012), would also be applicable to UAS reference data collection methods.

RESULTS

Optimal UAS Sampling Design

Although both the Aeronavics Skyjib and eBee plus UAS configurations were tested for their ability to capture imagery, only the fixed-wing eBee Plus could ultimately capture data used for further analysis. These samples, along with the multitude of training mission data products demonstrated the impractical nature of modeling with samples lower than 100m above the surface in densely vegetated areas (Figure 21a-b). Large regions of interpolation, uncalibrated images, and completely missing areas caused inoperative products (Figure 22). As a result, samples were further collected only at 100m and 120m above the forest canopy. Comparing flying heights of 100m and 120m during these same training missions, ground sampling distances (gsd) differed by only 0.01cm, however, the number of images taken decreased by roughly 30%, and there was a difference in image calibration of 3%. Comparing the sequoia

multispectral sensor to the SODA we saw an increase of 1.2cm (37%) in the gsd at the same flying height, and 13% decrease in image calibration results for the natural color products. Orthomosaics produced from the sequoia sensor incurred rampant image artifacts and visual distortions, being uninterpretable at even the maximum legal flying height (Figure 23). At equivalent flying heights, the sequoia sensor retrieved far diminished products, in terms of both completeness and resolution (Figure 24a-b). The remaining, optimal sampling protocol of 120m flying height, with the SODA sensor produced eight orthomosaics from 17 total mission blocks, covering 398.71 ha, (Figure 27 a-f).

Resulting in only 62% calibration success (green dots) with optimized calibration parameters, having a flying height of 50m above the canopy was not able to make complete orthomosaic models or DSMs. In figure 21, we see a 10.66ha area of Kingman Farm averaging 2,870.75 matches per image for the 209 calibrated images that could be found. A greater number of calibrated images were clustered within the southern portion of the focus area, which correlates with the woodland edge and adjacent agricultural field. The number of matches between these calibrated images in the southern region (weight of their connecting lines) was also greater. When matched, images experienced a mean re-projection error of 0.134 pixels. These models were generated with a ¼ image scale and a 7x7 pixel matching window size.
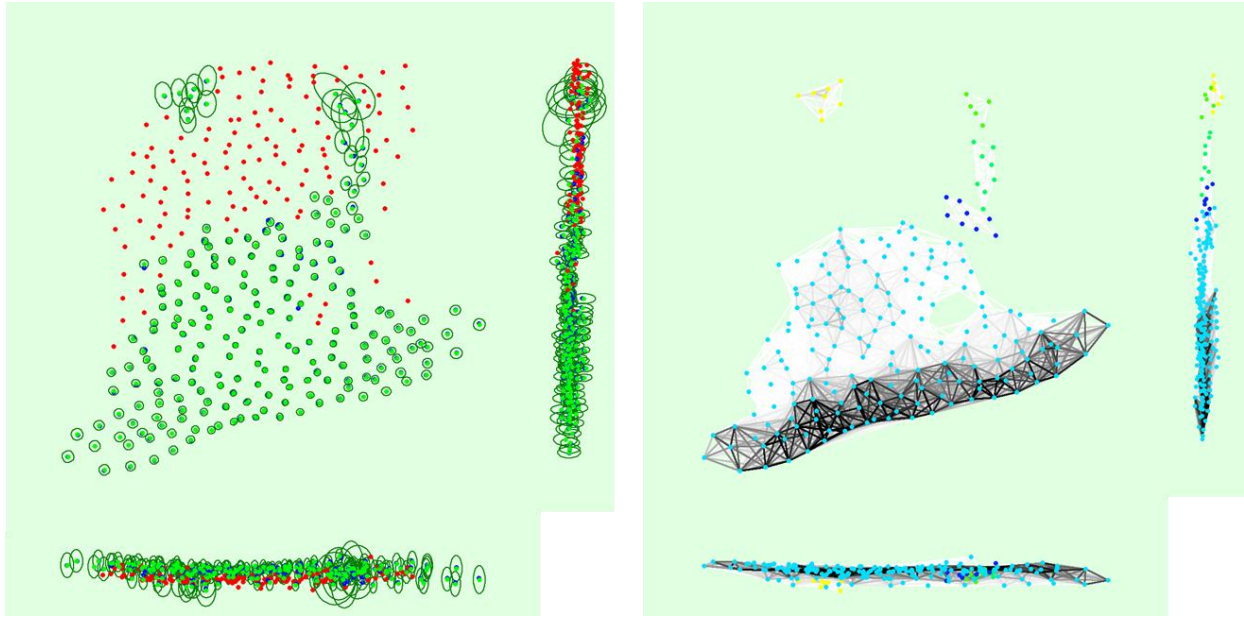
Figure 21. Image calibration statistics for 50m above canopy flying height, (left) showing calibrated images in green vs uncalibrated images in red and (right) image matching strength by line weight, captured with the SODA.

Produced from the above image matching statistics (Figure 21a,b), the orthomosaic had an average ground sampling distance (gsd) of 2.16cm or 0.85in (Figure 22). Faulty 2D image matching in the most densely vegetated regions led to errors which formed over-interpolated and fully absent patches. With standard processing parameters, namely full-scale image matching, the resulting product experienced an even lower calibration percentage and higher degree of geolocation uncertainty during matching.

Figure 22. Orthomosaic result for 50m above canopy flying height, captured with the SODA.

For the parrot sequoia, flying at such a low height above the surface produced (all altitudes) improper results. For the desired training region, matching the same area as above in previous figures 21 and 22, only 73 of the 322 images (22%) could be calibrated with optimized parameters. For the 22% that could be matched, with at least 2 points in the entire image, there was an average of 52.94 matched points per image. As shown in Figure 23, the image calibration details for the sequoia produced a rolling shutter effect (displayed by the blue lines distinguishing shutter activation point form image capture point) displacing image locations at low flying heights at standard flight speeds. As expressed, much of the total mapped area (68%) was not calibrated or modeled through automated processing.
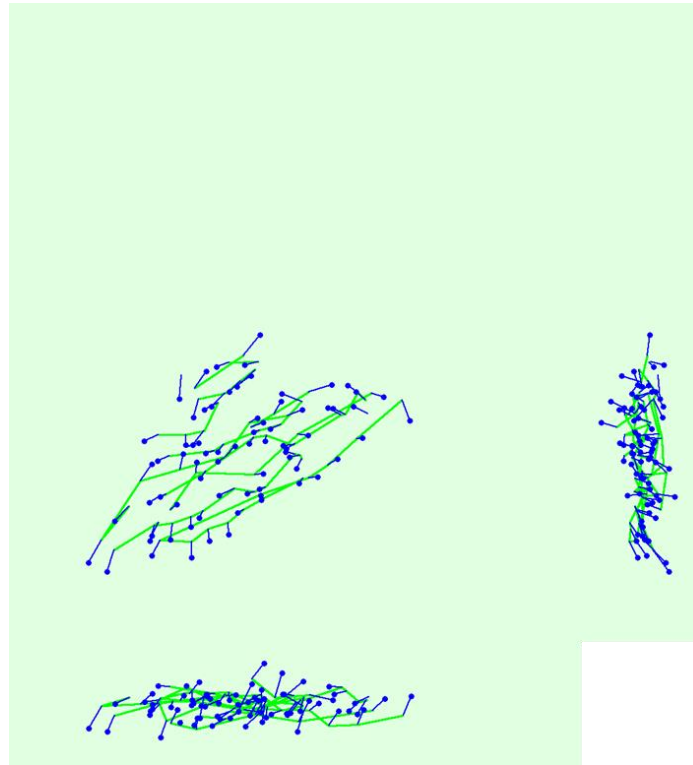
Figure 23. Image georeferencing for the normal color (RGB) sensor of the Parrot Sequoia optic, at 50m above canopy flying height.

