GEOBIA FOR POST-FIRE IDENTIFICATION OF JACK PINE SAPLINGS

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A THESIS

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Geography—Master of Science

2018

ABSTRACT

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Wildfire is a natural and necessary process which causes both devastation and regeneration to forested landscapes. One such event, the Duck Lake Fire, occurred in the Upper Peninsula (UP) of Michigan in the United States in 2012. The burn area is overseen by the Michigan Department of Natural Resources (MDNR) and encompasses approximately 8900 ha (21,000 acres) near the mouth of the Two Hearted River on the south shore of Lake Superior. After the fire, replanting by the MDNR and natural regeneration has taken place.
Unmanned Aerial Systems (UAS) imagery of ten 1-ha study plots were collected via a MicaSense Red Edge camera simultaneously capturing images in the Red, Green, Blue, Red Edge and NIR bands. Images were collected at 60 meters altitude with platform velocity of 6 m/s. Geographic Object-Based Image Analysis (GEOBIA) in eCognnition Developer was conducted to assess the regrowth of jack pine in the Duck Lake forest and answer three questions: *What is the level of accuracy that can be achieved via GEOBIA for detecting young jack pine saplings? How does the use of the Red Edge (RE) spectral band affect image classification accuracy? How does seasonal change affect the accuracy that can is achieved by the UAS and GEOBIA method?* GEOBIA classification accuracies ranged from 59.5-97.5% with the NIR-R band combination performing the best overall and RE performing the worst. An overall increase in accuracy was observed as the season progressed with the highest average accuracy in time three (T_3) at 78.4% across all bands

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1. Introduction

Wildfire is a natural and necessary process which causes both devastation and regeneration in forested landscapes. Mapping fire processes and impacts on forested ecosystems is of the utmost importance for informing fire-related management Meng et al. (2017). Traditionally, forest inventory analysis has been conducted through field surveys such as the U.S. Forest Service's Forest Inventory and Analysis (FIA) program (Burkmann 2002). Zobrist (2012, p. 1) suggests that inventories "not only ensure(s) your forest is healthy and productive but can meet your objectives as a landowner for years to come. After all, to assess the needs of your forest and plan for the future, you have to know what forest resources you have". Remote sensing (RS) technology has emerged as a timely and cost-effective addition to or alternative for evaluating forest changes, especially forest disturbances (Masek et al. 2008).

Forest disturbances are any events that disturb or disrupt the normal progression of growth in a forest environment. These disturbances can be anthropogenic (e.g., urbanization) or naturally occurring (e.g., fire, drought, disease). Remote sensing has been used to reconstruct and map past forest disturbances in a chronological manner providing a spatial environmental history (Masek et al. 2013). Remote sensing data can also be used to inform predictive models about what future forest disturbances may look like by observing or detecting patterns in disturbances and how a disturbed area recovered (Cohen, Yang and Kennedy 2010).

Aside from using this tool to observe the past or predict what may happen in the future, remote sensing has been employed to actively track wildfires (Chuvieco 2007), invasive insect outbreaks (Spruce et al. 2011), and logging (Hansen et al. 2008) to provide a "real-time" view of what disturbances are occurring around us.

Despite the success of satellite and aerial sensors in collecting data on burn severity, fire intensity, vegetation regrowth, soil condition, and other environmental factors, (Berni et al. 2009) suggest two critical limitations for using current satellite imagery in real-time or high temporal vegetation management: a lack of imagery with optimum spatial and spectral resolutions and an unfavorable revisit time for most stress-detection applications. The alternative to satellite imagery they propose is Unmanned Aerial Systems (UAS) which can collect data with higher spatial resolution and temporal frequency at a much more cost-effective rate than aerial and satellite sensors. Horcher and J. M. Visser (2004) recognized this potential and conducted a study on the applicability of UAS in a forest management context. Possible uses discussed included runoff and logging pollution inspections, property boundary and timber theft monitoring, trespassing and job site surveillance and road quality inspections. Horcher and J. M. Visser (2004) state that the ability of UAS to capture very high-resolution imagery, be deployed frequently and provide access to areas that cannot be reached on the ground are all advantages making UAS ideal for forest management including documenting forest disturbance and revegetation.

Remote sensing alone cannot provide the answers to our questions but is a means to understand better what is occurring around us. Each application and situation is unique for which human input is required, and a study-specific methodology is created. Because of this uniqueness, fine spatial and temporal resolution data alone are not enough to guarantee highly accurate mapping products. The purpose of this research is to *gain a better understanding of the spectral, temporal, and analytical requirements necessary for achieving optimal accuracy* in the detection of jack pine (*Pinus banksiana*) saplings in a post-fire environment through UAS.

Jack pine is a common species in northern Michigan. These trees are dependent on wildfire for regeneration and new growth, as fire exposes seedbeds for germination as well as opens serotinous cones that do not usually open until they are exposed to high temperatures (>120° F) (Cayford et al. 1983). Jack pine is an important commercial species used for pulpwood, construction timber, telephone poles, fence posts, mine timbers, railway ties, and Christmas trees (Cayford et al. 1983). Jack pine also provides habitat for the endangered Kirtland's Warbler, a native bird species found exclusively in this habitat. Without fire, jack pine dominated landscapes would eventually diminish leading to adverse economic and environmental impacts on the humans and wildlife that depend on them (Cayford et al. 1983). The early successional characteristic of jack pine made it the key species in this research, around which the research questions were formed. For this thesis research, I posed the following three research questions:

- *What is the level of accuracy that can be achieved by the combination of UAS and Geographic Object-Based Image Analysis (GEOBIA) for detecting young jack pine saplings?*
- *How does the use of the Red Edge (RE) spectral band affect image classification accuracy, in comparison to the use of the near-infrared (NIR) spectral band, or NIR -Red band combination or RGBNIRRE band combination?*
- *How does seasonal change affect the accuracy that can is achieved by the UAS and GEOBIA method?*

These questions framed this research as the first of its kind combining UAS, GEOBIA and jack pine sapling identification. This unique combination aims to fill voids in remote sensing, GEOBIA, and forestry management literature. This particular application has the potential to streamline aspects of post-fire forest management, expand the potential for OBIA in a geographic setting and better understand and show the capabilities of new remote sensing technology namely UAS for post-fire data collection.

1.1 Case Study: Duck Lake Fire 2012

This research uses the 2012 Duck Lake Fire in Northern Michigan as a case study for analysis and thesis. The fire burned approximately 8,900 ha of land in the Department of Natural Resources' (DNR) Newberry Conservation District, located northwest of Newberry, Michigan. After the fire, efforts by the DNR and private logging companies to salvage timber and replant portions of the burned area began. Since that time, both managed and natural vegetation regrowth have taken place. The site is optimal for testing UAS/GEOBIA methods for tree identification due to its isolation from dense urban sites, barren and sparsely vegetated landscape and few view obstructions allowing the pilot to observe the UAS at all times during data collection in compliance with FAA regulations.

2. Background

In order to understand the spectral, temporal, and analytical requirements of tree sapling identification using UAS imagery, it is necessary to review the current state of knowledge regarding the use of RS technology to aid in mapping and monitoring forest and post-fire landscapes. A review of literature pertaining to these aspects of post-fire forest mapping is presented here.

2.1 Forest Management

Forest managers face challenging decision-making tasks when ensuring the productivity and health of forests. Often times one management scheme is not sufficient to successfully manage or achieve sustainability. Combinations of management techniques which include private property owner programs, industrial logging operations, and ecological forestry often result in the healthiest forest environments (Price, Silbernagel, et al. 2016). Private-property owner programs are intended to keep tree populations on these properties healthy, by reducing the risk of plant diseases, and thus create better recreational use of the land. This practice can also result in small financial gains from timber removed to achieve this goal. In contrast to these private practices, industrial logging management is used to oversee timber operations assuring that the amount of timber removed is replaced through replanting and other mitigation efforts. The main goal of this forest management is revenue from the harvested timber. A third approach, ecological forestry, keeps the forest as sustainable, healthy and functional for wildlife as possible. Tree removal is only done when absolutely necessary to achieve this goal (Price et al. 2016).

Duncker et al. (2012) echo these management goals but with different terminology: (1) Combined-Objective Forestry focuses on a balance between economic and ecological concerns used to keep the forest environment healthy while allowing for recreational use, small-scale timber production and game management. (2) Intensive Short-Rotation Forestry has a main objective of producing as much timber as possible clearly placing economic gains above ecological concerns (pollution, habitat destruction etc.). (3) Low Close-to-Nature Forestry focuses on keeping or creating a forest environment that is as natural as possible while still permitting human interaction. (4) The most extreme version of these approaches is Unmanaged Forestry, which often comes in the form of nature reserves where human interaction is insufficient. These management schemes are never perfectly implemented because of a variety of challenges that occur.

Duryea and Hermansen (2002) discuss a number of concerns regarding problems that make forest management more difficult. They discuss how increased forest use, pressure from surrounding landowners or development on the boundaries, invasive plants and animals, more human interaction, and more complex decision making are making forest management harder. Additionally, Keenan (2015) reviews a multitude of papers discussing how climate change has forced foresters to rethink, adapt and continually evolve our forest management practices, showing a need for more knowledge across agencies on how forests are being effected. Much forest management knowledge is gained through observing data, collection of which is a challenge. The U.S. Forest Service has an extensive database on forests all around the country (Burkmann 2002). However, as Korjus (2014, p. e110) states, “Several features of forests cannot be described with conventional forest data and new approaches are essential for assessment of these features.” Innovative technology, models and methodologies need to be developed to provide the best understanding of forests possible, better informing our management decisions.

One management decision that has been debated is wildfire and more specifically how to handle it. The U.S. Forest Service lists multiple advantages to wildfire, but they are preceded by the phrase “The right fire at the right place at the right time” (McCaffrey 2006) . These advantages include reduced fuels, help limit extreme fires, minimize disease and insects spread, remove invasive plant species, improve habitat, place nutrients back in the soil and promote growth of trees, wildflowers and other vegetation (McCaffrey 2006). There are also strong disadvantages and devastating effects from wildfire, as discussed by Duryea and Hermansen (2002), including habitat destruction, damage to homes and other structures, erosion and mudslides, loss of harvestable timber, smoke and air quality concerns and loss of life both human and animal. Forest or wildfires are becoming a more frequent disturbance so what is the best way to react or study these disturbances when they occur?

