Collecting and Using sUAS Hyperspectral Imagery for Maple Tree Detection Through Multi-Sensor Data Fusion

A report by
Samuel Bearinger

Submitted for review to
Dr. Paul Kinder
Dr. Jamie Schuler
Dr. Michael Strager

Davis College of Agriculture, Natural Resource, & Design
West Virginia University

For the requirements of
M.S. Energy Environments

Summer 2020

Table of Contents

Abstract

Hyperspectral satellite data has long been used for land cover classification, but the coarse resolution does not lend itself to individual species classification. With recent advances in drone and sensor technology much higher resolution hyperspectral imagery can be collected on demand. However, these new sensors pose challenging workflows as well as data management problems as the high-resolution systems amass very large datasets quickly.

This project focuses on identifying maple trees using the advanced remote sensing technique of multi-sensor data fusion of LiDAR, RGB imagery, and hyperspectral data in order to produce a workflow that can help classify what percentage of a forest is made up of maple trees. West Virginia is a predominantly forested state that has a long history of traditional forest management practices and by exploring novel ways of forest inventory these tried and true methods have the potential to be improved or enhanced, benefitting the overall forest management in the state. Previous studies show that multi sensor fusion techniques can improve individual dataset limitations and provide better results than with the use of any one sensor. However, this study found many challenges to real world implementation of these workflows.

Introduction

The objective of this project is to use advanced SUAS remote sensing as a new technique for tree species identification with the purpose of applying established methods to a tailored workflow for West Virginia forests. This project uses a combination of cutting-edge cameras, LiDAR, and hyperspectral sensors available at West Virginia University (WVU) and the Natural Resource Analysis Center (NRAC) and addresses some of the challenges and limitations while providing a platform for future work using better technology, time, and resources.

Hyperspectral sensors measure narrow and contiguous wavelength bands and provide in-depth spectral reflectance for each pixel rather than just a single pixel value as is the case with traditional imagery. This allows researchers to contrast spectral curves between species that otherwise are indistinguishable via other visual methods (Shippert 2004). Much work has been done to date using hyperspectral imagery for detailed analysis and with the addition of sUAS to the available collection methods this has become a topic of even greater interest prompting a thorough literature review to be completed on the subject by Tusa et al. (2020).

One important work reviewed by Tusa et al. is the study done by Zhang et al using LiDAR and hyperspectral data for object-based tree species classification. This work uses airborne hyperspectral data at 3-meter resolution collected with an Integrated Spectronics HyMap sensor with a spectral range from VIS out to SWIR2 (.45µm-2.48µm). This is used in conjunction with 1-meter resolution LiDAR data through a data fusion workflow similar to this project and the LiDAR was used to produce a surface model from which canopy height models were extracted and used to delineate individual tree crowns. Tree crown data was then overlaid with the georeferenced hyperspectral image for species classification. This study boasts impressive overall accuracy ranging from 45 percent to 88 percent depending on data processing methods (Zhang et al. 2016).

Other studies likewise talk to the benefits of data fusion, using LiDAR to provide crown context to hyperspectral imagery. Dalponte et al. used 1-meter AISA Eagle hyperspectral data with a spectral range from 400 µm to 990 µm in conjunction with a 1-meter LiDAR DEM. This study acknowledges the narrow field of view associated with hyperspectral sensors and the challenges that can bring but overcomes these by mosaicking multiple flight lines together into one large image prior to co-registering with the DEM (2008). These studies, along with many others covered by Tusae et al. address and work through many of the challenges associated with advanced data fusion and hyperspectral data.

This project follows the workflow and methodology that is laid out in these papers using the sensors unique to the WVU NRAC. This is done in order to enhance the overall research lab capabilities and determine if these sensors possess the capability of advanced species classification for forestry applications in the state of WV.

Study area

The West Virginia University research woodlot in Morgantown, WV was selected for the study area due to its close proximity, species composition and ongoing research goals. The specific plot is approximately 2 acres of mostly maple trees ranging in diameter from <5” to >20”, along with a small component of black cherry, yellow-poplar, red oak, black birch, and American sycamore (figure 1). This plot was chosen because it is the site of an ongoing canopy thinning study, resulting in increased space between each canopy and easier canopy delineation.

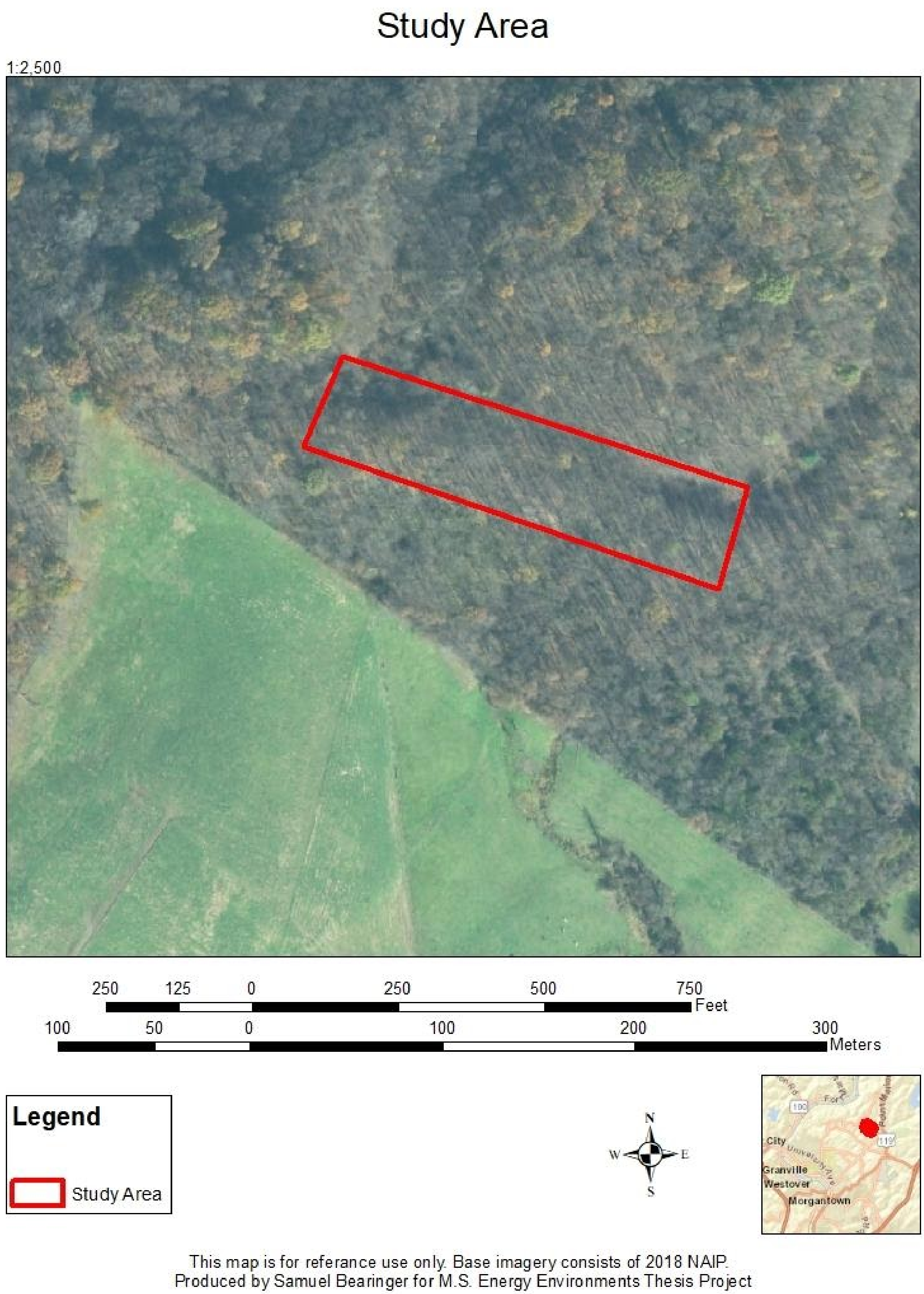
Study Area
1:2,500
250 125 0 250 500 750 Feet
100 50 0 100 200 300 Meters
Legend
Study Area
N
W
E
S
Granville
Westover
Morgantown
This map is for referance use only. Base imagery consists of 2018 NAIP.
Produced by Samuel Bearinger for M.S. Energy Environments Thesis Project

Figure 1

Sensor Overview

The sensors and equipment used for this project include commercial UAV platforms and sensors that are currently used at the WVU NRAC. Specifics of each sensor are discussed below.