Orthomosaics captured by the sequoia, normal color optic, resulted in an overall image calibration success of 87% (Figure 24). Due to the lower spatial resolution of the natural color sensor the gsd was 27% lower than those outputs produced by the SODA with the same mission parameters and processing options. Individual trees were hazy, blurred together, and pixelated in areas, leading to poor quality interpretation overall.
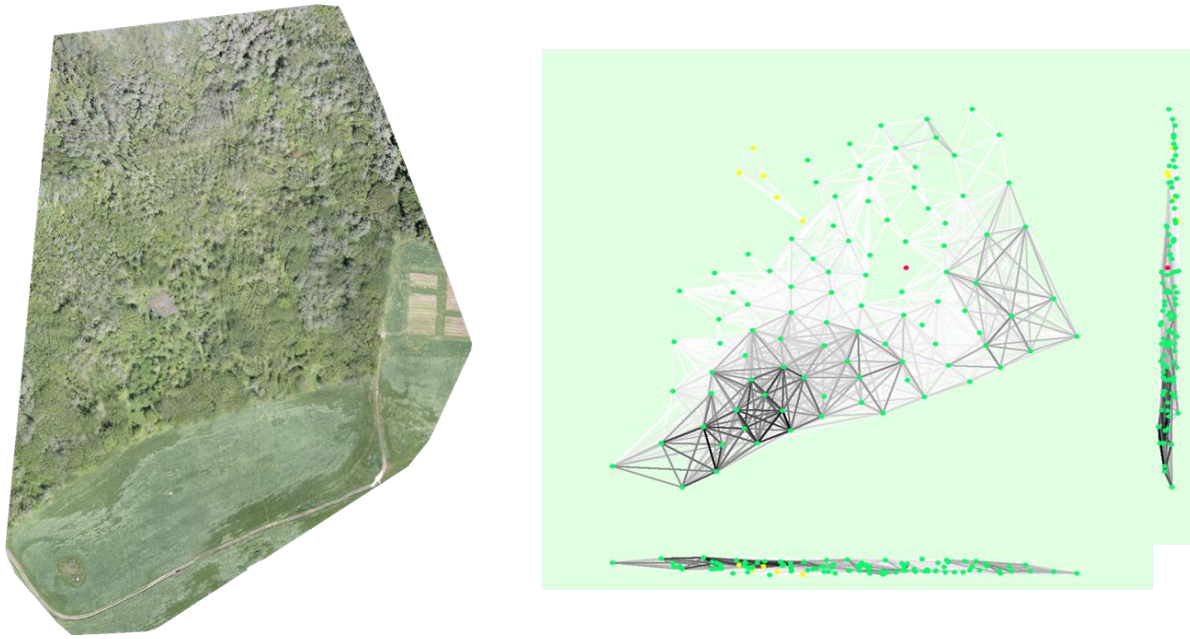
Figure 24. 120m above canopy orthomosaic (left) produced by the sequoia sensor, and associated image tie point densities (right).

The lack of accuracy reports in the Agisoft software result in a more black box approach in terms of its outputs. With the range of flying heights tested, and the difference in sensor resolution, orthomosaic models were created with ground sampling distance ranging from 2cm (SODA at 50m above canopy) to 17.17cm (Sequoia at 120m above canopy with Multispectral). For the data agreement analysis of this study however (the main objectives), Agisoft performed to a superior degree. In running both programs over entire woodland properties (Kingman Farm, Moore Field, and West Foss Farm) Agisoft outcompeted Pix4D (Figure 25), both in the number of images that it was able to calibrate (7.97% higher calibration of images on average), and the resolution of the orthomosaics used in photo interpretation (approximately 9.2% higher resolution on average). Pix4D was also found to create several erroneous regions when processing large data volumes at higher detail settings (Figure 26).
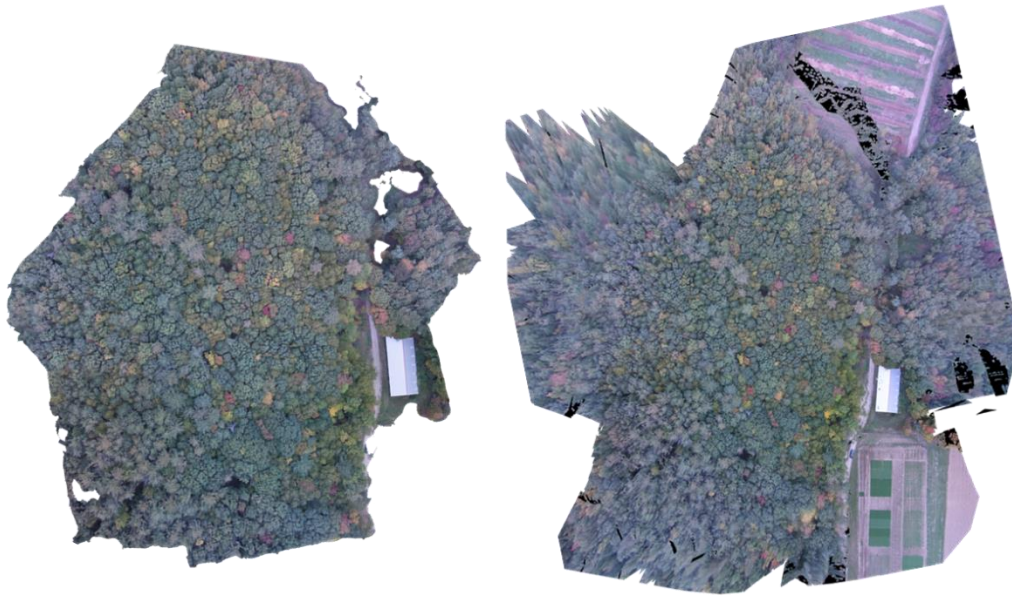
Figure 25. Orthomosaic output examples for Agisoft PhotoScan (left) and Pix4Dmapper Pro (right).
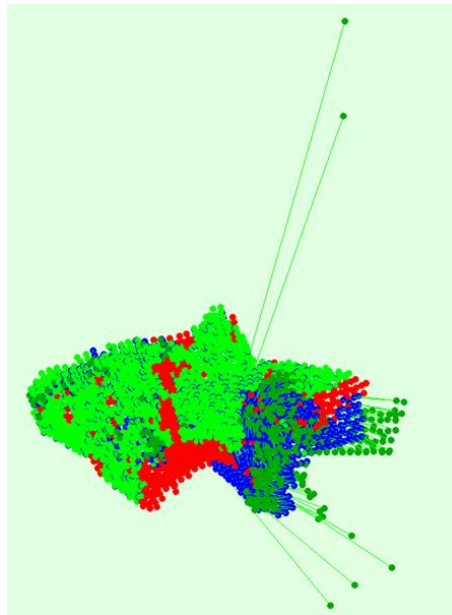
Figure 26. Kingman Farm, Pix4D Mapper Pro processing errors.

With higher density modeling parameters, the number of tie points and densification of the point cloud, used to generate other outputs, were increased. In testing this on Moore Field, this meant 31.3% more overall tie points (346,598 vs 264,015) over medium density parameters, and a 371% increase in dense cloud points (187.3m vs 50.5m). Looking at the representative orthomosaic models however, there was a difference of only 0.01cm between the high and medium processing resolution parameters. Considering the nearly 3-day difference in the processing time required per woodland when choosing the higher resolution options, and the overall objective of having photo interpretable models, it seemed ill-advised go above moderate resolution processing parameters.