After fire disturbances, data on burn severity, fire intensity, vegetation regrowth, soil condition, and other environmental factors are often collected one to five years post-fire, but this can vary depending on each situation. For example, Pinno, Errington and Thompson (2013) and Pinno and Errington (2016) each conduct a post-fire assessment at one year and five years post-fire, respectively, to track vegetation regrowth progression and patterns. Shatford, Hibbs and Puettmann (2007) observe conifer regrowth after fires that occurred between 9 and 19 years ago in California and Oregon to determine how much regrowth had occurred and how quickly it was happening. Amount and speed of regrowth is vital information, but Pausas, Ribeiro and Vallejo (2004) were also interested in what factors affect regrowth rate by observing two areas that burned at the same time, in the same fire, with the same tree species, but show very different regrowth patterns. Additionally, vegetation dynamics and composition after a fire disturbance, during the regrowth stage, are also part of many post-fire assessments (Crotteau, Morgan Varner and Ritchie 2013). All these post-fire assessments required acquisition of vast amounts of data which are inherently geospatial because it allowed the researchers to examine patterns and relationships across space in a geographic context.

Having adequate geospatial information and reliable information is required to support and formulate environmental policy related to fire management. Data types that support fire management include fire and disturbance histories, location of manmade structures, vegetation composition, fuel loads, fuel conditions and topography, among others (Chuvieco 2007). Prediction of fire risk using these data can inform different fire mitigation strategies, but in order to develop robust prediction models, it is imperative to collect geospatial data across multiple temporal and spatial scales.

Many post-fire assessments are conducted solely through fieldwork. These inventories help the landowner better understand what needs or opportunities there are in their land related to forest health, animal habitat, and economic gains from timber. Zobrist (2012) lays out guidelines for fieldwork to conduct a forest inventory. To conduct a forest inventory, many kinds of data need to be collected, first of which is an aerial image. This image is used to create a map of the area that needs to be surveyed, marking property boundaries, unique stands of trees and assessment plots in those stands. To determine locations of assessment plots, Zobrist (2012) suggests a systematic sampling method using a grid pattern, with a minimum of 1 plot per 10 acres of land. This differs with situation and study areas size as seen in Maltamo et al. (2011) who have one plot per every 400 acres or in Shifley and Brian (2000) with 70 plots per 600 acres sites (i.e., ~ 1 plot for every 8.5 acres). Once the map is created, plots need to be surveyed on the ground by using a compass for heading, tape measure for distances and marking tape to mark the plot boundaries. Often times the easiest plot shape to use for forest inventory are circular, making it easy to find the plot center and establish the perimeter via the plot radius (Zobrist 2012). To determine plot radius Zobrist (2012) suggests an area big enough to contain five to ten trees on average.

Once the plot boundaries are marked, and sample trees are determined, data collection begins, often including characteristics like tree diameter at breast height (DBH), total height, age, and live crown ratio. Additionally, percent slope, aspect, elevation and other topographic data can be collected to understand the land surface complexity better. Next, the plot samples are scaled up to provide an overview of a one-acre area. For example, if the plot covers 1/20th of an acre, the scale factor is 20, meaning that if there are 5 trees within that plot, the trees per acre (TPA) would equal 100. This upscaling allows for metrics such as basal area, TPA, and volume to be calculated across the whole forest landscape, not just in the plots (Zobrist 2012).

Shifley and Brian (2000) provide another example of ground data collection being the sole method of data acquisition, where they assessed vegetation plots throughout approximately 9,000 acres of land. They used aerial imagery to lay out the nine study sites containing plots based on a grid system similar to what Zobrist (2012) suggested. Shifley and Brian (2000) observed the difference in tree size (height and DBH) on areas that were logged to varying degrees at the same time to assess the effects of different management techniques on the vegetation. These inventories can be done at an individual case by case basis as seen above or as reoccurring assessments discussed below.

Additionally, the U.S. Forest Service has the Forest Inventory and Analysis (FIA) program. Every year data related to tree crown conditions, understory vegetation, downed woody debris, DBH, age and TPA are collected using the same or very similar grid patterns for plot planning and circular plots as used by Zobrist (2012), except that the FIA is done at a much larger scale (Burkmann 2002). This wealth of FIA data is made available in the form of a public report and is used to keep track of forest change, regulate resource use such as logging, and create a model or project what the forests will be like in the future, which together assure that the current practices are sustainable (Rudis 2002).

In all the forest inventory studies presented here, ground data collection was the primary method. Even though this method is useful and often necessary for most studies it can be excessively labor- and time -intensive. A potential alternative to field-based forest survey is remote sensing. In the following section, I examine how RS imagery has reduced labor and time costs related to forest inventory development, and yet can still provide high-resolution data about vegetation changes at "snapshots" in time.

2.2 Remote Sensing Data in Forest Management

RS data allow for tracking of forest loss, assessment of forest health, and species identification with much less time and effort than ground data collection. It is frequently used as both supplemental data to field-based inventories and as the primary data source for aerial inventories. In either case, the data RS technology can provide a better understanding of forests and what they contain. Boyd and Danson (2005) developed a three-category typology of satellite RS detection applications in forestry. The three categories include forest extent and change dynamics, forest or species type, and biophysical and biochemical properties. They also provide a history of how RS satellite technology has changed, enabling more useful data to be extracted. Lim et al. (2003) review how LIDAR RS data has been used to map canopy structure from which tree height, biomass, volume, and canopy gap information can be extracted. Also White et al. (2016) review RS technologies such as airborne and terrestrial laser scanning which provide comprehensive data for monitoring tree growth over time. These reviews only provide a small glimpse into the vast number of studies and applications for RS data in the management of forests.

One specific application of RS data applicable to this current research is observing and better understanding forest disturbances. Forest disturbance regimes affect the structure, function, and composition of forested landscapes. Dale et al. (2001) suggest that many forest disturbance regimes are being modified by climate change. Remote sensing is often used to monitor the outbreak and consequences of these disturbances (Hilker et al. 2009). Ecological factors such as Leaf Area Index (LAI), biomass, canopy moisture, and canopy cover as well as stand age, shade, soil moisture, and content have all been studied through RS data (Cohen 2004). Fuel quantity, type, and condition can all be mapped via RS data from which fire predictions can be made (Chuvieco 2007). This section shows many types of forest disturbances that RS data can help study but how can it be used for post-fire assessments?

Remote sensing data products have been used extensively to map the spatial patterns of post-fire characteristics by forest managers. Van Leeuwen (2008) used RS satellite imagery to observe forest regrowth and health in Arizona over time and quantify it via greenness information or the Normalized Difference Vegetation Index (NDVI). Similarly, Goetz, Fiske and Bunn (2006) used a time series or chronological set of satellite imagery to track pine forest regrowth from several different fire disturbances in Canada. Tracking regrowth is important, but other characteristics of the fire disturbance can also be studied in connection with how vegetation recovers, as seen in Díaz-Delgado, Lloret and Pons (2003) study where vegetation recovery was compared to levels of differing burn severity. These RS post-fire assessments not only focus on vegetation regrowth but also on other environmental factors that affect the forest system. Lentile et al. (2006) provide a review of post-fire characteristics that RS data are often used to track. Many of these characteristics are related to other applications outside of vegetation monitoring. Some include char and ash cover, surface temperature change, change in surface reflectance, soil charring and water repellency of soil. Fire extent or perimeter mapping is often included in these post-fire assessments as well (Eva and Lambin 1998).

All of the post-fire RS applications discussed here can allow for faster data acquisition than traditional field methods giving forest managers the data to make informed management decisions in a timely manner. However, with the use of any RS data products, there are several considerations that need to be addressed as discussed in the next section.

2.3 Spatial, Temporal, and Spectral Resolution Concerns

Important considerations when using RS data for forest disturbance mapping include the spatial, spectral, and temporal resolution. In RS *spatial resolution* refers to the area of ground that is represented by a single pixel. High-resolution imagery contains many smaller pixels allowing for higher detail analysis such as small tree sapling identification. Low or moderate resolution data are often used for conducting analysis at a regional or continental level where analysis detail is lower such as change detection or LULC classification. Temporal resolution is the revisit time or how often an area is study. This frequency of data collection can be daily, weekly, annually, decadal or some combination of these depending on the purpose. Finally, spectral resolution refers to the number of samples taken across the electromagnetic spectrum, in terms of spectral bands. This contrasts with radiometric resolution, which is an expression of the sensitivity of a sensor to measuring electromagnetic energy. Spectral resolution can vary from just a one (panchromatic) to hundreds of bands (hyperspectral). In post-fire assessments, natural color imagery may be adequate to visually demarcate the extent of a fire, however when assessing vegetation health or soil characteristics additional spectral information is needed. This additional data often come in the form of Near Infrared (NIR) data because the NIR band is sensitive to plant structure and composition characteristics related to moisture content. These resolutions vary for every study and situation; however, having the correct combination is the key to practical RS data use (Gibson 2013).

As an example of temporal resolution, consider change detection analysis to examine forest gain or loss for management purposes. There are many different techniques for conducting digital change detection (Singh 1989); however, the idea is to compare LULC classification from two or more time periods to determine which areas have changed and which have stayed the same. These changes in forest amount can then be further explored to look at underlying factors to better manage the forest and reduce loss or encourage new growth. In a study by Broich et al. (2011), 16-day MODIS data were used to track forest loss in Indonesia from 2000 to 2008. Hansen and DeFries (2004) use annual Advanced Very High-Resolution Radiometer (AVHRR) data to track global forest loss during the years of 1982 - 1999. Both of these studies have the same general goal, but use a different temporal scale to achieve it. Aside from studying loss of forest cover, change detection via RS data can also be used to track vegetation health. Spruce et al. (2011) track forest health changes, via NDVI, on a day to day as well as 16-day resolution. Other studies use monthly resolution to track seasonality and annual vegetation cycles. For instance, Hobbs (1990) who reviews how vegetation change happens over many resolutions of time from a single episode event like a fire to long periods of time from climate change. Forest disturbances are often unannounced and can happen quickly, meaning that if the RS data relied on to track them only collects data in that area every 2 weeks or more these events could be missed altogether. As seen here temporal resolution of data is a study-specific decision depending on the goals and objectives as well as what is being observed but in general, having access to higher temporal resolution is best.