LiDAR

LiDAR (Light Detection and Ranging) generates point clouds by using a complex laser scanner mounted on a small UAV (NOAA). For this project, a DJI Matrice 600 is used as the UAV and the Redtail RTL-400 is the LiDAR sensor. This sensor uses a complex Microelectromechanical Mirror (MEMS) to direct a laser beam at the ground, collecting up to a million points per second. This laser data is corrected using an Applanix APX-18 inertial measurement unit (IMU) to compensate for the roll, pitch and yaw of the UAV and to provide highly accurate GPS positions. The system itself is capable of producing points that are accurate to 15mm range accuracy and spatially accurate below 20cm (RedTail LiDAR). LiDAR is becoming more widely used in natural resource management and forestry, with much focus being directed on gathering forest metrics. There are many suites of software for LiDAR data processing, but this study uses software produced by Green Valley International called LiDAR360 for processing and analysis.

Similar sensor fusion studies use LiDAR data collected via manned aircraft, however this data has a much lower point density resulting in canopy measurements that are averaged using canopy closure and stand density (Popescu et al. 2000). This method is useful for average stand metrics but is limited for research on individual trees. Popescu et al. conducted more work using a similar LiDAR dataset from a plane developing other ways to measure tree crown diameter, however this method is limited by the 1m grid size from the data (2003). The Redtail data used in this project averaged over 200 points per m^2, with some areas exceeding 700 points per m^2 in density. This high resolution lends itself to detailed work on individual trees that is used for detailed Digital Surface Models (DSM).

Hyperspectral

The Hyperspectral sensor employed for this study is produced by Bayspec, a California company. The sensor is the OCI-F model which measures the full visible to near infrared spectrum (VIS-NIR 400-1000µm). It is an innovative push-broom sensor capable of being used for bench mounted studies, or in this case, mounted on a UAV via a gimbal. The UAV used for this sensor is also the DJI M600 that carries the LiDAR sensor, however these collections are not conducted simultaneously. The company claims the sensor provides “versatility on various platforms such as UAVs with perfect hyperspectral image stitching” going on to say that the sensor is “ideal for applications such as precision agriculture, remote sensing, conveyor sorting, forensics and all airborne applications” (Bayspec). The sensor comes with proprietary processing software to stitch the hyperspectral images together into a hyperspectral data cube post collection. A hyperspectral data cube is a layered image of all the bands that the sensor records. Each band has a unique reflectance for a given pixel with the compiled cube giving the full range of the spectrum broken up into individual bands (Shippert 2004). In other words, each pixel will show the reflectance for each of the 120 bands in the image and display these values in a graph. This graph is the detailed spectral curve and can be displayed for one pixel or a region of averaged pixels such as a tree canopy.

Photogrammetry

The camera used to collect the RGB imagery is the DJI X5s camera mounted on a DJI M200 UAV. Images collected are processed using a technique known as photogrammetry with software produced by Agisoft called Metashape. Photogrammetry is the method of three-dimensional image combination using advanced pixel matching to generate a to-scale and spatially accurate model from many overlapping photos (Gatziolis and Strigul 2018). It also produces a composite orthomosaic while preserving the high resolution of the individual photo.

Methods

This section will discuss the methods used for data collection and processing, along with challenges encountered. This project started with the plan to use the three types of remote sensing data to narrow down the hyperspectral data cube into a usable product with which to

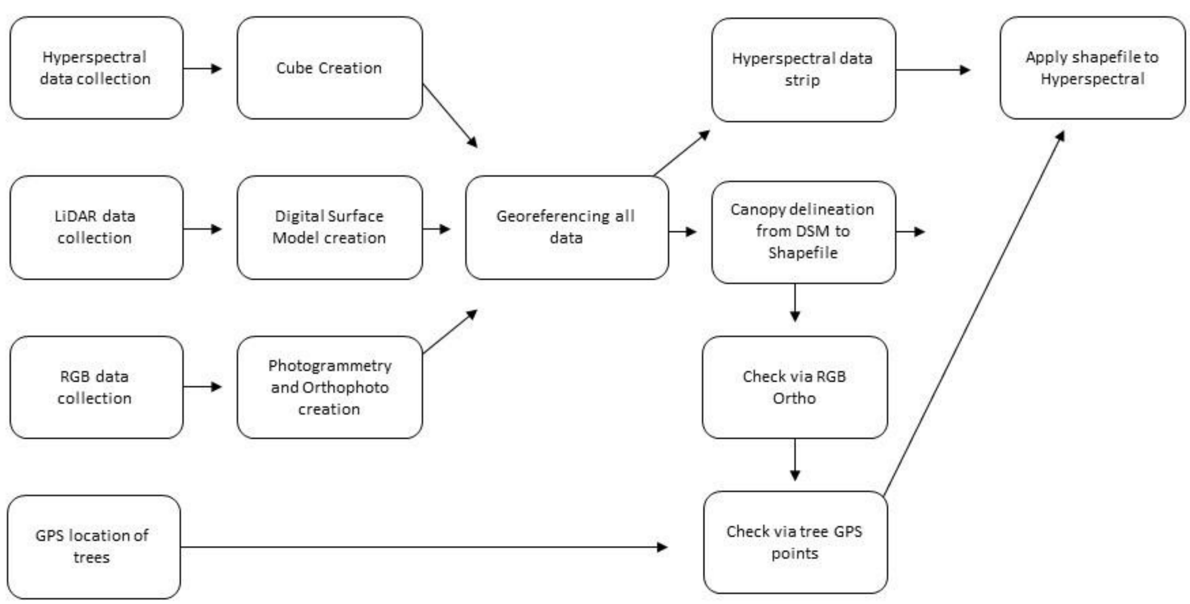

Figure 2

conduct tree species analysis. The workflow progression for the data fusion process is shown in figure 2. This is similar to the workflow of reviewed literature and provides the best use for all data types in this study (Lee et al. 2016, Zhang et al.).

We flew the study area over the course of one week in early May 2020 on days when weather was permitting and during the times when the best conditions for each flight type could be achieved. Hyperspectral data collection requires calibration for each flight and requires consistent lighting throughout the collection period. All data collection is best done with low wind as tree movement causes many problems during processing. Since this study is looking at spectral signatures of tree canopies, data could not be collected until the trees had leafed out. GPS data was recorded for 25 trees using a Spectra SP-60 survey grade GPS receiver, however the full leaf on conditions proved problematic for precise GPS collection.