Using Agisoft PhotoScan medium densification and resolution parameters produced eight total orthomosaics covering a total of 398.71 ha. These models were generated from 9,173 images taken from the eBee plus platform. The eight orhtomosaic models of the study areas required a total of over 100GB of data to form and process. Figure 27 shows all eight study area planimetric models (top left to bottom right): Kingman Farm at 2.86cm gsd, Moore Field with a 3.32cm gsd, East Foss Farm with a 3.54cm gsd, West Foss farm with a 3.18cm gsd, Thompson Farm with a 3.43cm gsd (Northern portion) and a 3.1cm gsd for the southern portion, and lastly, College woods with a 2.9cm (western) and 3.24cm (eastern) gsd. Combined these orthomosaics average a gsd of 3.23cm (Figure 27a-f). Image calibration regions can be seen in Appendix F, to acknowledge the distribution of interpolation and uncertainty within their features.
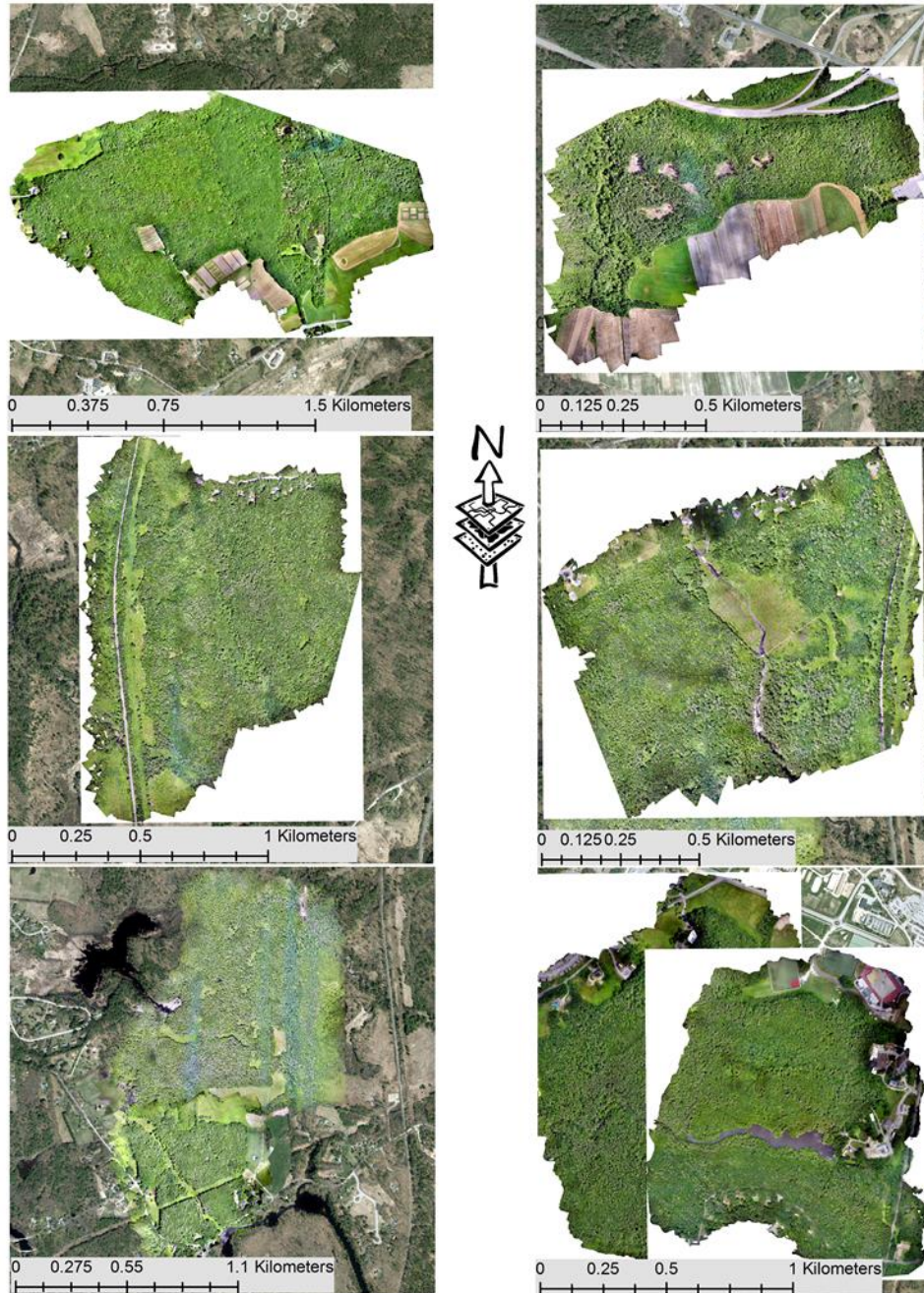
Figure 27. Study area orthomosaics for the six UNH woodland properties.(Top left to bottom right); (a) Kingman Farm, (b) Moore Field, (c) East Foss Farm, (d) West Foss Farm, (e) Thompson Farm, (f) College Woods.

PBC and OBIA Accuracy Assessments

For pixel-based classification reference data units a total of 48 pixel-based classification reference samples were analyzed for their agreement with the CFI plot classification of forest areas. The first method, assessing the photo interpretation potential of the UAS orthomosaic samples analyzed 29 PBC reference data units (Table 7). The second method, comparing the UAS PBC reference data samples to the CFI plot classifications, analyzed 19 samples (Table 8). Overall accuracies for pixel-based classification reference data collection were 68.9% and 73.86% respectively. The first PBC assessment resulted in the highest producer's accuracy for deciduous forest areas, and the highest user's accuracy for coniferous forest areas.

Table 7. PBC UAS photo interpretation potential thematic accuracy assessment error matrix.

		Ground Data Classification			
		Coniferous	**Mixed**	**Deciduous**	**User's Accuracy:**
UAS Classification	**Coniferous**	4	1	0	80%
	Mixed	3	8	2	61.54%
	Deciduous	0	3	8	72.73%
Producer's Accuracy:		57.14%	66.67%	80%	29

Overall Accuracy = 20/29   **68.97% Accuracy**

UAS, PBC reference data samples located directly at known CFI plots achieved an overall accuracy of 73.68%. With the highest user's accuracy (100%) and the highest producer's accuracy (83.3%) in the coniferous stands. The largest margin of uncertainty was found in the classification of the mixed forest areas (Table 8).

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Table 8. Error matrix of direct comparison between PBC of CFI plots by forest biometrics and UAS image interpretation.

		Ground Data Classification			
		Coniferous	Mixed	Deciduous	User's Accuracy:
UAS Classification	Coniferous	5	0	0	100%
	Mixed	1	5	2	62.5%
	Deciduous	0	2	4	66.66%
Producer's Accuracy:		83.33%	71.43%	66.66%	19

Overall Accuracy = 14/19   **73.68% Accuracy**

For each method of OBIA thematic accuracy assessment two error matrices were generated. First, the individual UAS orthomosaic reference data sample units were evaluated against the classification of the forest stands derived from the ground sampling data (Table 9 and 11). Secondly, each method was assessed to determine the agreement for the forest stand classifications between the UAS and ground data reference samples (Table 10 and 12).

For the OBIA method, agreement of the OBIA UAS orthomosaic reference data sample units with ground samples varied similarly between user's and producer's accuracies (Table 9), ranging between 50 and 70%. Overall agreement between the UAS orthomosaic samples and the classification of the forest stands by the ground data was 63.81% for the 268 sampled locations.

Table 9. Error matrix showing the accuracy of 268 individual orthomosaic subsamples, used to derive object level classification.

		Ground Data Classification			
		Coniferous	Mixed	Deciduous	User's Accuracy:
UAS Classification	Coniferous	40	18	1	67.78%
	Mixed	23	90	15	70.31%
	Deciduous	3	37	41	50.62%
Producer's Accuracy:		59.70%	62.07%	71.93%	268

Overall Accuracy = 171/268   **63.81% Accuracy**

For the classification of the forest stand objects, the randomly sampled UAS orthomosaic units resulted in a 71.43% agreement with the ground data (Table 10). User's accuracy was highest at 100% for the coniferous forest stands. Producer's accuracy among the three land cover classes was highest at 81.82% for the pure deciduous forest stands.

Table 10. Object-based image analysis accuracy assessment error matrix for the stratified randomly distributed reference data units.

		Forest Stand Classification			User's Accuracy:
		Coniferous	Mixed	Deciduous	
UAS Classification	Coniferous	7	0	0	100%
	Mixed	4	9	2	60%
	Deciduous	0	4	9	69.23%
Producer's Accuracy:		63.64%	69.23%	81.82%	35

Overall Accuracy = 25/35   71.43% Accuracy

When comparing the classification agreement of the UAS reference data sample units directly to that of the CFI plots a sample size of 202 was used. This secondary method resulted in in a 62.87% accuracy for the individual UAS OBIA reference samples (Table 11).

Table 11. OBIA thematic mapping accuracy assessment, comparison of UAS samples to classification derived from CFI ground sampling plots.

		CFI Plot Classification			User's Accuracy:
		Coniferous	Mixed	Deciduous	
UAS Classification	Coniferous	58	1	4	92.01%
	Mixed	40	38	16	40.43%
	Deciduous	7	8	31	67.39%
Producer's Accuracy:		55.24%	80.85%	60.78%	202

Overall Accuracy = 127/202   62.87% Accuracy

The UAS OBIA reference samples linked to CFI plot locations produced forest stand polygons with an accuracy of 85.71% (Table 12). Producer's and user's accuracies for each of the three and cover classes varied only slightly for this method.