When considering spatial resolution, the 30 by 30-meter resolution Landsat imagery is acceptable when conducting LULC classifications and change detection, to observe forest loss or vegetation change discussed above, but when conducting GEOBIA, as reviewed by Blaschke (2010), a much higher spatial resolution image is often required. High-resolution imagery such as Quickbird satellite imagery with a spatial resolution of 2.4 meters, should be used as it can provide information about local issues or individual objects (Ke, Quackenbush and Im 2010). Running this GEOBIA or other classification analysis on high spatial resolution imagery is essential for understanding forest composition characteristics like species location and density, which often cannot be studied with moderate to low-resolution imagery.

In addition to temporal and spatial, a sensor's spectral resolution also needs to be considered. There are some sensors which collect in single bands of the spectral wavelengths, (panchromatic) or a few (multispectral) compared to satellites sensors such as the Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) that collects up to 224 bands or more (hyperspectral). This high spectral resolution is necessary because the unique reflectance from surface materials allow for object discrimination, and in the case of trees, gives us further insight into species type. When conducting forest composition analysis as in Ke et al. (2010) and Martin et al. (1998) high spectral resolution of imagery allows for better distinguishing between each species resulting in a better understanding of the spatial patterns in the forest (Martin et al. 1998). Knowing the composition of a forest is important for timber production, analyzing animal habitat Walton et al. (2013), stand volume Næsset (1997), fire risk and many other factors. This species composition can be done at a basic level of deciduous versus coniferous species, or it can be done to differentiate between each of the specific species types keeping in mind that the spectral resolution of the RS data is a limiting factor (Martin et al. 1998).

Vegetation indices, "are a spectral transformations of two or more bands designed to enhance the contribution of vegetation properties and allow reliable spatial and temporal inter-comparisons of terrestrial photosynthetic activity" (Huete et al. 2002, p. 195). In simpler terms, these bands are indicators that describe greenness, density, and health of vegetation and are excellent options for extracting additional information from spectral data. Spectral analysis is a standard practice for observing vegetation health as well as to view a wide variety of phenological factors that can be applied to either satellite imagery at a lower spatial resolution or to UAS imagery at the highest spatial resolution. The most common spectral index used to assess vegetation health is the Normalized Difference Vegetation Index (NDVI). The NDVI makes use of the R and NIR bands to calculate a greenness value or overall health. This value can be used to track the reduction in greenness due to an outbreak of invasive insects, such as Gypsy Moths and their devastating impact on forest health, and other prolonged forest disturbances that occur at a pace slower than wildfires (Spruce et al. 2011).

In the last few years, a pair of new indices has been developed which make use of the RE band in spectral imagery. The NDVIRE and NDVRE are mostly the same index using the RE band in place of the NIR. These indices serve the same purpose as the NDVI to analyze vegetation health however it has also been shown that integration of the Red Edge (RE) band leads to a more accurate plant species classification and LULC classification (Schuster, Förster and Kleinschmit 2012). They found that RE increased overall classification accuracy by about 3% but more importantly found that RE helps differentiate between plant species better with a 12% increase in classification accuracy. Similarly, Adelabu, Mutanga and Adam (2014) found that use of the RE band increased their classification accuracy by 19 to 21%. Kim and Yeom (2014) also saw an increase in rice patty classification accuracy using RE. The RE band can also be used to calculate more than just vegetation health. It can be used to calculate nitrogen levels in plants as well as chlorophyll content (RapidEye). All of these further details that can be extracted when studying forest composition lead to better object-based species classification and better overall understanding of the forest.

The effectiveness of the RE band compared to NIR band for either pixel-based or GEOBIA is by no means set in stone, or that one is better than the other. Further research such as this current study is needed to compare the two.

Aside from the temporal, spatial, and spectral concerns, there are some additional limitations that can make satellite RS data challenging to work with both in the field of forestry and elsewhere. The first and possibly most difficult limitation of satellite RS data is interference. This can come in the form of atmospheric scattering from aerosols, moisture or small dust and other particles. Additionally, extensive cloud cover, especially in mid-latitude regions, can cause interference in the imagery. Availability of satellite RS data is another problem both in regards to temporality and cost. Most sensors now collect imagery of the earth's surface in biweekly intervals (~16 days), but some repeat intervals are lower, and sensor malfunction or failure can decrease temporal resolution even further. Satellite RS data can also be costly. In most cases, coarse-resolution imagery (30 m or lower) is free and available to the public, but high-resolution imagery, such as Quick Bird (2.4m) or Worldview (1.5 m), can cost thousands of dollars. These limitations can make RS data from satellites frustrating, difficult to work with and unreliable. For this reason, alternative, lower risk, and more cost efficient RS options should be considered. One such option is Unmanned Aerial Systems or UAS.

2.4 UAS and Forest Inventory

Among the many applications for UAS technology, forest inventories or assessments are some of the most frequent. Their versatility enables studies with many different objectives to be conducted in the realm of forestry with promising accuracy. For example, Lehmann et al. (2015) made use of UAS to study the Splendor Beetle pest in Germany which was killing trees and leading to unplanned lumber harvests. Their high spatial and temporal resolution NIR imagery was used with NDVI to identify defoliated trees which indicated beetle infestation. They achieved an 85% accuracy for defoliated tree classification. Lehmann et al. (2015) stated that the UAV was chosen because satellite imagery was not current enough and could not provide the temporal aspect needed to study the progression of the beetles. Näsi et al. (2015) took this type of analysis to the next step and used a hyperspectral camera to map Bark Beetle, a destructive insect, in Spruce trees in Finland. Their camera was capable of capturing up to 41 spectral bands in the images. This high spectral variation allowed for better detection of infestations and helped them achieve 76% classification accuracy on a more robust classification of 3 categories healthy, infected and dead trees. Insect devastation often leads to gaps in a forest canopy. Getzin, Nuske and Wiegand (2014) studied canopy gaps via UAS in Germany with the goal of determining what caused each gap based on its size. They concluded that most of the gaps smaller than 5m^2 were caused by small-scale, often natural, disturbances while larger gaps were linked to logging disturbance. From this analysis Getzin et al. (2014) categorized the forests into types such as selection cut, unmanaged, and age cut forests. The authors showed that it is possible to understand causes of disturbance via UAS, not just observe the aftermath. Other canopy characteristics such as height have been evaluated using UAS. Lisein et al. (2013) created a canopy height model (CHM) from an UAS imagery point cloud and measured the heights of 86 individual trees to within 1 m of their actual height. They also showed this technology to be comparable in accuracy with that of Light Detection and Ranging (LIDAR) systems which are more often used for these CHM applications. LIDAR is an active sensor, sending out laser pulses which create highly accurate point cloud models of physical objects based on the return time of the pulses. For the same area, LIDAR data achieved an RMSE of 0.83m while the UAS imagery resulted in 1.04 m RMSE.

Forest regeneration is another area of forestry that UAS shows promise. UAS imagery along with visible vegetation indices (VVI) were used by Goodbody et al. (2017a) to classify recovering forest areas into three forest cover types including conifer, deciduous and ground or shrub. Through a GEOBIA analysis, they achieved overall accuracies of 86 to 95 percent across their study plots. Aside from these studies showing individual forest inventory applications, other studies (e.g., Puliti et al. (2015) have been conducted completing a comprehensive range of inventory tasks. Mean height, dominant height, stem number, basal area and stem volume were all extracted from UAS imagery in this study. The above examples of how UAS can be used in forestry and forest inventory clearly demonstrated this technologies utility but only scratch the surface of its full ability in this field. An in-depth review of UAS in forest inventory is presented by Goodbody et al. (2017b) discussing the components of UAS, platforms, and sensors, as well as how they've been used in the past, current uses and what they may provide in the future.

The application of UAS to forestry, including data collection for forest management, as described in this thesis offers several advantages. UAS provides ultra-high-resolution data at temporal, spatial and spectral scales, as well as offers excellent data quality, availability and reasonable cost. Above I described the advantages of UAS for data collection in forest inventories. The next section identifies how this methodology can be used for GEOBIA.

2.5 UAS in GEOBIA

Applications of GEOBIA are similar to those of traditional pixel-based analysis. Possible forestry applications include forest structure models, canopy gap analysis, species richness or differentiation, habitat models, pre and post-logging analysis and many more. Most of these applications are conducted on moderate resolution imagery such as Landsat (30 m) imagery. While Landsat's spatial resolution may be sufficient for conducting GEOBIA on most applications in forestry, there are situations where higher resolution imagery should be used as supplemental data or the primary data source for GEOBIA in forestry. A specific forestry application where this is especially true is using GEOBIA to conduct sapling counts after a massive fire event. Many saplings will not even show up in satellite imagery due to poor spatial resolution, so a very high-resolution data option needs to be used. Unmanned Aerial Systems (UAS) can serve as that option, having the capability to collect imagery at a 5 cm resolution giving the GEOBIA the needed data to successfully classify saplings as they regenerate. This section first explores the use of UAS imagery for performing GEOBIA and secondly the use of GEOBIA for sapling identification in aerial imagery.