LiDAR data (figure 3) was collected using the RTL-400 sensor at a height of 60m and processed from the raw point cloud using LiDAR360 v4.1. Noise within the point cloud was classified out via a filter noise tool as well as ground and vegetation which was classified to create a Digital Surface Model (DSM) in TIFF raster format at .25m resolution (figure 4). This DSM has high spatial accuracy because of the spatial accuracy that the LiDAR sensor provides and is therefore used as the basis for georeferencing all other datasets. The plan was to polygonise each tree canopy in the study from the DSM with a raster to vector tool; however, complications with the hyperspectral image that are discussed later in this report rendered this step unnecessary as it would not provide data that could be used as intended.

Photos were taken over the study area using a DJI m200 UAV with the X5s RGB camera, flown as a grid via DJI pilot software. These photos were taken at a height of 200', the max allowed in this area of class D airspace, with an 80% front and side overlap. Placing targets was challenging in the densely forested area, however four targets were placed over the study area and the locations were collected via GPS. These were used during post-processing to provide higher spatial accuracy than could be achieved through the GPS native to the UAV.

Processing of this imagery was done using Agisoft Metashape v1.6.2 photogrammetry software and the final orthophoto (figure 5) was exported to use for analysis in Arcmap software.

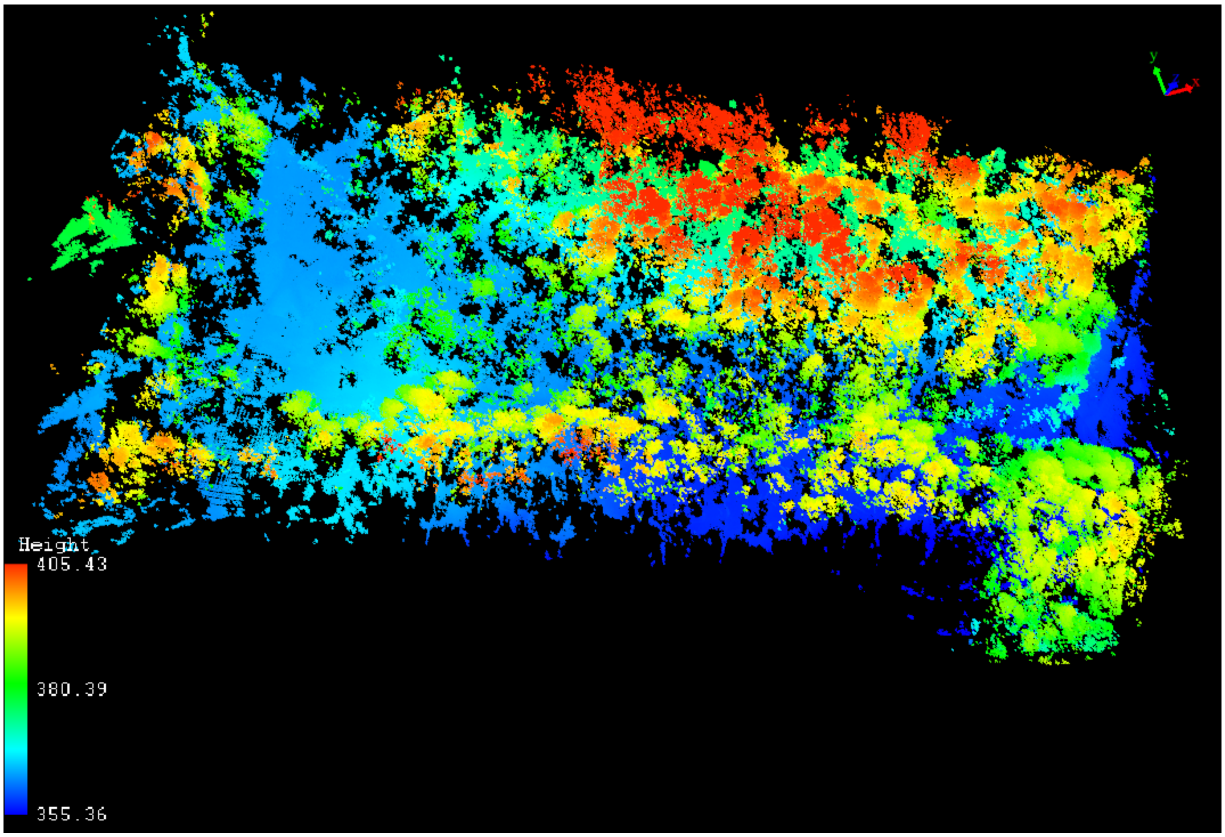

Figure 3

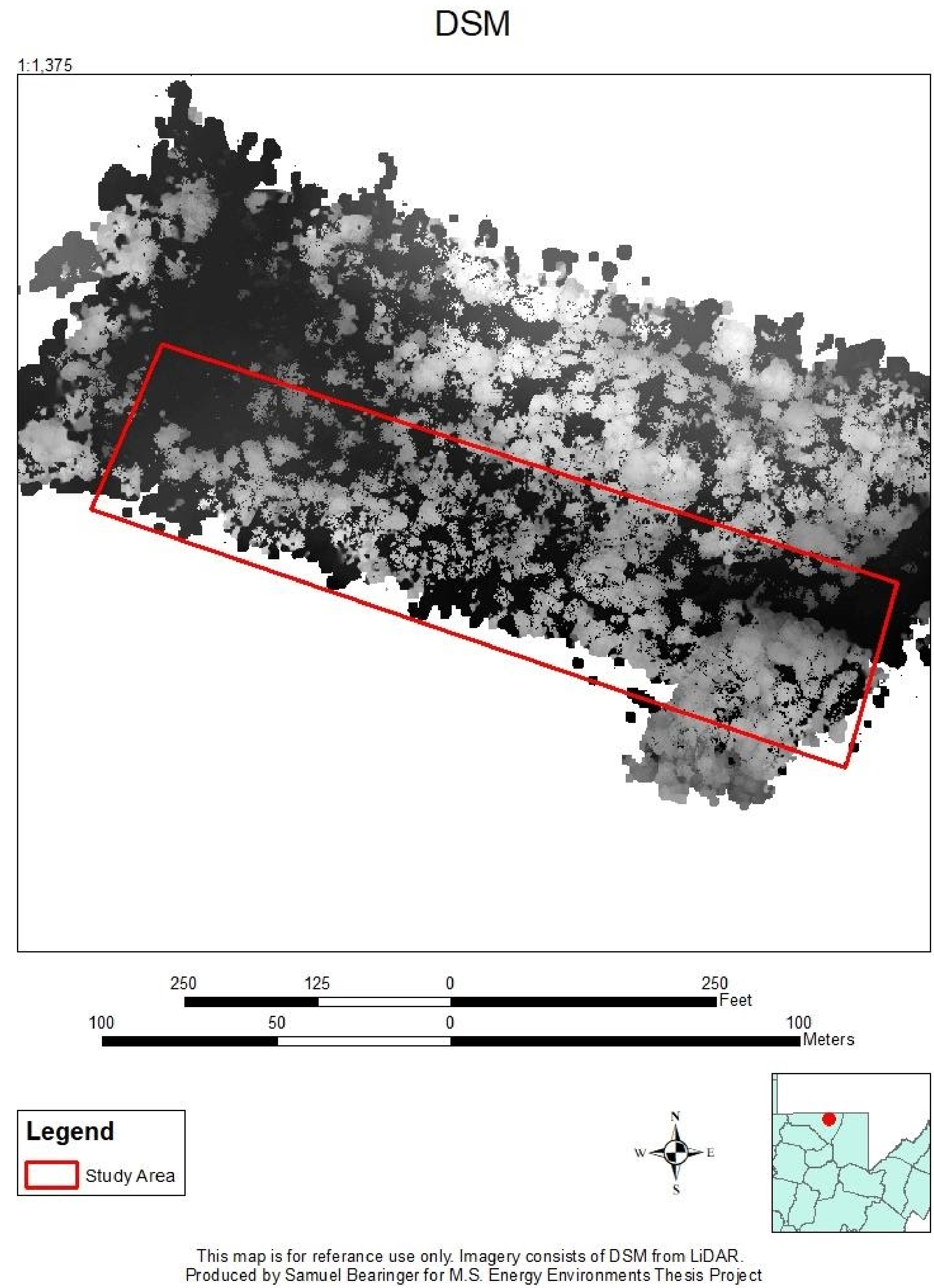
DSM
1:1,375
250
125
0
250
Feet
100
50
0
100
Meters
Legend
Study Area
N
W
E
S
This map is for referance use only. Imagery consists of DSM from LiDAR.
Produced by Samuel Bearinger for M.S. Energy Environments Thesis Project