Table 12. OBIA thematic classification accuracy assessment in comparison to ground reference data.

		Ground Data Classification			
		Coniferous	**Mixed**	**Deciduous**	**User's Accuracy:**
	Coniferous	5	1	0	83.33%
UAS Classification	**Mixed**	1	10	1	85.71%
	Deciduous	0	1	7	87.50%
Producer's Accuracy:		83.33%	83.33%	87.50%	28

Overall Accuracy = 24/28   **85.71% Accuracy**

Sampling Efficiency

Bootstrap resampling estimates for each land cover class ran 1,000 iterations to determine the change mean classification accuracy estimations. Table 13 shows the calculated averages of classification accuracies among the viable forest stands for each land cover class, based on the full number of iterations and samples. Using these averages, the probability of accurate classification derived under Fitzpatrick-Lins, (1981) 4-10% reference data accuracy thresholds were evaluated to determine if an equivalent number of minimum sample points to MacLean *et al*., (2012) could be used for deriving forest stand image object classifications. Here we tested the bootstrap resampling classification estimates for 6 forest stands. For each forest stand, 1,000 random samples were selected from its population of OBIA UAS reference data samples. These

iterations were analyzed at sample sizes ranging from ten to two.   Each set of iterations were classified to determine the overall accuracies of the estimation. Accuracy thresholds of 99%, 96%, and 90%, were used to suggest different qualifications of adequate reference data. Using regression analysis, each forest stand could be assessed for a minimum number of samples required for each accuracy threshold.

Overall, forest stand objects could be correctly classified to with fewer than 10 samples per object. Some of the sampled forest stands surpassed 96% accuracy with as few as 3 samples. Averaging across all 6 analyzed forest areas, 7 samples were needed per stand to determine classification, to a 96% accuracy threshold. When estimating the majority classification with fewer than 3 samples, an exact accuracy could not be reached. This minimum sampling result was shown in many of the forest stands, not able to reach a defined threshold for 90% classification accuracy (N/As).

Table 13. Efficiency comparison of UAS to ground sampling.

Image Object Number	Class	Classification Accuracy		
		$\geq 99\%$	≥96%	≥90%
1	M	7	4	N/A
2	M	8	7	N/A
3	D	7	5	N/A
4	M	9	9	7
5	C	7	3	N/A
6	M	10+	10+	10+
Overall Average		8	7	N/A

DISCUSSION

Investigation of Results

The objective of this research was to determine if UAS were capable of efficiently and effectively collecting reference data for use in assessing the accuracy of thematic maps. Our assessment evaluated both: pixel-based classification approaches, and object-based classification approaches. As part of the classification accuracy assessment process it was imperative to also understand the possible sources of error and uncertainty (Congalton and Green, 1993; Lu and Weng, 2007; Congalton and Green, 2009). These errors, for most projects reside as sample design considerations, are commonly impacted by cost or subject matter experience.

The CFI plots, intended for long-term monitoring, were sampled as far back as ten years ago (Kingman Farm). Forests are dynamic systems, constantly growing and transitioning. The difference between the CFI datasets observations and the current forest stand compositions will have changed, although, only marginally as management has permitted. Using forest type rather than a finer scales species-specific classification alleviated lag-time issues between ground sampling and UAS flights. Any recently disturbed areas, within the course of CFI plot sampling to now, was knowingly avoided due to its discontinuity. CFI plots were known to have a sizeable GPS positional error, more than ten meters, associated with their mapped projections. Hardware positional uncertainty, further diminished by canopy signal interference, obscured what should be a regular network of plots into more of a randomized placement. As observed from the study, the high variability in forest composition over short distance could have altered the classification

of the UAS reference data sample if not in positional agreement with the ground data sampling location. To counteract uncertainty in positional agreement between the ground data, the forest stand edges, and the UAS imagery products, high-resolution DOT imagery was used to guide observable edges during digitizing. Furthering the manual digitization of the forest stands, our procedure included guidance from the manager of the studied woodland properties. In comparing the classifications of the individual CFI plots to the greater forest stands there was only an agreement of 54.46% agreement. The 54.46% agreement was not seen as error in either classification but rather the severe heterogeneity in species composition found in the New Hampshire landscape. Other minimal changes between the time of ground sampling and UAS imagery sampling could not be accounted for.

The novelty of UAS and their performance caused limitations and errors which were recognized using our training missions. Through training missions and support knowledge base review (Pix4D, 2017a; Pix4D, 2017c) it was determined that an optimal flying height for current systems would be our maximum legal altitude of 120m above the average surface. Although lower flying heights and alternative sensors could be employed for possibly high-resolution results, image calibration success was found to be significantly lower (Figure 21 and Figure 23). Additionally, model artifacts and distortions became more prevalent at the lower imaging heights, to the point of only forming unworkable products (Figure 24). Using the SODA sensor on the eBee plus UAS, the optimal UAS image sampling design provided 398.71 ha. of orthomosaic models at an average gsd of 3.23cm for thematic accuracy assessments (Figure 27). The resulting diversity and magnitude of outputs giving testament to the effectiveness of the platform. Photo interpretation samples were more than capable of devising classification of the

three-category scheme used in this and previous projects (Justice *et al*., 2002; MacLean *et al*., 2012) at such a resolution.

During testing with Pix4D, geolocation error for the eBee plus system averaged 7m in the x, y, and z axes. Even at our maximum legal flying height (120m), flying during optimum sun angle hours, and using a higher than recommended 85% overlap, some images were not calibrated during processing. Other studies and even the user manuals for these systems recommend ground sampling distances of at least 10cm/pixel, requiring a flying height over 400m (Dandois *et al*., 2015; eMotion3, 2017; Pix4D, 2017a; Pix4D, 2017b). For the eight final orthomosaics 97.49% of the images were calibrated (9,135 out of 9,370). Our high image calibration percentage was the result of two UAS mission planning considerations. First, ensuring mission blocks overlapped on their edges, a product of their design. Secondly, when necessary, we flew areas of especially dense vegetation in a repeated session. Other parameters of the UAS flight mission planning were structured as their only possible option. The orientation of mission blocks, their delineation, and the tested flying heights were set within the legal and moral guidelines of UAS operations (FAA, 2016c; FAA, 2017c). Being able to adjust these parameters based on the weather conditions of the day or UAS properties could have reduced minimal distortions, sun angle effects, and model processing errors (Dandois *et al*., 2015).

For the analysis of the two classification approaches a total of 581 samples were taken among the four UAS reference data sampling procedures. Even with this sampling size, distribution among the methods formed a lack of statistically valid assessments. Forest stand configuration, the need for independence of samples, and the size of each sample (90x90m and 30x30m), eliminated the possibility of increasing the sample size. PBC approaches were drastically affected by this, with only 29 samples for first method (assessing the photo

interpretation potential of the sample units) and 19 samples for the second method (the direct

comparison to CFI plots procedure). To appropriately validate the accuracy of thematic map

classes, distinct areas should contain at a minimum 30 samples for a classification of this

complexity (Congalton and Green 2009). The sample size of this project aimed to maximize its

efforts and create a statistical valid evaluation of thematic accuracy reference data collection

(Congalton and Green, 2009). Unfortunately, even among the nearly 400 ha. of forest lands

processed by the UAS data, forest stand structure and placement severely limited the number of

samples which could be assessed. During PBC the difference in accuracy of only a single sample

unit caused considerable changes in the overall, producer's, and user's accuracy of the resulting

assessment. With such a small reference data sample size, definitive assessment of validity could

not be determined.

Possible errors during the image analysis methods included: the subjective nature of the

visualization process, the difference between the variable plot inclusion zone factoring of basal

area species composition percentage (Kershaw *et al*., 2016), and the perspective view canopy

composition process. All UAS reference data sample units were categorized using the same

interpreter, with interpretation key training sets (Appendix C) from West Foss Farm, and photo

interpretation guides of vegetation as aides. Although branching patterns and distribution trends

were used to guide their assessment (Avery, 1977; Avery and Berlin, 1985) I was still not a

professional forester with extensive knowledge in this process. The representation of percent

composition for each class within the imagery and the actual composition sampled on the ground

could have alluded to a source of uncertainty. Inter-annual variation of the forest stands also led

to confusion in the categorization of orthomosaic samples (Townshend *et al*., 1991). Noticeable

differences among the appearance of specific individual species were found even within the

same property. This combined with the subjective nature of the class assignment could have induced error, intensified by the low sample size of some methods.