The power of UAS to be low cost, offer high temporality for data collection and collect imagery of the highest resolutions was demonstrated above in various applications but what can it offer in terms of geographic analysis? The potential of UAS has been recognized since the 1970s, but it has only been recently that such technologies were adopted for geographic applications (Colomina and Molina 2014), particularly GEOBIA. UAS technology allows for collection of data at very high resolutions. The maneuverability, versatility, and convenience of UAS make it ideal to supplement satellite imagery or conduct alone for entire studies, so UAS can be readily applied to assessments of forest composition (Tang (2015). Often times UAS offers the user the same analytical capabilities that are available with satellite data. For example, the same GEOBIA techniques used with satellite data to map forest structure can be used on UAS imagery at a much higher spatial resolution leading to a better classification of species (Laliberte and Rango 2009). Hung, Xu and Sukkarieh (2014) explore this UAS GEOBIA concept in connection with classifying different weed species. Although they aren’t looking at forest composition, the same basic analysis applies and could easily be used in a forestry context. Gap analysis and forest structure studies are also conducted using UAS imagery. One example is reported by Getzin, Wiegand and Schöning (2012) who conducted image segmentation on UAS imagery in GEOBIA to perform statistical analysis and assess the biodiversity of forests.

Outside of forestry applications, there are a variety of uses for UAS imagery in GEOBIA to capture characteristics in non-forested landscapes. Rango et al. (2009) use an UAS to collect imagery of a rangeland and classify the different plant species growing there. In another rangeland study, Laliberte et al. (2010) use GEOBIA on UAS imagery to monitor rangeland over time to keep track of vegetation expansion and contraction and species distribution throughout their properties using methods similar to those of Hung et al. (2014). Another vegetation classification paper is by Peña et al. (2013) who use UAS imagery to separate weeds from crops in maize fields and also calculate percent weed coverage through GEOBIA. Torres-Sánchez, López-Granados and Peña (2015) conducted a similar study a few years later but took the analysis to the next step in that they came up with an automated way for eCognition software to recognize crop vegetation in the fields and classify it as such, separating it from the soil allowing them to estimate germination percentages.

The majority of UAS-GEOBIA studies so far pertain to the study of vegetation; however, there have been a few other applications. Fernandez Galarreta, Kerle and Gerke (2015) used UAS imagery of buildings after natural disasters to conduct infrastructure assessments via GEOBIA by classifying the damaged versus undamaged components of the buildings, which helped detect cracks, sagging roof lines, and missing shingles. A somewhat similar application is that of Vasuki et al. (2014) who used GEOBIA on UAS images to detect and classify faults or cracks in a geologic surface such as bedrock outcrops. Their methodology is semi-automated, and they are working to improve it, so that little to no human input is necessary to get an accurate classification. Another GEOBIA surface classification study done by Kraaijenbrink et al. (2016) used UAS imagery to identify geologic features on a glacier. They classify features such as ponds, cliffs and large debris (rocks) in the snow and ice. All of these uses of UAS imagery in

GEOBIA show its usefulness and relevance but more clearly demonstrate the need for more research on this topic as the papers included here mostly exhaust the available literature.

2.6 GEOBIA for Sapling Identification

GEOBIA has many uses in forestry and other disciplines as seen above but how does it work and is it sufficient for identifying tree saplings? Johansen et al. (2007) make use of GEOBIA in order to classify a forested landscape on Vancouver Island in Canada that was logged during the 1970s. From QuickBird 2.8m resolution satellite imagery they extracted textural features such as variance, homogeneity, contrast, and dissimilarity as well as spectral reflectance features derived from NDVI and EVI calculations of the vegetation in the landscape. This paired with ground truth data enabled them to divide the study area into the forest types, which were shrub/brush, pole/sapling, young forest and old forest. Overall they achieve a classification accuracy of 78.95% and note that inclusion of the textural characteristics in the GEOBIA process increased the individual forest type classification from 2 to 19% (Johansen et al. 2007). Accuracy for just the pole/sapling forest type, which is directly applicable to this current research, was 83%. A similar study conducted by Machala and Zejdová (2014) used LIDAR and 0.6-meter multispectral aerial imagery to classify a forested area in the Czech Republic. Twenty-six customized features were used to train the classifier (NDVI, Mean NIR, Max diff. etc.), all of which were combinations of the Red, Green, Blue and Near Infrared spectral bands and elevation data (DSM). They discovered that in this study textural features did not improve their classification accuracy and were therefore excluded. With GEOBIA they were able to classify the study area as sapling/young forest, old forest, clear-cut, plantations, etc. Overall classification accuracy was 89.5%, and the sapling/young forest type classification accuracy was 92.9%, again demonstrating the ability of GEOBIA analysis to recognize saplings in a landscape.

Sapling identification is a particular topic and application which is often covered in more extensive vegetation classification studies as seen in both Johansen et al. (2007) and Machala and Zejdová (2014). Although the papers discussed above are helpful for understanding methods of GEOBIA in classifying forest types in a forest setting, they are not specific to individual tree sapling recognition. This gap in the research literature related to individual tree sapling identification is one this study aims to add to.

The literature reviewed here points to the potential for RS data and particularly UAS imagery to contribute to the development of forest inventories by providing both high spatial and temporal resolution imagery of saplings, indicating forest regeneration after fire. Also, this UAS imagery has spectral resolutions similar to multispectral satellite sensors. Already UAS have been successful in a number of published scientific studies addressing forest disturbance and health, but questions remain regarding their use for identification of forest saplings in fire-disturbed conifer ecosystems. This review also shows the successful use of GEOBIA in a wide range of forestry applications including sapling landscape or sapling-dominated forest identification. However, given the limited literature on GEOBIA for individual sapling detection or identity, further GEOBIA research needs to be done to more fully understand this application. In the methods described below, I address the spectral, temporal, and spatial requirements to use UAS imagery in identity GEOBIA for jack pine sapling identification. This research draws upon GEOBIA feature methodologies, as explained by Johansen et al. (2007) and Machala and Zejdová (2014), as well as sampling methodologies and equations for accuracy assessments discussed by Goldbergs et al. (2018) and Radoux and Bogaert (2017) .

3. Methods

As the previous research has illustrated, UAS applications for forest management are relatively new, and a great deal of research still needs to be conducted to identify the optimal conditions for achieving precise and accurate results. The purpose of this thesis research was to *gain a better understanding of the spectral, temporal, and analytical requirements necessary for achieving optimal accuracy in the detection of tree saplings in a post-fire environment using UAS imagery and GEOBIA.* I posed three research questions:

- What is the level of accuracy that can be achieved by the combination of UAS and Geographic Object-Based Image Analysis (GEOBIA) for detecting young jack pine saplings?
- How does the use of the Red Edge(RE) spectral band affect image classification accuracy, in comparison to the use of the near-infrared(NIR) spectral band, or NIR -Red band combination or RGBNIRRE band combination?
- How does seasonal change affect the accuracy that can is achieved by the UAS and GEOBIA method?

To answer the questions mentioned above, three analyses were undertaken. First, object identification GEOBIA was conducted using multiresolution segmentation and a Random Forest classifier along with an edge analysis via the Hausdorff distance measure. Next, an accuracy assessment was conducted to observe the level of identity accuracy and explain which of the band combinations performed the best. Finally, an additional accuracy assessment was conducted to observe the effect temporal or seasonal change has on GEOBIA for identity detection. The following section provides details regarding data acquisition, analysis, and accuracy assessment. First, the study area is described.

3.1 Study Area

The Duck Lake Fire was located in the Upper Peninsula (UP) of the state of Michigan in the United States (Figure 1). The study area is within the Michigan Department of Natural Resources (MDNR) Newberry Management Unit. It is also part of the Lake Superior State Forest. There are also privately owned portions that are being actively managed using different logging techniques for profit, but this research was only conducted on the state-owned land. The fire area encompasses approximately 8,900 ha (21,000 acres) in the north-eastern portion of the UP near the mouth of the Two Hearted River on the south shore of Lake Superior.

On May 23rd, 2012 a lightning strike, 2 miles south of the Little Two Hearted Lakes started a fire that burned northward. The majority of the area burned by this fire occurred between May 24th and 26th ; however, over the next three weeks, the Duck Lake fire became the third largest fire in the history of Michigan before it was fully contained on June 15th, 2012. The latitude for the burn or study area is approximately 46°39’20.84”N 85°26’11.59”W. The northern half of this 8,900 ha (21,000 acres) area served as the study for this project because it is the portion under state ownership and was most easily accessible.

The sandy nature of soils in this area is likely the result of being covered by Glacial Lake Algonquin which extended over much of the Eastern Upper Peninsula circa 11,000 BP. This glacial lake deposited a wide variety of sediment from the sands found around Seney to heavy clay in Chippewa County (William L. Blewett and Schaetzl 2009). This study area is characterized by having sandy well-drained soils (Schaetzl 2009) with reduced nutrient content.

The UP of Michigan is categorized as having a humid continental climate. The highest average temperature occurs during the month of July at 78° F (25.7°C). The lowest average temperature during the year occurs in January at 24°F (-4.5°C). August and September have the highest average precipitation at 3.5 inches per month; February is the driest month on average with only 1.18 inches of precipitation. There is a fair amount of cold weather with temperatures below freezing, leading to a change in precipitation from rain to snow. This usually occurs in late November or early December when the average temperature drops below freezing at 29°F (-1.8°C). Snow usually continues until March when the average temperature returns to the mid-30s (37°F, 2.5°C) (US Climate Data 2018).

Figure 1: Duck Lake Study Area in UP of Michigan, USA

3.1.1 Land Cover

The Duck Lake Fire consumed an area with Mixed Coniferous-Deciduous forest cover and sparse human settlement. The combination of National Forest and protected areas in this region, its remote location to major urban centers, and infertile (sandy) soils, together explain why agriculture and urbanization had not occurred in the study area. Prior to 19th-century logging, the area was dominated by conifer forest but is now characterized by a mixture of coniferous and deciduous tree species. Conifer species include white spruce (*Picea glauca*), jack pine (*Pinus banksiana*), and balsam fir (*Abies balsamea*) in upland locales, which in this study area occurred in the northern portion where the 10 study plots were located. Black spruce (*P. mariana*) and tamarack (*Larix laricina*) were prevalent further to the south in swamps, marshes, and other lower lying areas. The deciduous species include maple (*Acer*), hemlock (*Tsuga*), American beech (*Fagus grandifolia*), white birch (*Betula papyrifera*) and aspen (*Populus tremuloides*) (Zhang, Pregitzer and Reed 2000) very few of which were present in the study area for this research as the soils were too sandy and nutrient poor. Of all the species listed here, the one best adapted to infertile sandy soils and fire is jack pine, which was the dominant species in the area that burned during the Duck Lake Fire and the species of focus for the DNR who has planted thousands of jack pine seedlings in the area.