Figure 4

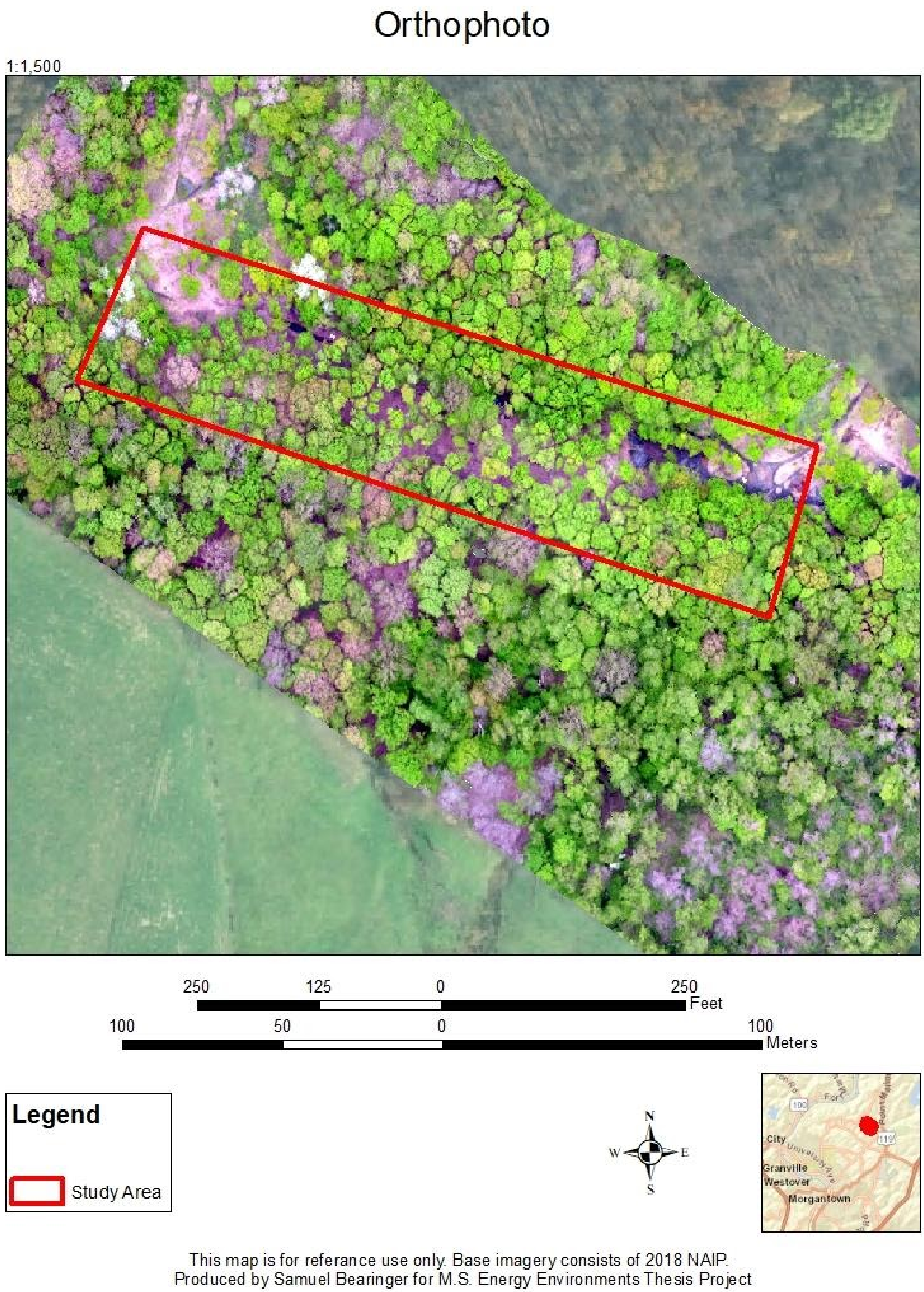
Orthophoto
1:1,500
250
125
0
250
Feet
100
50
0
100
Meters
Legend
Study Area
N
W
E
S
City
Granville
Westover
Morgantown
This map is for referance use only. Base imagery consists of 2018 NAIP.
Produced by Samuel Bearinger for M.S. Energy Environments Thesis Project

Figure 5

We used the Bayspec sensor to collect hyperspectral data which produced over 66,000 raw images amounting to a total dataset of 104GB of data in a matter of minutes. This was processed using the proprietary Bayspec software into flight line strips that were individual hyperspectral data cubes (figure 6). Each strip was approximately 30m wide, which was the sensor footprint on the ground. The program to stitch those strips into one large area would not produce satisfactory results, likely due to a combination of software flaws and the nature of processing trees. Because of the issues presented by the hyperspectral data collected with the Bayspec sensor, the decision was made to perform independent analysis on just a single strip of hyperspectral data. Single strip analysis is also how others chose to address the problems that arise from stitching together hyperspectral data of forest canopies. Also, using one flight line is beneficial because illumination and atmospheric data is consistent throughout the data cube (Lee et al. 2016).

Figure 6

Atmospheric correction is commonly applied to commercial satellite hyperspectral imagery; however, it poses a challenge with unique third party sUAS based systems. Similar studies focusing on species classification from hyperspectral imagery find no major benefit to applying atmospheric correction (Hoffbeck and Landgrebe 1994, Kim et al 2006, Dalponte et al 2008, Dalponte et al 2014, Lee et al 2016) therefore this project follows their example and spectral data is analyzed without atmospheric correction.

It is important to co-align datasets when using multisensory fusion (Lee et al 2016). This was conducted using the georeferencing tool in ArcMap 10.7.1 using easily distinguishable trees between the DSM and the orthophoto. Initial spatial accuracy was close between datasets, but not close enough to accurately identify which tree belonged to which GPS point. Upon georeferencing the orthophoto to the DSM, the datasets became more closely aligned to each other and were then layered with a dataset containing tree locations. This dataset was collected with a spectra GPS receiver through a RTK streaming system provided by the WV Department of Highways (DOH). To produce centimeter accuracy a fixed solution is required, however under the canopy the best that could be produced was a floating solution which can be a few meters off from ground truth. This prevents accurately matching which tree is which in the dataset and impairs the ability to determine which tree is which species (figure 7). Despite the good matching between the DSM and the orthophoto, those datasets did not match the GPS tree point dataset. This lack of accuracy in the GPS tree point dataset is likely due to the nature of collecting GPS points under a mostly closed canopy.