Analysis of the four classification sampling methodologies showed how effective UAS image modelling products can be as reference data acquisition tools for thematic classification validating. In the first method of each thematic mapping classification approach, the UAS were assessed as a platform for collecting reference data through photo interpretation without additional ground sampling. The random sampling distribution of these reference data units, imposed additional uncertainty for the accuracy assessment. Being that New Hampshire forest landscapes, and these study areas more specifically, are heterogeneous patchworks of composition and structure, the specific location of each sample does influence its class assignment. For the second method of each classification approach, our accuracy assessments portrayed how directly comparable these same products were to forest stand classification derived through forest biometric variable plot ground sampling. Using the UAS orthomosaics for the collection of thematic mapping accuracy assessment reference data in PBC methods showed an agreement 68.97% for samples located at the center of forest areas (Table 7) and 73.86% for samples located at known CFI plot locations (Table 8). Both PBC accuracy assessment methods suffered from the mischaracterization of the mixed forest class. For the two object-based classification thematic accuracy assessment methods, resulting agreements were higher at 71.43% for randomly located sampling locations within forest stands, and 85.71% for the direct comparison to CFI plot approach (Table 10 and 12). Both of these methods were hindered by the small sample sizes within the smaller forest stands, forming exceedingly high inaccuracy with each misclassified sample.

Looking at the efficiency of the second method (non-random) object-based classification

sampling approach, we saw that even with as few as 3 samples within a complex forest stand/

image object, UAS reference data samples could precisely and accurately label the category. The

average of this limited analysis determined that an average of 7 samples were needed per stand to

determine an accurate classification, to a 96% accuracy threshold. These efficiency evaluations

adhered to the proposed thresholds of accuracy required by validation data in thematic mapping

(Fitzpatrick-Linz, 1981). The evaluated subgroup of forest stands, which contained at least 10

samples each, achieved a heightened agreement to the ground data classification as compared to

smaller forest stands (those with less than 10 subsamples). Low sample size during bootstrapping

formed inconclusive results, however, when tested average estimations were able to classify

polygons with at least 90% accuracy with as few as 3 UAS orthomosaic sample units (Table 13).

Further analysis should work to increase the sample size and also form a relation with the forest

stand size.

Difficulties Experienced with this Novel Research Platform
Before establishing the difficulties of integrating UAS into a research sampling design,

the first obstacle for this research was determining the optimal level of detail to be used for the

classification scheme of this project. Both Justice *et al*., (2002) and MacLean *et al*., (2012)

utilized hierarchical classes with coniferous, mixed, and deciduous at the first level during their

operations of classification schemes for local forest composition. The original sampling design

was constructed to capture an adequate sample size for the analysis. Unfortunately, the extreme

heterogeneity of our woodland properties devalued this proposition. Forest stands were

structured such that they could not be further sampled using our UAS acquisition while

maintaining spatial independence.

As with any novel technology, being at the forefront of an innovation comes with its challenges and limitations. The first and foremost for this research project was the lack of formal training or knowledge base for using UAS as an applied tool for scientific observation. This is not to say there is no background theory for aerial photography mission planning, photogrammetry, or photo interpretation, but rather basics for the characteristics unique and intrinsic to UAS. Although application papers and review forums are sprouting pervasively, few pass on concrete knowledge needed to get a UAS into the air and keep it there for the duration of the mission. These studies also glide over how to successfully handle the large amounts of data that are collected. Companies such as Parrot, DJI, Microdrones, and Pixhawk are advancing, in large part, due to their user-bases sharing knowledge vital to their operations. Much of the first year of this master's research project was spent deciphering technical specifications, devising distance and duration thresholds for the system, and formatting the images that they acquired into something that a processing software could handle. Numerous training and calibration missions were run to ensure methodology (see Appendix E) before data collection could even be attempted. In total, this project required learning four manual UAS controllers, four mission planning software packages, and two processing programs to optimize the outputs that were generated. These factors though, are all likely to be significantly marginalized in the coming year as methods are recorded and shared, and programs become more ubiquitous. As noted, two rotary-winged UAS were also used during testing and scouting but not during actual primary data collection. This was due to their reduced flying characteristics (primarily flight time and maximum distance of data link communication operability).

Taking into consideration the roles of privacy, safety, and policy for this and future research was itself an endeavor limiting data collection potential and efficiency. The integration

of UAS into the NAS for the majority of this project's duration, August 2015 to August 2017, was a gray area of contention. Until the Remote Pilot in Command license, Part 107, became functional on August 29th, 2016 the FAA had a rudimentary and somewhat lacking process for being granted approval for research or public operations. Many of the early reports in the scientific exploration and application of UAS show this hazy understanding under federal law (Anand, 2007; Dalamagkidis *et al*., 2008; Rango and Laliberte, 2010; Hugenholtz, 2012; Colomina and Molina, 2014). Such uncertainty in policy limits expansion and potential. Here specifically, policy reform blocked months of possible data collection time, and restricted flying heights to 120m above the surface. It is also recommended for UAS that mission planning blocks be established perpendicular to the wind and, as per efficiency, parallel to the long side of the focus area (eMotion3, 2017) to maintain optimal calibration and the lowest number of images necessary for coverage. Due to public concern awareness and known regulations, these conditions were not possible for several sections of the various woodland properties. Surrounding private residence at sites such as Kingman Farm and West Foss Farm forced angled flight lines in reference to wind angle, reducing the certainty of constant spacing between images. Steps were taken to capture additional imagery where needed and to fly on days where wind direction and speed better suited mission block orientation. Some days, even when clear skies were present, would simply just not accommodate complete mission image calibration. As more sophisticated and observable applications come into play, it is the hope that trends will follow these past few years, and regulations will become more steadfast to match the technologies available, no longer limiting growth.

During training missions, it was noticed that uncalibrated regions within the final outputs were clustered within densely vegetated stands. With the complexity of the imagery at such a

fine scale, finding tie points at the level of individual branches or even leaves challenged the aerial triangulation algorithms. Adding in the effects of sun angle, wind displacement, and optical perspective forced unavoidable loss of including some images (Dandois et al., 2015; eMotion3, 2017). These influences were amplified at the lower flying heights, causing completely inadequate models. Some of these effects were mitigated by flying a repeated pass over the same area in less severe conditions. We also attempted to fly flight perpendicular to the wind, as suggested by Pix4D support (Pix4D, 2017c). Such mission block orientations, however, proved inaccessible for most locations, or did not observably improve results.

Orthomosaic processing resulted in several difficulties in handling the UAS imagery. The sheer volume of data (over 100GB), in the short time span for which it was processed, tested the maximum potential of even our most powerful computers. Both Agisoft and Pix4D were shown to be effective in their outputs however, slightly varying among final resolutions (Figure 25). While learning to use these software package, it became apparent that the expense of time needed for ultra-high resolution and accuracy products (up to a week or more) would not be worth the potential improvement in the photo interpretable results. Even at moderate level processing parameters, the procedure of aligning photos, determining tie points, interpolating a mesh/ surface, and constructing the orthomosaic could take over 20 hours per step with multiple 1,000 image models.

Automated processing of the images using classification and regression tree (CART) analysis and multiresolution segmentation algorithms was an early goal of this project. OBIA is praised for its ability to delineate and extract specific features within remote sensing imagery (Blaschke, 2010). Within heavily forested environments individual tree detection algorithms have been formulated to remove background noise and estimate biometric parameters (Pouliot *et*

al., 2002; Hay *et al*., 2005; Kim *et al*., 2009). The challenge for integrating these procedures into our research was having additional contextual data that matched the resolution of the imagery in order to aid the computer vision classification. Such high-resolution imagery, absent of multispectral sensing, texture models, or distinct radiometric properties lacks the accuracy needed in removing noise (e.g. shadow, ground, or understory vegetation) for reference data creation.