"Jack pine is a pioneer tree species that historically regenerated almost exclusively after forest fires. Fire regimes of varying intensity and frequency resulted in pine-dominated ecosystems ranging from open Pine Barrens to very dense jack pine stands" (Wisconsin Department of Natural Rescources 2016, p. 33-5). In this study area there are two distinct types of jack pine landscapes. The majority of the area is Pine Barren covered in grasses with jack pine sparsely distributed throughout. However, there are some areas of the old forest that did not burn where dense jack pine stands are still present. The jack pine presence in this study area is a direct result of the Duck Lake fire providing optimum growing conditions for jack pine. The fire opened the jack pines' serotinous cones releasing their seeds, exposed the mineral soils in this area, burned seedbeds killing much of the competition and provided ample amount of sunlight by removing the dense jack pine stands that covered this area. These characteristics have allowed the jack pine to be the dominant tree species in this area once again. The ability of jack pine to thrive in the dry, sandy, nutrient-poor soils of this area has allowed them to dominate this landscape as well (Dickmann 2009).

Figure 2: Current landscape highlighting the devastation to the jack pine forest and the vegetation recovery as of Summer 2017.

3.1.2 Study Plots

Initially 15 1-ha plots were chosen through using a stratified random sampling technique across the study area. The plot locations were stratified based on total area of the three days of burning so that larger areas had more sites and smaller areas had less. Due to limited field access and time constraints, only ten of these 1-ha plots were collected, and the methods applied to two of those ten plots. As shown in Figure 3, these plots still represented each of the three days of this burn.

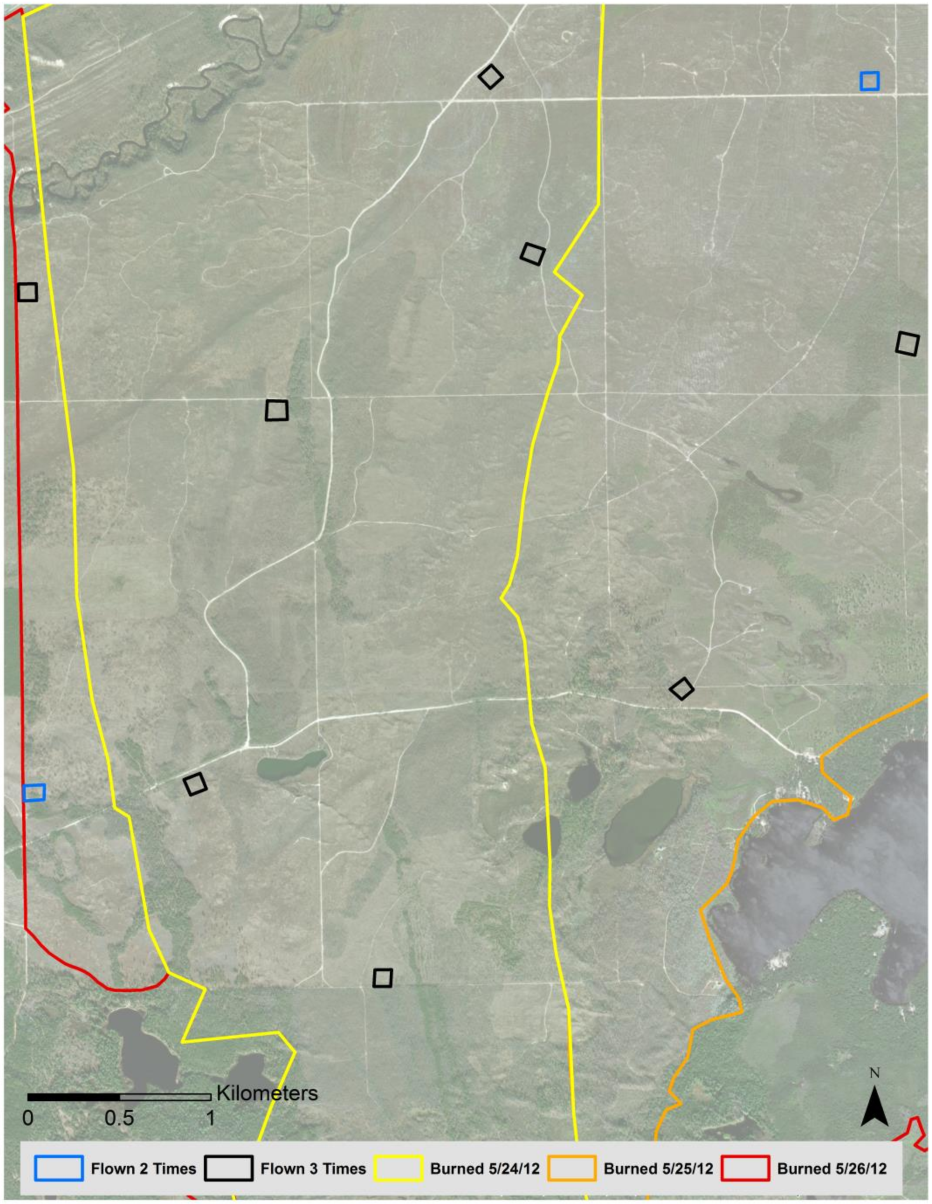

Figure 3: Location and spatial extent of 10 study plots

3.1.3 Aerial Imagery

Aerial imagery of these sites was collected using a 3DR IRIS quadcopter UAS platform. Attached to the IRIS was a MicaSense Red Edge camera, a 5-band sensor simultaneously capturing images in the Red (R), Green (G), Blue (B), Red Edge (RE) and Near Infrared (NIR) spectral bands. Pre- and post-flight calibration images were collected using a reflectance disc to increase reflectance value accuracy.

Mission Planner software was used on a laptop to create the autonomous data collection flights. Flights were conducted between 8 am and 6 pm EST (Table 4) to take advantage of calm winds and less active weather at these times, which was crucial as this research was conducted close to the Lake Superior shoreline. Images were collected every two seconds with a flight altitude of 80 meters (240 feet) above the ground. The UAS traveled at a velocity of 6 m/s or approximately 18 mph. Similar lighting conditions and saved mission paths increased data consistency and imagery, while side lap of 80% and end lap of 70% assured sufficient plot coverage. Due to limited cellular connection needed to obtain sub-centimeter GPS data, Ground Control Points (GCPs) were not collected as planned. Use of inaccurate GCPS to spatially rectify imagery would further distort the spatial accuracy.

A strict preflight checklist was followed, and at least two people were present for every flight as a Pilot in Command (PIC) and spotter. UAS data collection was planned to take place every two weeks from the middle of June to mid-August 2017. However, equipment failure and unavoidable circumstances limited the collection to roughly once per month from the middle of June to middle of August 2017, for a total of three successful data collection sessions (T_1=6/30/17, T_2=8/5/17, T_3=8/19/17). All FAA rules and regulations were strictly followed.

3.2 Data Analysis

The UAS imagery collected for this study was used in a 4-step analysis process. First, the raw imagery was mosaicked or stitched together and stacked into 5 band images. Following the image processing, GEOBIA was conducted to identify jack pine saplings in the images. Next, the accuracy of this identity OBIA was assessed and expressed as a percentage. Additionally, an edge similarity assessment was conducted to test how entirely the identified jack pine saplings were classified. Finally, based on these analysis, the effect seasonality has on this classification process was observed.