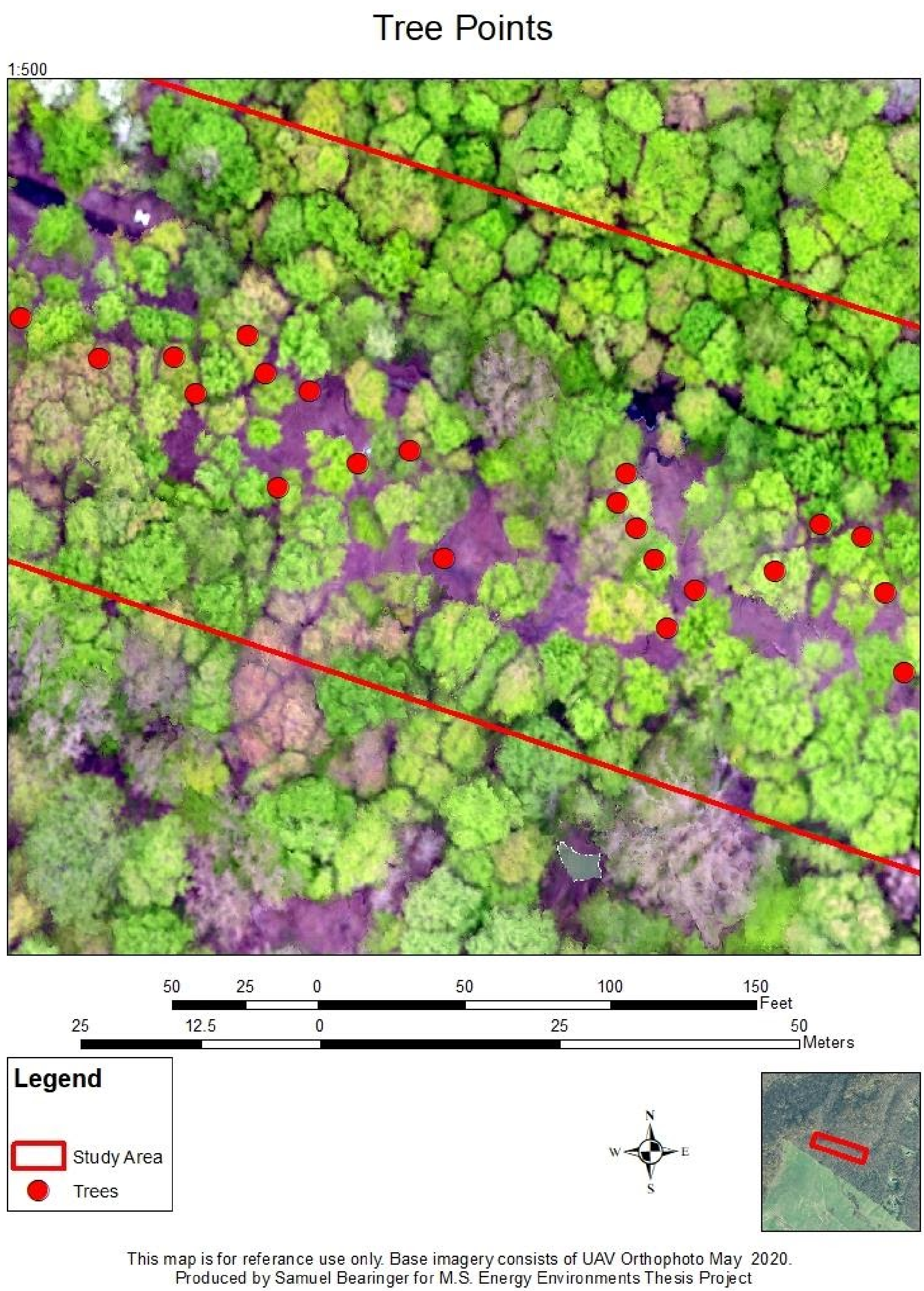
Tree Points
1:500
50 25 0 50 100 150 Feet
25 12.5 0 25 50 Meters
Legend
Study Area
Trees
N
W
E
S
This map is for referance use only. Base imagery consists of UAV Orthophoto May 2020.
Produced by Samuel Bearinger for M.S. Energy Environments Thesis Project

Figure 7

Attempts were made to georeference the hyperspectral data strip using the ArcMap tool, however the linearity of the data, along with data distortion caused by the sub-par Bayspec sensor and processing software, caused the image to warp and distort during every attempt (figure 8). This is a major issue at this time when working with data produced by this hyperspectral sensor; likewise, the total size of datasets, and the low-tech processing workflow provided by the company imposes hurdles and challenges to advanced analysis.

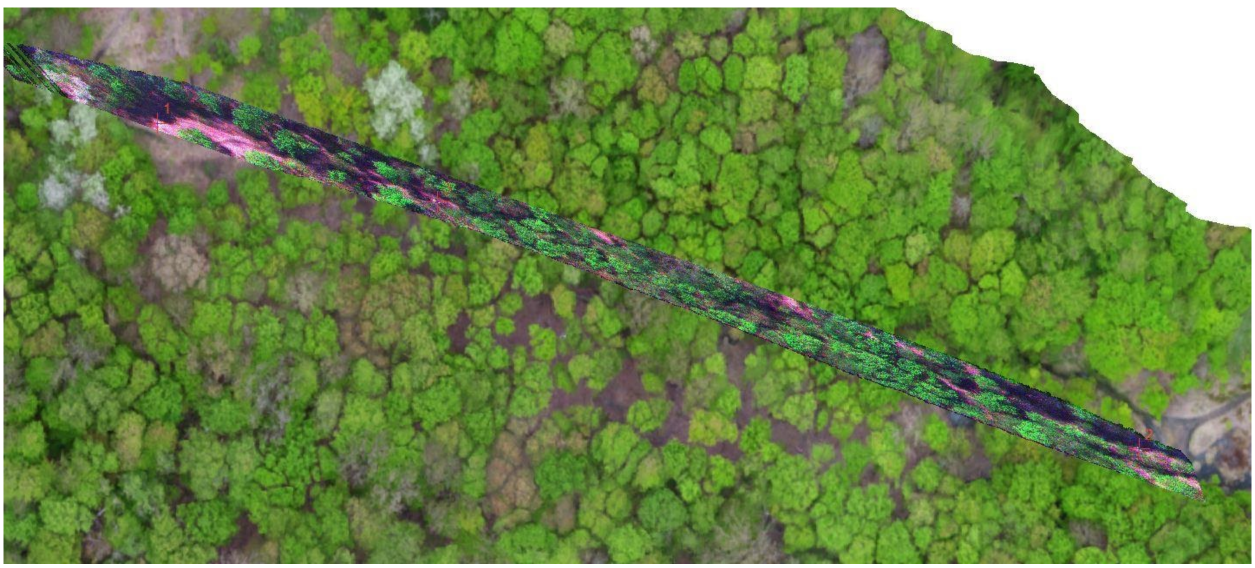

Figure 8

Given the findings and failures during the data fusion step the decision was made to proceed with analysis using just the hyperspectral data through ENVI software. The nature of this study on a patch of forest that had been recently thinned provides the unique opportunity of being able to easily distinguish the differing tree canopies—something that would not be easy given a normal forest. The workflow illustrated in figure 2 is optimal for producing canopy segmentation from the LiDAR data that can be applied to the hyperspectral data, however in this case, similar results can be attained through visual methods. Figure 9 shows an example of how the canopy can easily be segmented from the hyperspectral data the same image is displayed in both RGB and false color. The yellow polygon covering the tree in the lower of the two images (the one displayed in false color) represents the tree canopy as manually defined.