Future Considerations

The potential for UAS to reduce the cost of reference data sampling is a significant progression for scientific research and overall spatial data validation. Despite the temptation to minimize costs to the maximum potential, we should still keep in mind that no matter how much the technology advances it should never fully remove the human element from the sampling. To remove the human element during sampling would diminish the potential observations. In this study, we saw that design of the sampling frame significantly changed the results of the agreement between the ground and UAS data sources. UAS were capable of collecting and processing nearly 400 ha of forest area into planimetrically correct models with supplemental high-resolution DSMs in well under a months' time. Even in complex environments, with less than ideal conditions, high levels of accuracy were achieved. With the incorporation of expert knowledge-driven interpretation and decreased landscape heterogeneity, this platform proposes a significant advantage to projects which undertake their use. Even apart from reference data sampling, the high resolution of UAS imagery provides access to spatial data not found by any other remote sensing platform for the equivalent cost and temporal resolution.

UAS present a wide array of possibilities for the future of science and technology. Due to their widespread adoption in the consumer market, more and more individuals and companies are becoming accustomed to remote sensing and the products that it can provide. Specific examples of their versatile nature being found in major review papers for the platform (Watts *et al*., 2012; Kakaes *et al*., 2015; Cummings *et al*., 2017). It is unquestionable that an extraordinary number of creative people are thinking about how they can use these systems to best suit their needs; from Universities (UNH, 2015) to big name corporations like Amazon and Dominos. The adoption of novel technologies has never been easy. As we progress as a society however, the necessity for efficiency drives the strength of platforms such as UAS.

One of the most promising outcomes form this project was the generation of dense photogrammetric point clouds. For some forest stands this initial processing step, structured hundreds of millions of points in space, across the perspective of the aligned images. As these SfM 3D modeling algorithms advance, their overall efficiency and potential to model systems will continue to grow. A few groups, working directly with the software companies, have already begun to explore this greater potential (Fonstad *et al*., 2013; Micheletti *et al*., 2015). Others are adding in multispectral imaging, already found in several UAS formats (Laliberte *et al*., 2011), and seasonal variation or multi-temporal coverage. A frontier of possibilities presents itself here, with a probable future in the rapid acquisition of data which can process and simulate holistic large-scale area landscapes.

The influence of flying height restrictions by the FAA on our realized level of detail and calibration success is very much a time explicit obstacle. Progress for UAS regulations over the recent past, the duration of this research project (Rango and Laliberte, 2010; FAA, 2015; FAA, 2017a), and foresight into the near future shows a trend of rapid evolution and expansion of

operations within the NAS. Future consideration of use for UAS would be expected to be much expanded and simplified in comparison to today's authorization system.

Conclusions

The assessment of UAS for acquiring thematic mapping accuracy assessment reference data of both pixel-based and object-based approaches presented unique considerations as a remote sensing platform. The diversity and magnitude of products generated during this project, for use in the four sampling procedures, demonstrated the potential of the platform for rapidly developing high-resolution products over considerable areas. Introductory training missions with the three UAS (an eBee plus with two possible sensors, an Aeronavics Skyjib X-8, and a Phantom 2 Vision+) indicated that the eBee plus platform with its SODA sensor provided the greatest ability to collect quality data efficiently. This system, when operated at its maximum legal flying height of 120m above the surface generated planimetric models of the nearly 400ha of forest landscapes at an average ground sampling distance of 3.23cm. Using these outputs, two PBC reference data collection procedures achieved 68.97% (Internally centered procedure) and 73.68% (linking CFI plot location to UAS orthomosaic sample) accuracy. Next, two OBIA thematic classification reference data collection procedures achieved 71.43% (stratified random sampling) and 85.71% (direct comparison to ground data sampling network) accuracy. Assessing these methods together provided insight into the severity of influence the heterogeneous landscape had on the location of the chosen reference samples for labeling the greater forest stand object/area. Although promising, these results are still obscured by the low sample size due to sampling frame restraints. This low sample size forced a lack of statistically valid inference for thematic accuracy validation the PBC methods. Future research should consider maximizing their intended flying height to minimize distortions and other external influences on the

modeling process. Other recommendations include the addition of seasonal variation for interpretation or multispectral imaging context, and augmenting the complexity of the landscape studied. Despite the noted error sources and obstacles, the accuracy assessments demonstrated high accuracy reference data collection in complex forest communities. Widening exploration and acceptance of UAS use is expected to continue well into the future, as experienced by the prolific evolution of applications, modifications, and legislation just over the time of this project.

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APPENDICIES

## APPENDIX A. GROUND DATA COMPOSITION FINIDINGS

Table 14. Study Areas CFI plot networks. In total there are 354 variable radius, CFI ground sampling plots across the 377.57 hectares of forested land. Pictured are (top left to bottom right): (a) Kingman Farm, (b) Moore Field, (c) Thompson Farm, (d) College Woods, (e) East Foss Farm, and (f) West Foss Farm.
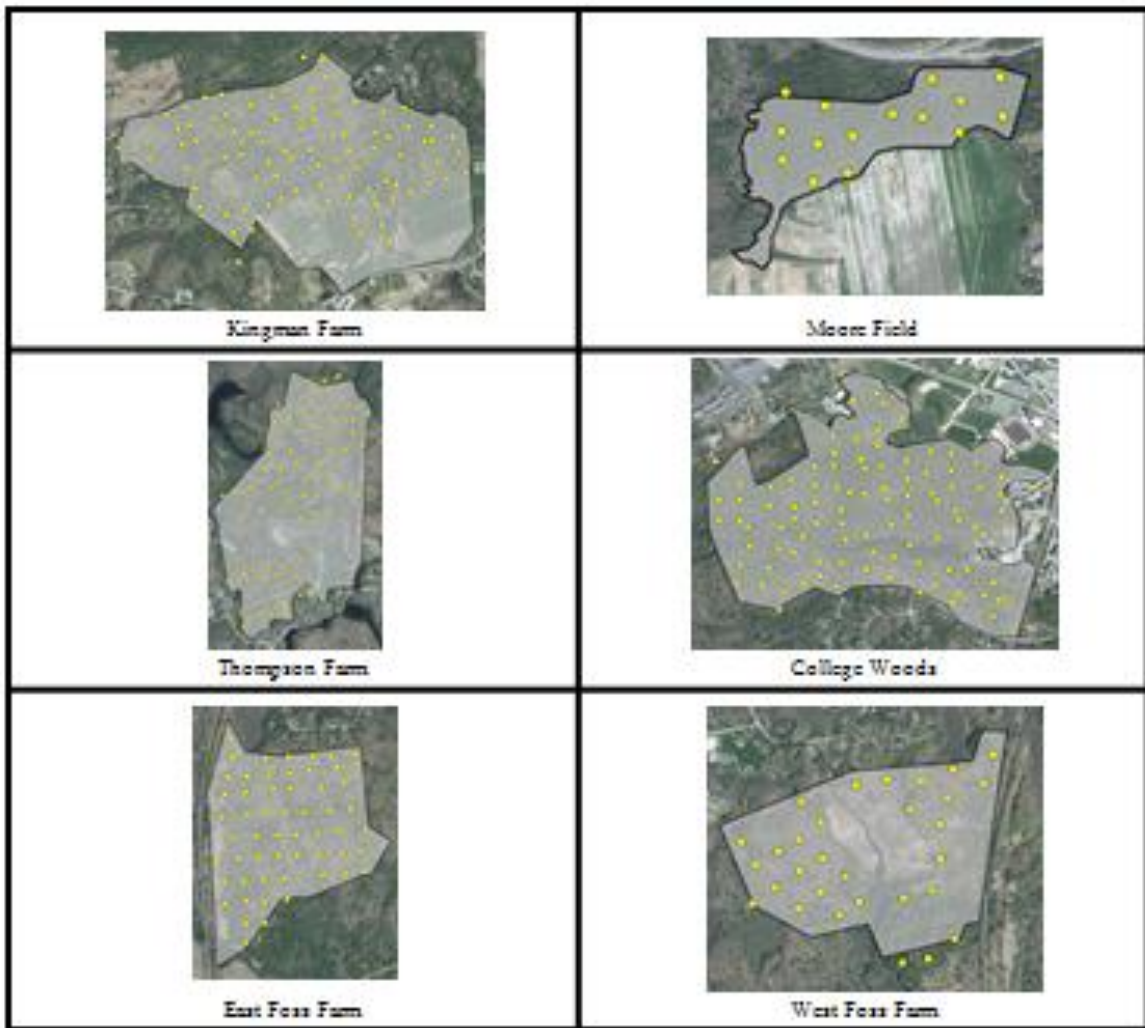
Table 15. Out of the 154 woody vegetation species recorded on UNH woodland properties, throughout the state of New Hampshire, 31 are recorded as dominant forest species for the CFI plots of the study areas used for this research project.