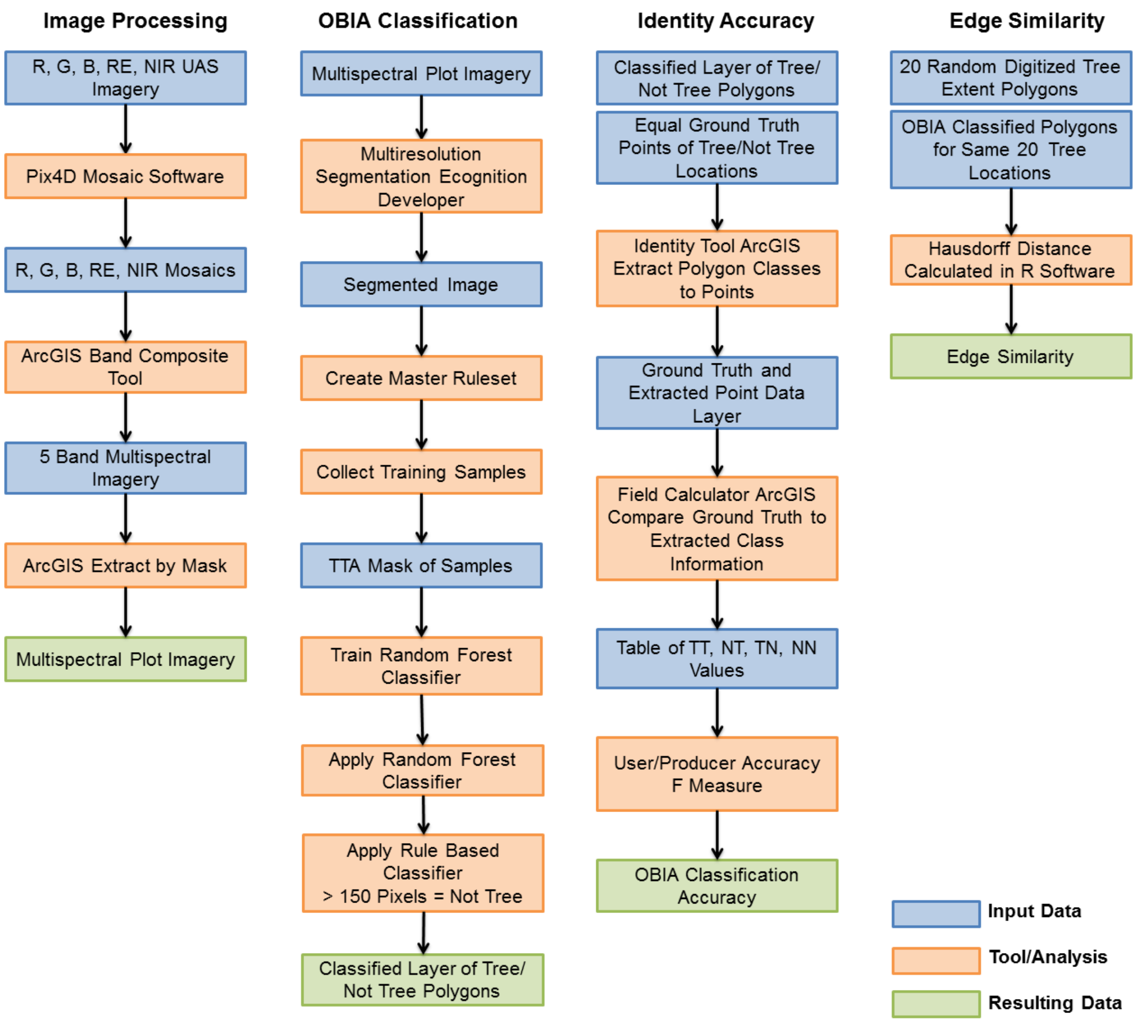

Figure 4: Workflow for all processing and analysis

3.2.1 Image Processing

The RGB, RE and NIR images were processed with the agriculture mosaic option in Pix4D 3.3 (Pix4D 2017) as it takes the NIR and RE bands into consideration, in addition to the RGB bands. This software mosaics the images together based on their spectral properties, objects in the imagery, and image location from geotag coordinates or the images latitudinal and longitudinal position on the earth's surface. Pix4D created 5 mosaics, one for each spectral band captured by the RedEdge camera (Figure 5). The band composite tool in ArcMap 10.4.1 (ESRI 2016) was then used to stack the R,G,B, RE and NIR mosaics into multispectral files. Two mosaics were made for each set of flight images. One contained the R,G,B, NIR and RE bands while the other combined the RGB with a NIR - R band combination. The mosaics were then clipped to the plot boundary using the extract by mask tool in ArcGIS.

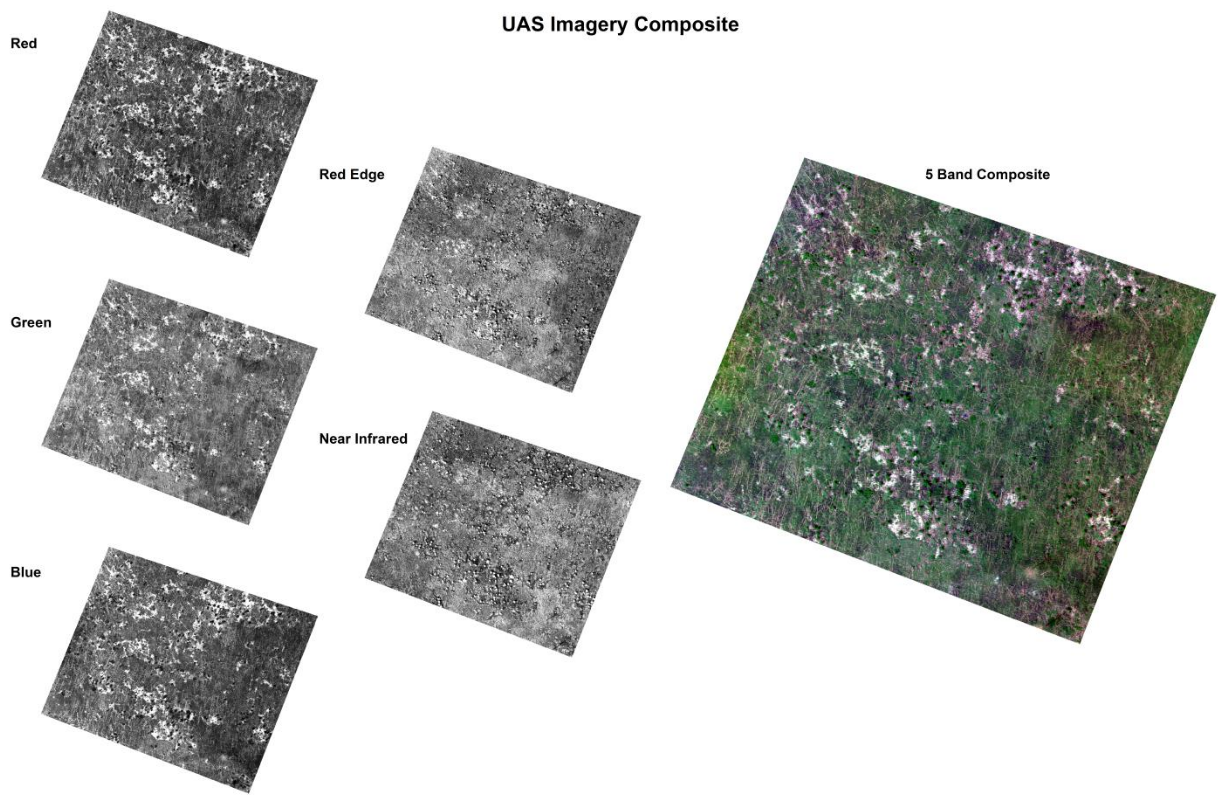

Figure 5: Individual band and composite imagery mosaic

3.2.2 GEOBIA Process

The pre-processed plot images were analyzed in eCognition Developer 9.2, a GEOBIA tool developed by Trimble (2016). Geographic Object-Based Image Analysis (GEOBIA) requires individual pixels be grouped into candidate objects often based on spectral similarity.

This process is called image segmentation. The resulting objects are then categorized into classes by spectral, geometric and neighborhood features. Examples of spectral features include mean value or maximum value of a specific spectral band. Geometric features include number of pixels, area, or perimeter and neighborhood features describe the relationship one object has to another, for example, an object is darker or lighter than the one next to it. Once classification of objects is complete, the quality is assessed via an accuracy assessment, often in the form of an error matrix, which reports accuracy based on a comparison of the classified objects to ground truth data and expressed as a percentage (Blaschke 2010). This general workflow is explained in more detail below with specific details of the process used in this study.

To conduct the GEOBIA the first step was to run image segmentation. The basic concept of segmentation is to divide the images into objects or polygons based on spectral and textural characteristics. In this study, a multiresolution segmentation was used. It not only takes spectral and textural characteristics into consideration but also observes shape and size of image objects when segmenting the image with the expectation that those objects would vary in size depending on the image scale but still be recognized as objects by the classifier (Baatz and Schape 2000). This method was particularly crucial in this study because the scale or size of the jack pine saplings in the imagery varies.

The image features related to spectral and textural characteristics included mean and max brightness and mean spectral reflectance for each band, as well as mean texture and textural dissimilarity in all directions. The scale parameter which partially determines the size of the segmentation polygons was set at 100. The shape parameter which determines how much the segmented polygons resemble real-life image objects was 0.9, and the compactness value which determines how much emphasis is placed on the spectral characteristics was set to 0.8. The compactness and shape values range from 0 – 1 with 0 being less emphasis and 1 being highest importance. In this study both compactness and shape were important assuring that the saplings were recognized as objects (shape parameter) by the classifier and separated from the understory vegetation (compactness parameter). Supervised classification was carried out using manual sampling (40 Tree sapling samples, 200 Not Tree sapling samples). The samples were saved as Test and Training Area (TTA) masks so that they could be applied to each of the band combinations to improve repeatability. Next, these samples were used in a classification process to develop a Random Forest classification. Random forest classifiers make class assignment decisions based on a "vote" from multiple decision trees that it "grows." When a new vector is being classified each tree "votes," and the classification with the most "votes" is assigned to that vector. Some advantages of this classifier are unmatched accuracy among current algorithms, efficiency when working with large datasets and quickly saved structure for future use (Breiman 2001).

The Random Forest (RF) classification extracted image features of mean brightness, max brightness, mean spectral reflectance for each band (R,G,B,RE,NIR and NIR-R), mean texture (GLCM mean) in all directions, and textural dissimilarity (GLCM dissimilarity) in all directions in order to train the classifier. This master rule set was then modified four times to account for the four different band combinations by changing which mean spectral reflectance features were included. For example in an R,G,B,NIR combination the mean spectral reflectance features for the R,G,B,NIR bands were included but for a R,G,B, RE combination the R,G,B, RE the RE instead of NIR mean feature was included in the rule set. All other parameters of the master rule set stayed the same.

After the RF classification, a rule was used to classify any polygon that was greater than 150 pixels as Not Tree because none of the classified Tree polygons were greater than 150 pixels. This rule helped to increase accuracy and remove errors in the classification. Each flight mosaic (RGBNIR, RGBRE, RGBRENIR, RGBNIR-R) was analyzed using each its respective ruleset: The first classification used the RGBRENIR mosaic, the second with the RGBNIR mosaic, third with the RGBRE mosaic and the fourth with the RGBNIR-R mosaic.

3.2.3 Object Detection Accuracy Assessment

The accuracy assessment of the GEOBIA results was based on best practices presented by Radoux and Bogaert (2017). The goal was to determine how accurate the classification was at performing object identification. In order to create the ground truth dataset three persons with various levels of expertise in RS (novice, intermediate and expert) marked the location of each jack pine entity they could visually detect in the aerial imagery by placing a point over the centroid. The novice went first followed by the intermediate skilled followed by the expert. A sapling had to be identified by at least two of the three participants to be considered a sapling. This 3-step process assured that the entities identified really were jack pine saplings. A total of 369 tree centroids were identified, and a set of 369 points representing locations where no trees were located was also developed. In ArcGIS, the Random Forest classification’s resulting thematic map polygons were merged so that two polygons were created, one for all ‘Not Tree’ polygons and one for all ‘Tree’ polygons.