From the multiple flight lines collected, the hyperspectral image that covered the most of the study plot was selected to use for analysis and the canopies of 30 trees were manually delineated in the manner described above into regions of interest (ROI) in ENVI. The average mean spectral curve was then generated for each tree independently. One such curve is displayed in figure 9.

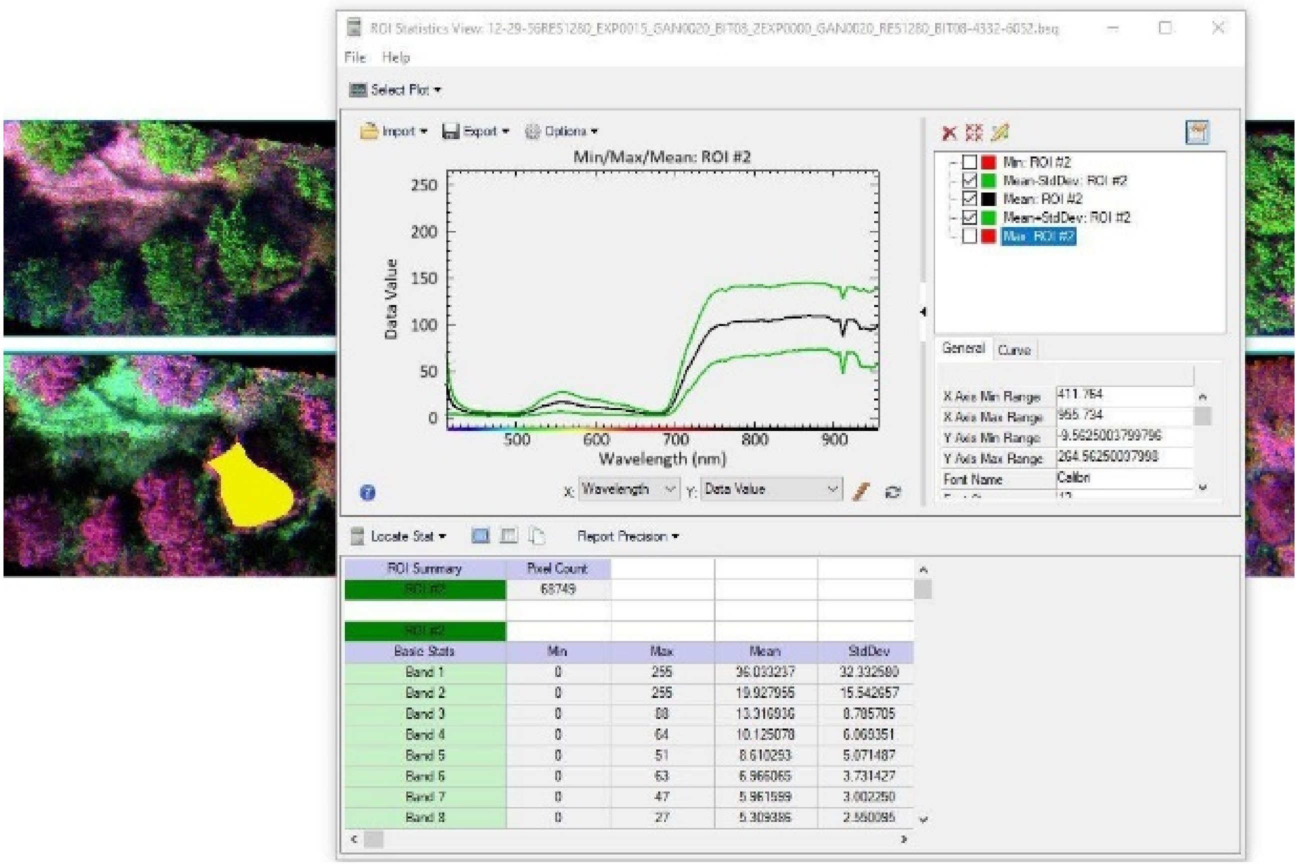

Figure 9

Given the challenges posed by GPS collection under leaf on canopy, individual tree canopies were not able to be matched to the GPS points for species determination so we used a ground target for reference and matched the imagery to the trees while standing in the forest. The location of five maple trees (figure 10) was confirmed and these trees were used as a control with which to compare the spectral curves of unidentified trees.

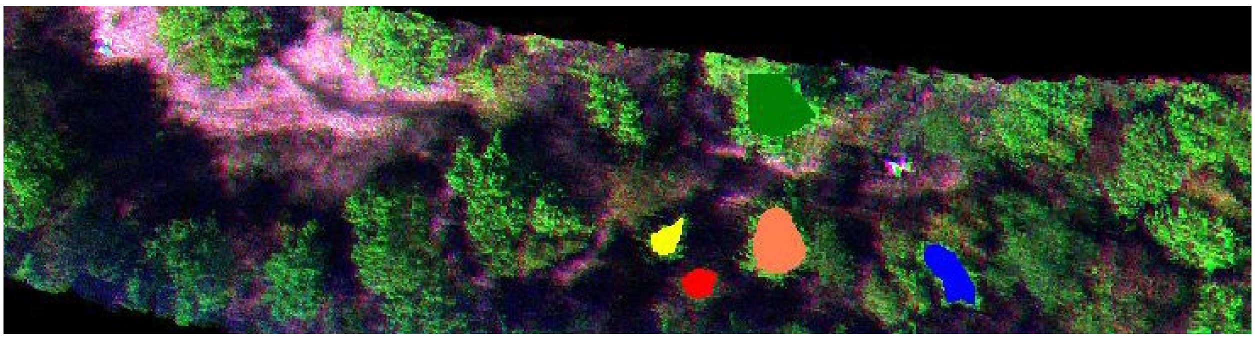

Figure 10

Results

Detailed statistical analysis is beyond the scope of this project, so visual analysis of the spectral curves is used to provide insight into the benefits of future more detailed analysis. The hyperspectral dataset was segmented into 30 trees as shown in figure 11, with the 5 trees identified as maple shown in figure 10. Figure 12 shows the mean spectral curves from all the trees in flight one (bottom) versus the five maples (top). They appear to have a similar shape, however the spread in intensities in the NIR part of the spectrum is vast. This cannot be explained by suggesting it is the result of different species, since the five maple trees are spread throughout the entire group of trees (red curves).