Species	Scientific Name	Classification	Kingman Farm	Thompson Farm	College Woods	West Foss Farm	East Foss Farm	Moore Field
American Beech	*Fagus grandifolia*	D	x	x	x	x	x	
American Elm	*Ulmus americana*	D	x	x	x	x	x	
Balsam Fir	*Abies balsamea*	C			x			
Basswood	*Lindens spp.*	D	x		x	x	x	
Bigtooth Aspen	*Populus grandidentata*	D	x	x	x	x	x	
Black Ash	*Fraxinus nigra*	D	x					
Black Birch	*Betula lenta*	D	x	x	x	x	x	
Black Cherry	*Prunus serotina*	D		x	x	x	x	
Black Oak	*Quercus velutina*	D	x	x	x	x	x	x
Black Spruce	*Picea mariana*	C	x					
Blue Beech	*American hornbeam*	D		x	x			
Eastern Hemlock	*Tsuga canadensis*	C	x	x	x	x	x	x
Eastern Hophornbeam	*Ostrya virginiana*	D				x	x	
Gray Birch	*Betula populifolia*	D					x	
Northern Red Oak	*Quercus rubra*	D	x	x	x	x	x	x
Norway Maple	*Acer platanoides*	D	x					
Paper Birch	*Betula papyrifera*	D	x					
Pitch Pine	*Pinus rigida*	C		x			x	
Quaking Aspen	*Populus tremuloides*	D	x		x	x		
Red Cedar	*Thuja spp.*	C		x	x	x	x	
Red Maple	*Acer rubrum*	D	x	x	x	x	x	x
Red Pine	*Pinus resinosa*	C			x		x	
Shagbark Hickory	*Carya ovata*	D	x	x	x	x	x	x
Sugar Maple	*Acer saccharum*	D	x	x	x	x	x	
Swamp White Oak	*Quercus bicolor*	D		x				
Unknown	*N/A*	N/A					x	
White Ash	*Fraxinus americana*	D	x		x	x	x	
White Oak	*Quercus alba*	D		x	x	x	x	x
White Pine	*Pinus strobus*	C	x	x	x	x	x	x
Winged Euonymus	*Euonymus alatus*	D	x					
Yellow Birch	*Betula alleghaniensis*	S	x	x				
TOTAL			20	18	20	18	21	7
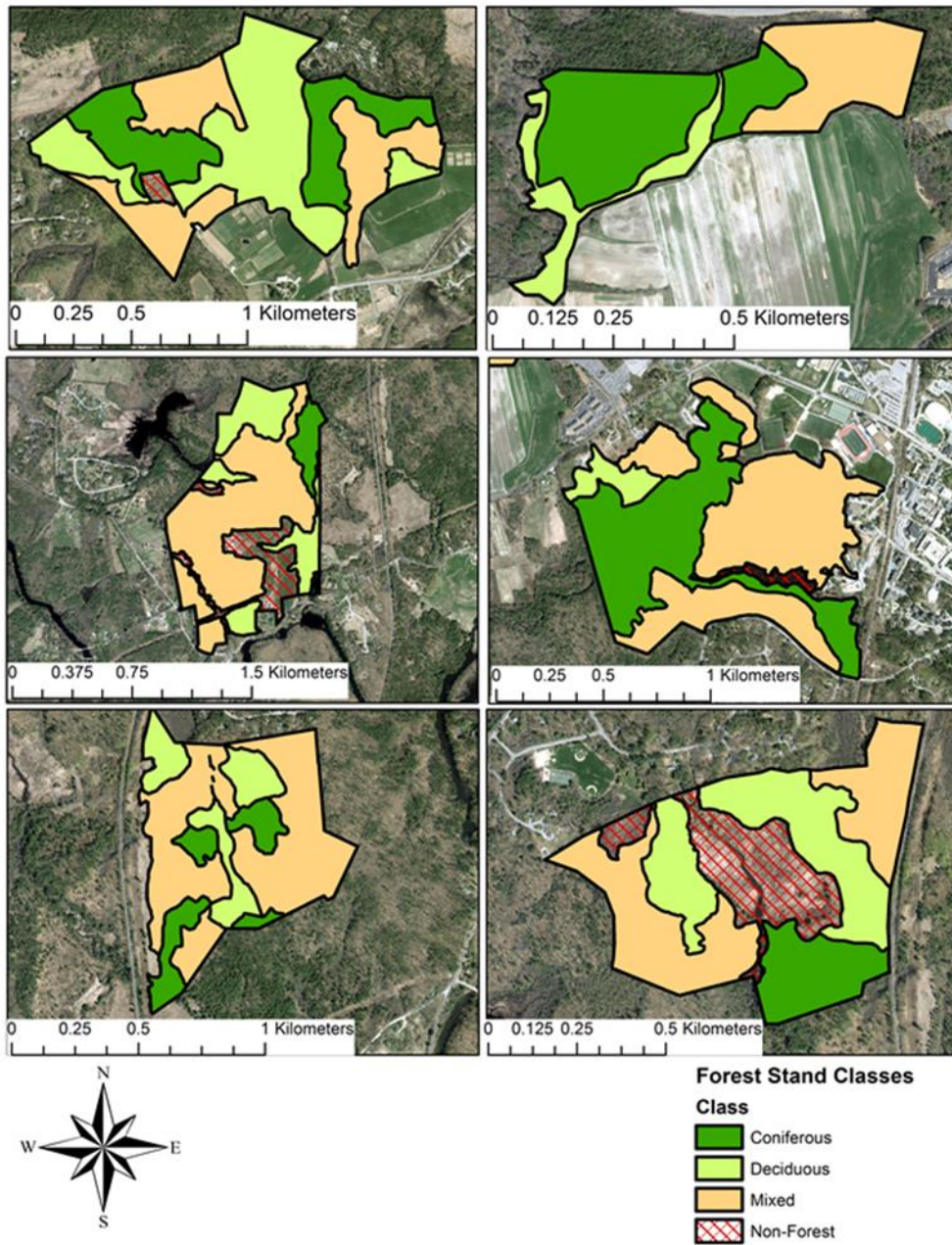
Figure 28. Ground data forest stand maps for each of the six study areas.

Table 18. Conducting UAS research requires appropriate conduct and permission at many levels of authorization. Shown above are points of contact used for federal, local, and site specific control. These contacts were notified in advanced of any UAS mission, training, or otherwise, for their respective locations. In addition to these individuals, my advisor Dr. Russ Congalton was informed of any use of the UAS, and on-site personal were cautioned when necessary.