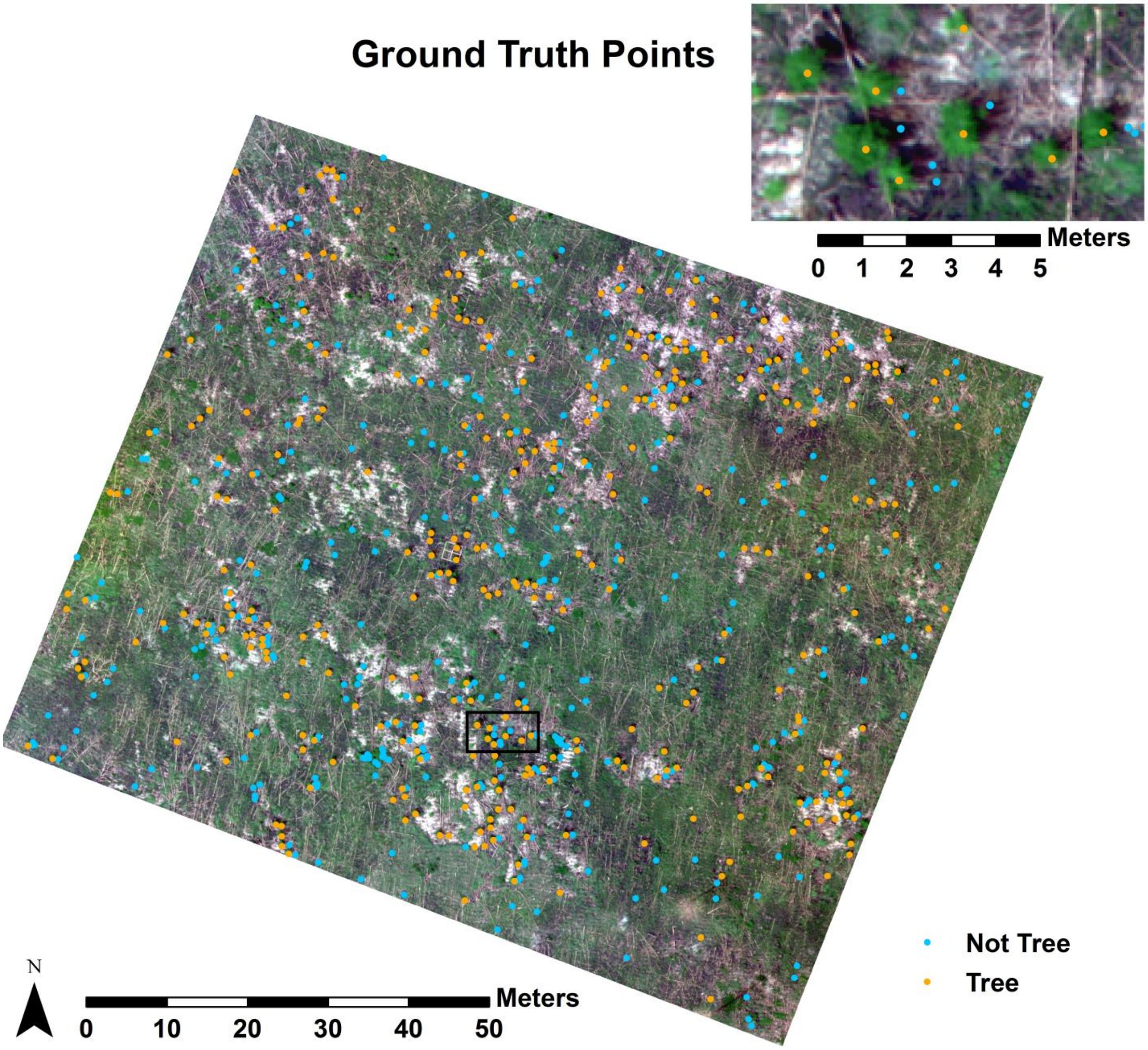

Figure 6: Tree and Not Tree ground truth points for OBIA accuracy assessment

Next, the 369 tree centroid points from above were used for the ‘Tree’ polygon, and the 369 not tree location points were used for the ‘Not Tree’ polygon. The points were assigned to one of the two classes using the Identity tool in ArcMap. Next, Field Calculator was then used to concatenate the values of the ground truth column to the classification column which contain values of T for tree and N for not tree. This resulted in four two-letter combinations; TT or True Positives (actually a tree and classified as a tree), NT or False Positives (not actually a tree but classified as tree), TN or False Negatives (actually a tree but classified as not a tree), and NN or True Negatives (is not a tree classified as not a tree). It should be noted that for a tree to be considered correctly classified as ‘Tree,’ the Identity point must fall completely within a ‘Tree’ polygon. With all 738 points assigned to one of the four classes (TT, TN, NN, or NT), the following equations used by Radoux and Bogaert (2017) and Goldbergs et al. (2018) were used to calculate the User (UA) and Producer (PA) classification accuracy as well as the overall accuracy or F measure (F). UA accuracy measures errors of commission (areas that were classified as class X but in reality should not be). PA accuracy measures errors of omission (areas that weren’t classified as class X when in reality they should be). The F measure is then the overall accuracy achieved calculated from the UA and PA.

$$UA=TP/(FP+TP)$$

Equation 1: User Accuracy

$$PA= TP/(FN+TP)$$

Equation 2: Producer Accuracy

$$F = 2(UA*PA)/UA+PA$$

Equation 3: F measure

Once the UA and PA were calculated they served as the inputs for a third equation which calculated the F measure or an overall classification accuracy assessment. The percentages of these equations were used to measure the ability of the classifications to correctly identify the center point of a jack pine sapling as tree or not.

3.2.4 Edge Similarity Accuracy Assessment

The next part of the accuracy assessment analyzed how accurately the GEOBIA was able to delimit a tree object. In other words, how does the boundary of polygon A (classified tree polygon) compare to polygon B (digitized tree polygon)? The methodology for this assessment is similar to that of Lizarazo (2014) who developed what is known as the STEP process. The STEP process is a way to assess multiple dimensions of accuracy of object-based analysis. There are four parts to the process each dealing with a different similarity attribute; they are Shape, Theme, Edge, and Position. The shape similarity is not ideal because the digitized tree polygons are circular while the classified polygons are made up of squares or pixels. Vector and raster data cannot be accurately compared without one being converted. Theme similarity is based on comparing total area of the classified and digitized polygons. This is not ideal for this study either because there could be classified and digitized polygons of equal area, but the classified polygon may not lie entirely within the digitized polygon resulting in false results. More specifically, these errors of commission and omission were due to data representation or vector and raster comparison, rather than to outright misidentification. Finally, positional similarity does not help determine how entirely an object is classified, it only tells how polygon A and B relate to each other spatially comparing their x, y coordinates.

Recognizing these limitations, the edge similarity attribute was chosen for this study to test how the jack pines were classified as the other similarity measures did not apply. To determine the similarity of the edges or boundaries, two shapefiles were created in ArcGIS. One file contained 20 manually digitized polygons representing the outlines of 20 randomly selected sample trees in the imagery. The other file contained the polygons at these same tree locations that were created in the GEOBIA classification process. These two files, which held equal amounts of ground truth and classification or test data, were then loaded into R 3.4.3 a statistical analysis software (R Core Team 2017). The rgeos package (Rundel 2017) which contained the distance or Hausdorff distance tool was used to test the edge similarity. The two files were labeled poly1 and poly2 in R and are called into the Hausdorff distance tool by the following code `gDistance(poly1, poly2, hausdorff = TRUE)`. The tool works by placing a vertex at each corner or intersection of both the ground truth and test data polygons. It then tests OBJECTID 1 of ground truth data versus OBJECTID 1 of the test data by looking at each of those vertices and determining what the furthest distance is from a given vertex to the closest vertex in the other polygon. This number is known as the Hausdorff distance and helps evaluate how similar two polygons are. A polygon compared to itself would yield a Hausdorff distance of 0 and thus the less similar two polygons are, the higher the Hausdorff distance value will be. The spatial measurement for this study is meters, so the Hausdorff distances were also calculated in meters.

3.2.5 Seasonality Effects on Identity and Edge Similarity Accuracy

In addition to conducting the identity and edge similarity accuracy assessments on all 16 image combinations from Plots 11 and 2, a temporal accuracy assessment was conducted on just the images from Plot 2 to determine the best collection time period within the summer months. Plot 2 had the best quality data for all three flight times with the fewest shadows and defects, making it an ideal setting to observe how seasonal change or vegetation progression throughout the summer affected the accuracy of both the identity and edge similarity assessments. The accuracies from both the identity and edge similarity analysis for plot 2 were viewed in a time series to observe the effects seasonal change or green up had on the classification accuracies.

4. Results

Below are the results for plots 2 and 11 which offered the cleanest and best quality data sets. Difficulties with weather, cloud cover, wind, shadows and off-nadir image collection in the other plots excluded them from being thoroughly analyzed. Additionally, plots 2 and 11 were chosen because of time limitations and these data sets were sufficient in quality and therefore, adequate to test the study’s research questions and show quality reproducible results.

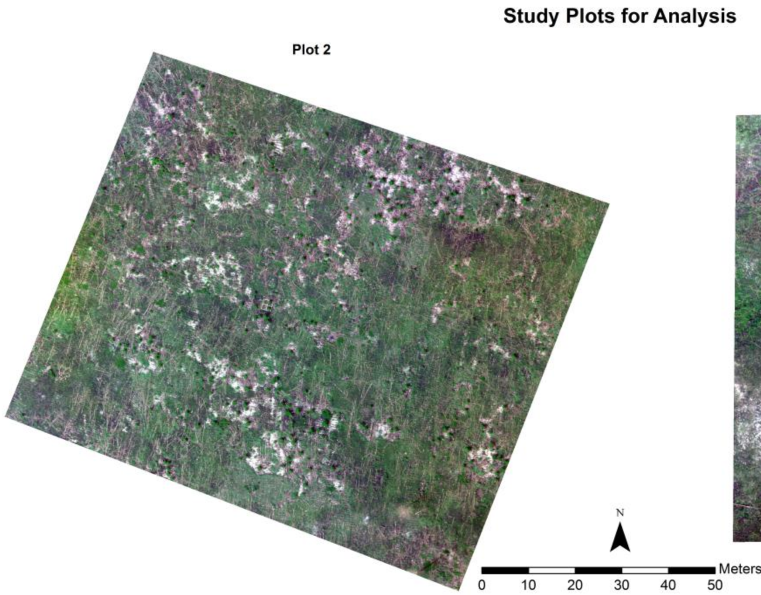

Figure 7: Study Plot 2 and Plot 11 UAS imagery mosaic

4.1 Object Detection Accuracy Assessment

4.1.1 Band Combinations

The goal of this analysis, simply put, was to determine which of the band combinations (RGBRENIR, RGBRE, RGBNIR, RGBNIR-R) resulted in the highest object detection accuracy in the GEOBIA process. A multiresolution segmentation followed by a Random Forest classifier was used for the object detection. Literature about imagery classifications has shown that the RE band often enhances classification accuracy (Kim and Yeom (2014); Schuster et al. (2012); Adelabu et al. (2014)). Because of this, it was expected that the RE band would improve classification results and likely show the highest accuracy of all the band combinations in this present study.