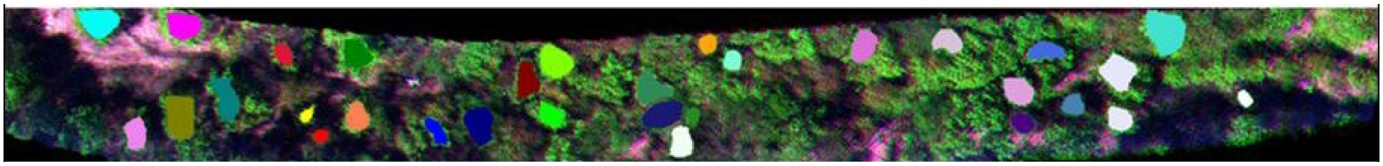

Figure 11

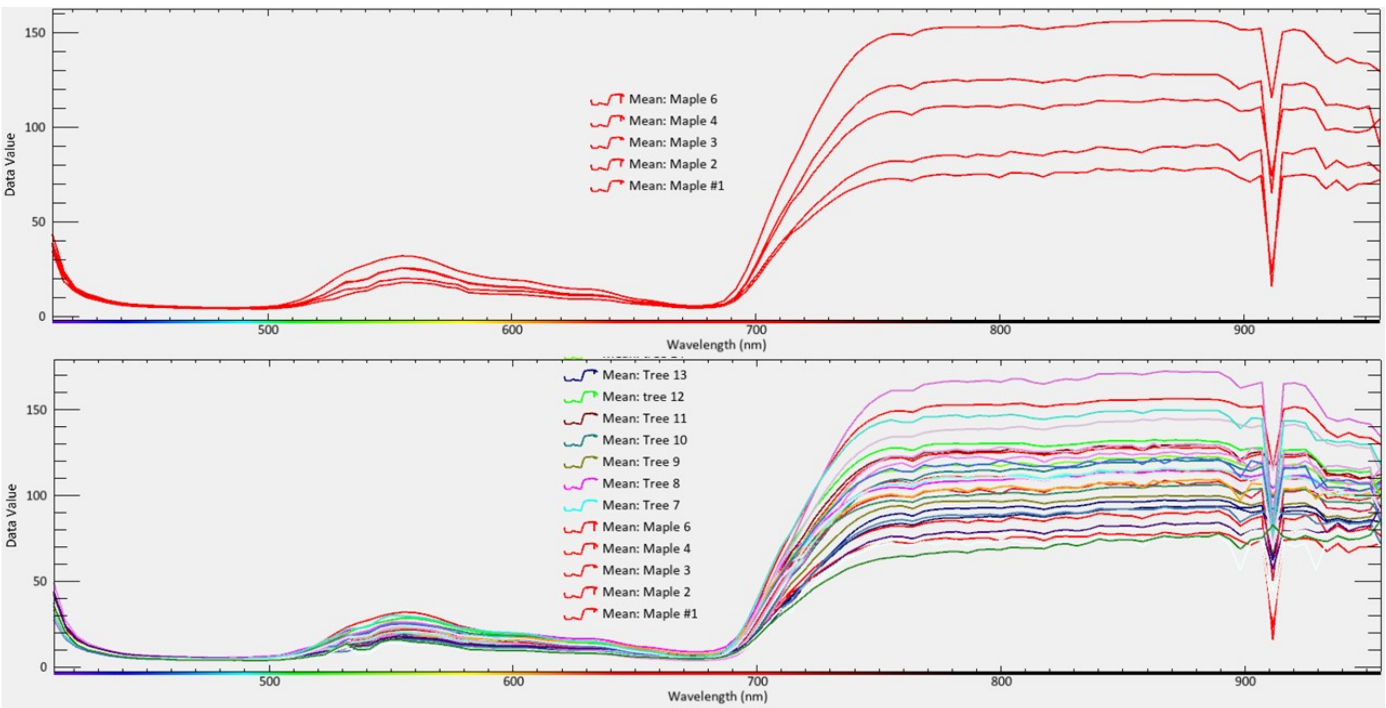

Figure 12

The curves appear to be very similarly shaped, which could indicate promise for species detection; however, the range of reflectance values causes more questions to be raised about the sensor. To provide more species with which to compare the curves generated from the maple plots shown in “Maples Morgantown”, three other datasets were used. One dataset was flown in June over a fence row containing a maple tree in Tucker County (“Maple Tucker CO”), a second was flown in June over a clump of American sycamore in Tucker County (“Sycamores Tucker CO”), and a third was flown in the winter over pine trees at the WVU portion of Coopers Rock State Forest (“Pines CRSF”). These datasets were processed in the same fashion as before, with individual trees segmented into ROI’s and mean spectral curves generated. Figure 13 shows a comparison between the maple curves from flight one, the second maple flight, the third sycamore flight, and the fourth pine flight.

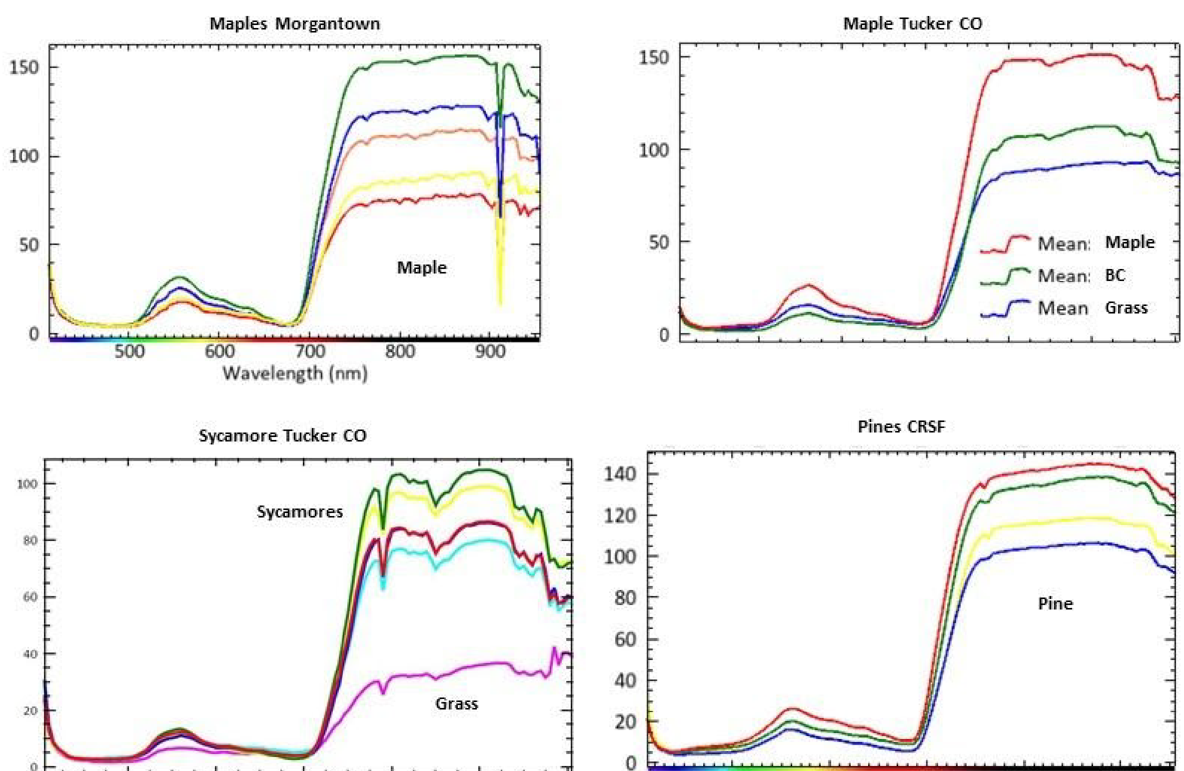

Figure 13

Looking at the graph of the five maple trees in the thinned maple plot named “Maples Morgantown” in figure 13, there are strong visual similarities between the spectral curves from the different maple trees but a large shift from one curve to the next in the near infrared part of the curve. In the graphs “Sycamore Tucker CO” and “Pines CRSF”, the curves from the sycamore and pine plots both show marked differences from the maples that can be explained by many other factors besides difference in species such as daily weather conditions or different times of the year. To attempt to assess whether this difference was due to species or another variable, another flight was conducted that included one maple tree and a few cherry trees and is shown in the graph “Maple Tucker CO”. These trees were in a fence row and quite easy to distinguish one from another due to their placement in a line.