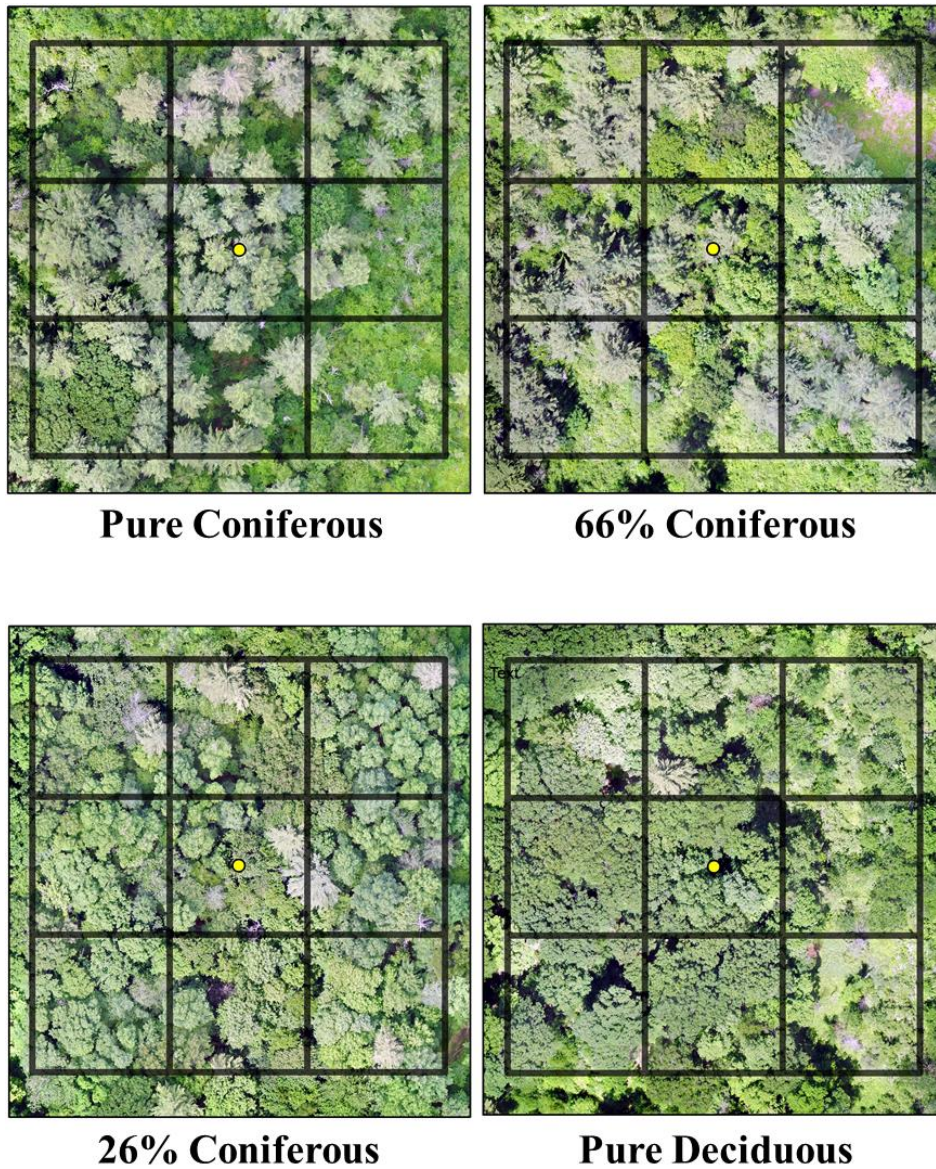|	Kingman Farm	College Woods	Thompson Farm	West Foss Farm	East Foss Farm	Moore Field
FAA	Remote PIC	Remote PIC	Remote PIC	Remote PIC	Remote PIC	Remote PIC
Police	Chief Dean	Chief Dean	Chief Dean	Chief Dean	Chief Dean	Chief Dean
UNH	Evan Ford Steve Eisenhauer	Steve Eisenhauer	Tom Oxford Steve Eisenhauer Bill McDowell John Palmer Lucie Lupine*	Steve Eisenhauer	Steve Eisenhauer	Tom Oxford John Palmer Steve Eisenhauer

APPENDIX C. FIELD DATA NOTES AND CHECKLIST FOR FLIGHT

#_____
Collectors:_____   Date:_____

Location:_____   Shapefile_____

Elevation Data:_____   Start/End Time:_____

Wind Direction and Speed:_____   Weather:_____

Mission Checklist Complete:_____

Mission Planning Software and Project File:_____

MissionComments:_____

_____

_____

#_____
Collectors:_____   Date:_____

Location:_____   Shapefile_____

Elevation Data:_____   Start/End Time:_____

Wind Direction and Speed:_____   Weather:_____

Mission Checklist Complete:_____

Mission Planning Software and Project File:_____

MissionComments:_____

_____

_____

Figure 29. Field data collection records for use during UAS missions to ensure comprehensive control and use of each flight.

Figure 30. Photo interpretation keys derived from basal area per unit area calculations of CFI plots at West Foss Farm. Thresholds between classes here are not exact, but serve as guides for simple visual reference of relative percentage of coniferous composition within effective areas. 90x90m areas are partitioned into 30x30m boxes
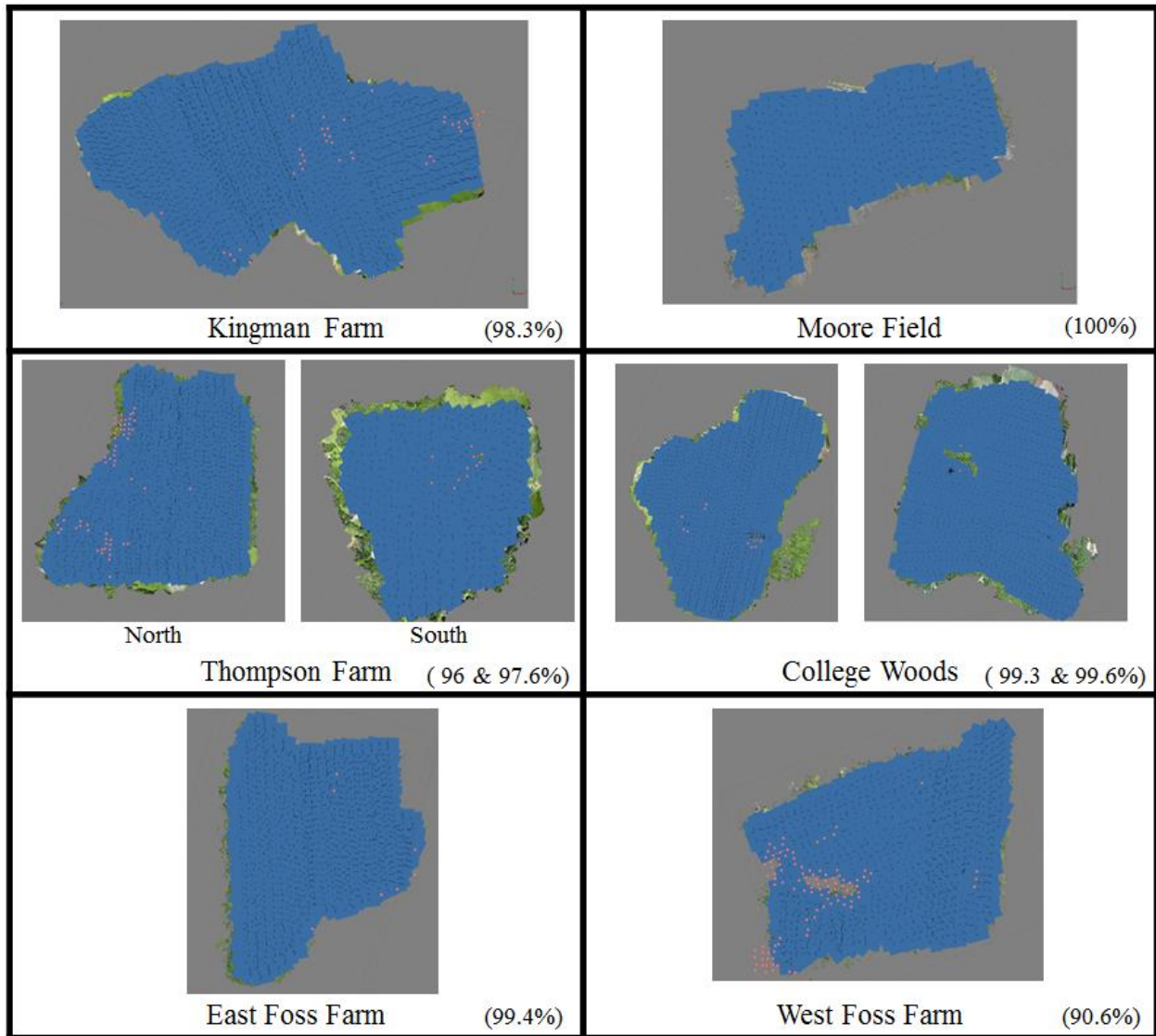
Figure 31. Initial calibration of UAS flight protocol and image processing procedure, taken by a Phantom 2 vision + at Wildcat Stadium, Durham, NH.

Figure 32. Distributions of the uncalibrated images (points in pink) across the eight final orthomosaics. Captured, but not used during point cloud densification or orthomosaic model generation. Project averaged 97.49% image calibration for these models.