The spectral curves from this final flight show visual similarities between the maple tree and the black cherry tree, despite the difference in species. The maple in “Maple Tucker CO” also shows a dissimilar visual curve to the maples flown in “Maples Morgantown”. Overall, the similarities in the curves between trees of different species as well the differences between the curves of trees of the same species deem the Bayspec hyperspectral sensor to be unpromising for species classification. However, a future more in-depth study would be needed to determine if detailed testing and advanced statistical analysis would enable this sensor to differentiate between trees of multiple species.

Limitations and Discussion

Using hyperspectral data to accurately quantify the species composition of a forest would be very beneficial for many types of land management applications. Unfortunately, the OCI-F sensor from Bayspec was not able to provide the data needed to accomplish this objective during this project.

There were many limiting factors to this project that have been mentioned throughout this report, most of all the hyperspectral sensor itself. It appears that the visual commonality in spectral curves on this study are within each flight, not from one species to another. However, given that each flight was conducted on a separate day over different trees in different parts of the state there are many other variables that need to be accounted for.

Also, unlike spectral curves measured with handheld spectrometers on single leaves, this sensor is measuring the entire canopy, including branches and twigs. This will have an effect on the overall mean spectral curve and will likely change over time as the density of the canopy changes. This cannot be avoided as the resolution of the sensor is not high enough to measure individual leaves from any reasonable altitude that would allow the collection of a reasonably sized dataset.

Many flights would be needed to dial in this sub-par sensor to determine if there is a way to better calibrate the sensor to tune out atmospheric and other interference effects to the data. That experiment would need to be constructed so as to minimize variables. A study looking at pasture vegetation is ongoing at WVU Wardensville farm and will produce a dataset over the same area on multiple days in a short time span. This study should shed better light onto whether much of the variability in this maple study was due to the sensor or if changing location and time of year played a prominent part.

The issues encountered with GPS collection of tree points were a factor in the first flight and for future research need addressed if ground truthing of data is to be expected in a mixed forest. But for this project, a more accurate dataset of tree points would not have changed much since subsequent flights were over trees that were not problematic to identify in the image because they were in single species clusters.

The glaring issue with stitching the hyperspectral data from individual strips into a large orthophoto need to be addressed by the company. The Bayspec software was not capable of doing this despite the overlap being greater than 50% from one image to another. The company suggests using Microsoft's Image Composite Editor (ICE) to stitch images if their software fails, however this did not produce satisfactory results either. The photogrammetry software Metashape used to process the RGB imagery also claims to be capable of working with hyperspectral data and this was tried with the same failed results as the other methods. This may be due to the movement from trees in the images causing blur that confuses the software (the same issue is problematic even with RGB photogrammetry data over trees) and it also may be heightened by the lack of spatial data applied to the hyperspectral data during the earlier stages of processing with the Bayspec software. Because of these issues, analysis of the hyperspectral data in narrow strips leads to the warping effect caused by trying to georeferenced an image with linear tie points. These issues need to be addressed before this sensor is capable of producing data that can be used for any type of large-scale project.

Conclusion

With all the work that has been done to date, it seems that the technology to accurately and easily identify tree species in a natural forest is still outside the grasp of normal use. Advances in technology and sensors have still not reduced the size of the datasets nor the processing power needed to work with them in a mainstream package that can be simply purchased and used. The BaySpec sensor causes problems during collection, results in corrupt datasets, and creates the need for data to be re-collected, making this sensor overall unreliable.

As companies continue to conduct research and narrow down the bands of interest into a sensor that produces accurate and low volume data, this technology has the potential to change the future of forest inventory. However, care should be exercised when purchasing these new sensors as companies seem to enjoy the freedom of stretching the bounds of what is truly possible when conducting advertising campaigns.

Works Cited

Bayspec Hyperspectral Sensor Datasheet
Accessed from https://www.bayspec.com/spectroscopy/oci-f-hyperspectral-imager/ on 6/01/2020.

Dalponte, M. Bruzzone, L. & Gianelle, D. "Fusion of hyperspectral and LiDAR remote sensing data for classification of complex forest areas," IEEE Trans. Geosci. Remote Sens., vol. 46, no. 5, pp. 1416–1427, May 2008.

Dalponte, M. Ørka, H. Ene, L. Gobakken, T. & Næsset, E."Tree crown delineation and tree species classification in boreal forests using hyperspectral and als data," Remote Sens. Environ., vol. 140, pp. 306–317, 2014.

Hoffbeck J. P. & Landgrebe, D. "Effect of radiance-to-reflectance transformation and atmosphere removal on maximum likelihood classification accuracy of high-dimensional remote sensing data," in Proc. Int. Geosci.Remote Sens. Symp. Surf. Atmos. Remote Sens.: Technol., Data Anal. Interpretation., 1994, vol. 4, pp. 2538–2540.

Lee, J. Cai, X. Lellmann, J. Dalponte, M. Malhi, Y. Butt, N. Morecroft, M. Schonlieb, C.-B. & Coomes, D. Individual tree species classification from airborne multisensor imagery using robust PCA, IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 9 (6) (2016) 2554e2567.

National Oceanic and Atmospheric Administration (NOAA) Coastal Services Center. (2012). "Lidar 101: An Introduction to Lidar Technology, Data, and Applications." Revised. Charleston, SC: NOAA Coastal Services Center.

Popescu, S.C., Wynne, R.H., & Nelson, R.H. (2000). Estimating forest vegetation biomass using airborne lidar measurements. In Proceedings of the Second International Conference on Geospatial Information in Agriculture and Forestry, 10–12 January 2000, Lake Buena Vista, Fla. ERIM International, Inc., Ann Arbor, Mich. pp. 346–353.

Popescu, S.C., Wynne, R.H., & Nelson, R.H. (2003). Measuring individual tree crown diameter with lidar and assessing its influence on estimating forest volume and biomass. Canadian Journal of Remote Sensing. 29. 564-577. 10.5589/m03-027.

Probst A, Gatziolis D, Strigul N. 2018 Intercomparison of photogrammetry software for three-dimensional vegetation modelling. R. Soc. open sci. 5: 172192. http://dx.doi.org/10.1098/rsos.172192

RedTail LiDAR datasheet.
Accessed from https://redtaillidar.com/ on 6/01/2020.

Shippert, P. Why use hyperspectral imagery? Photogramm. Eng. Remote Sens. 2004, 70, 377–396.

Sun-Hwa Kim, H.-R. Y. Jung-Il Shin, and. Lee, K.-S "Effect of atmospheric correction for the land cover classification using hyperspectral data," presented at the Asian Conf. Remote Sensing, Ulaanbaatar, Mongolia, 2006.

Tusa, E. & Laybros, A. & Monnet, J & Dalla Mura, M. & Barré, J. & Vincent, G. & Dalponte, M. & Féret, J. & Chanussot, J. (2019). Fusion of hyperspectral imaging and LiDAR for forest monitoring. 10.1016/B978-0-444-63977-6.00013-4.

USGS LANDFIRE Program -- **https://gapanalysis.usgs.gov.**