Plot 2

The overall identity accuracy for Plot 2 across all band combinations was 72.3%. This overall percentage translates to approximately 267 of the 369 saplings being correctly identified in the imagery. The individual band combinations can be seen in Table 1 below.

Plot - Time	Bands	Identity Accuracy %	Time Average %
2-1	Both	62.8	66.9
	NIR	72.5	
	RE	59.4	
	NIRR	72.9	
2-2	Both	66.2	71.2
	NIR	66.4	
	RE	70.5	
	NIRR	81.7	
2-3	Both	77.7	78.4
	NIR	77.5	
	RE	71.5	
	NIRR	87	

Table 1: Plot 2 identity accuracy results

Plot 11

The overall identity accuracy for Plot 11 across all band combinations was 92.3%. This overall percentage translates to approximately 19 of the 21 saplings being correctly identified in the imagery. The individual band combinations can be seen in Table 2 below.

Plot - Time	Bands	Identity Accuracy %	Time Average %
11-3	Both	91.4	92.3
	NIR	91.4	
	RE	88.9	
	NIRR	97.5	

Table 2: Plot 11 identity accuracy results

In both plots, the NIR-R band combination achieved the highest accuracy. Surprisingly these results show that the RE combination, which was hypothesized to produce the highest accuracy, performed the worst. The overall accuracy for plot 11 is higher than that of plot 2 however in both cases these accuracy results are quite good. The range of accuracies between band combinations for plot 2 is approximately 13.5 percent while the range for plot 11 is only 8.5 percent. These more consistent (less variance) accuracy percentages again showed that the identity GEOBIA was more effective in plot11.

4.1.2 Seasonality Effects on Identity and Edge Similarity Accuracy Results

Plot 2

Aside from the overall identity results for the 16 GEOBIA classifications, a temporal accuracy assessment was also conducted. The imagery from Plot 2 was used, and the three data collection dates are the 3 time stamps (T_1=6/30/17, T_2=8/5/17, T_3=8/19/17). The identity GEOBIA accuracy for T_1 was 66.9%, T_2 was 71.2%, and T_3 was 78.4% showing an overall trend of increased accuracy as the summer progressed.

This same overall increasing trend is again seen looking at each of the individual band combination classification for T_1, T_2, and T_3. Figure 8 below shows an apparent increase across all times for all band combinations with the exception of the NIR band which is lowest in T_2 instead of T_1. Additionally, there is a minimum of 10% classification accuracy increase from T_1 to T_3 again with the exception of the NIR combination (5% increase).

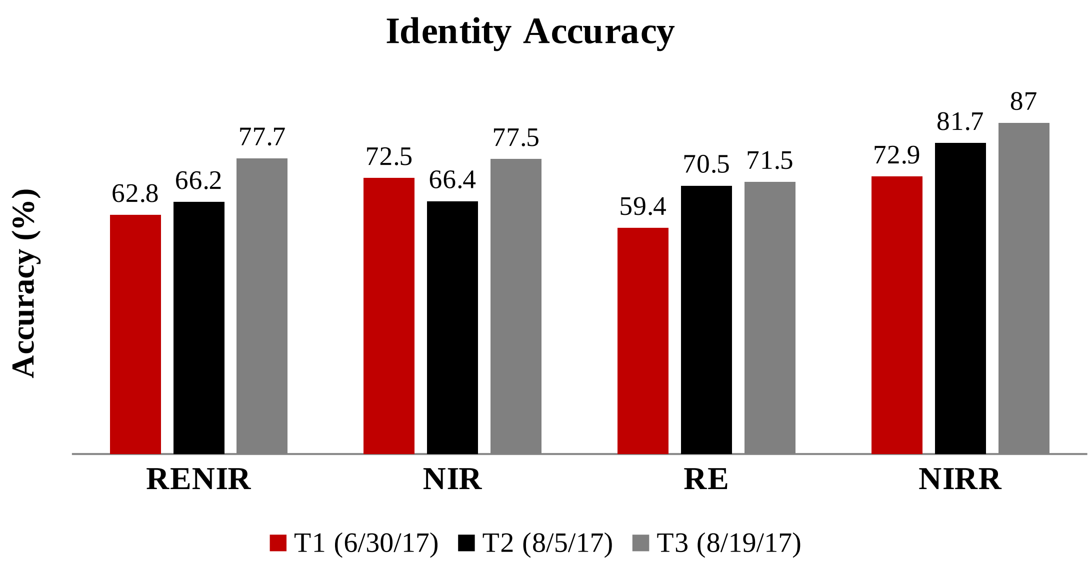

Figure 8: Identity OBIA accuracy across all band combinations and time (T)

Increases in classification accuracy can also be seen not only through the percentages reported but by looking at the classification polygon layers. Figure 9 contains a higher number of black points (tree centroids) surrounded by red polygon (classified tree area). This is to be expected because the accuracy percentages are based on this same relationship. In Figure 10 the opposite relationship is observed where many of the black points are not surround by red polygon meaning those tree areas were not recognized and classified by the GEOBIA process. This relationship results in the lower classification accuracies. Also in Figure 10, there are a number of areas that have been incorrectly classified as tree or are covered by red polygon when there is no tree centroid there. In Figure 9 many of these misclassifications did not occur.

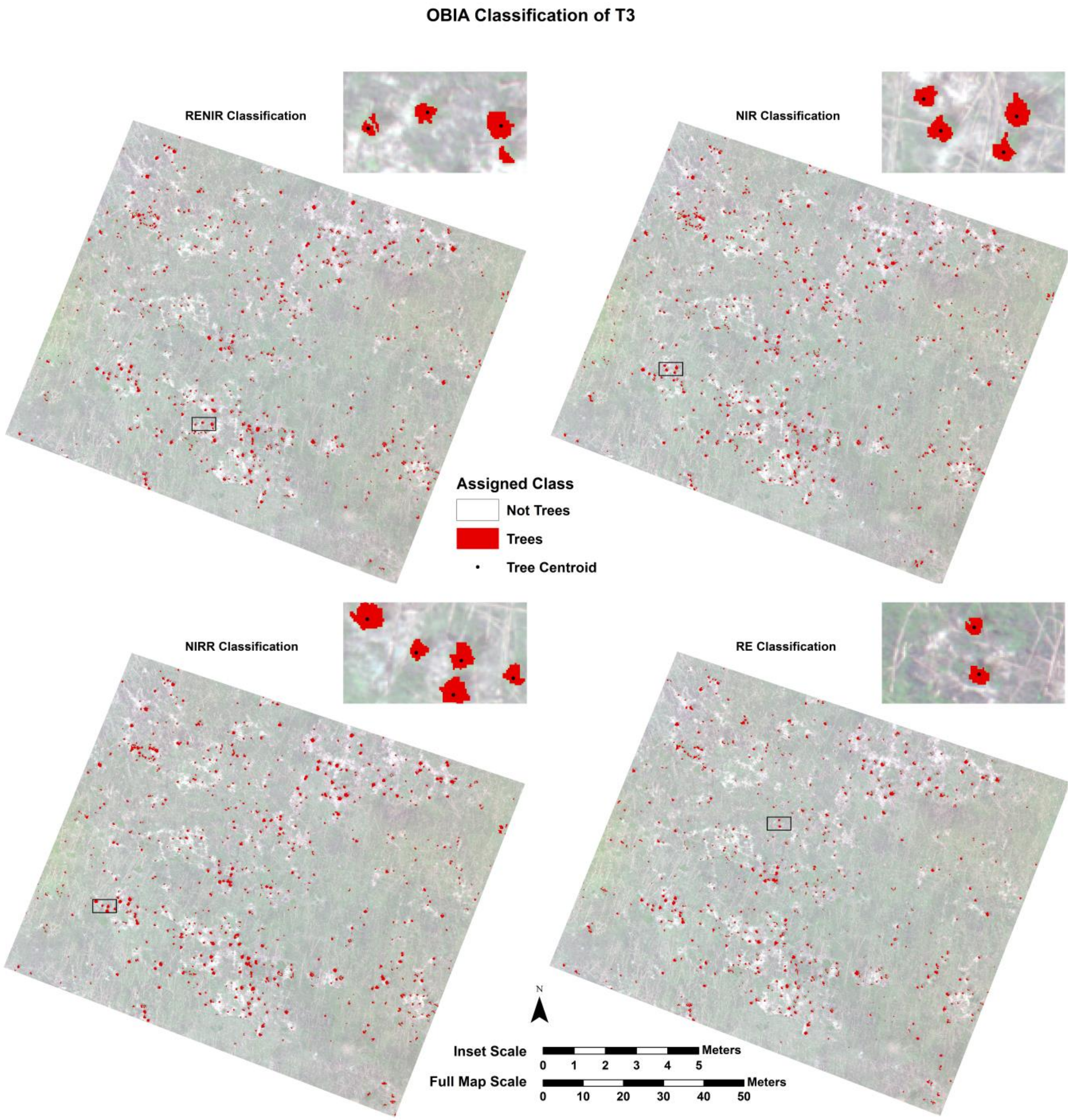

Figure 9: OBIA classifications for T_3 (Highest accuracy)

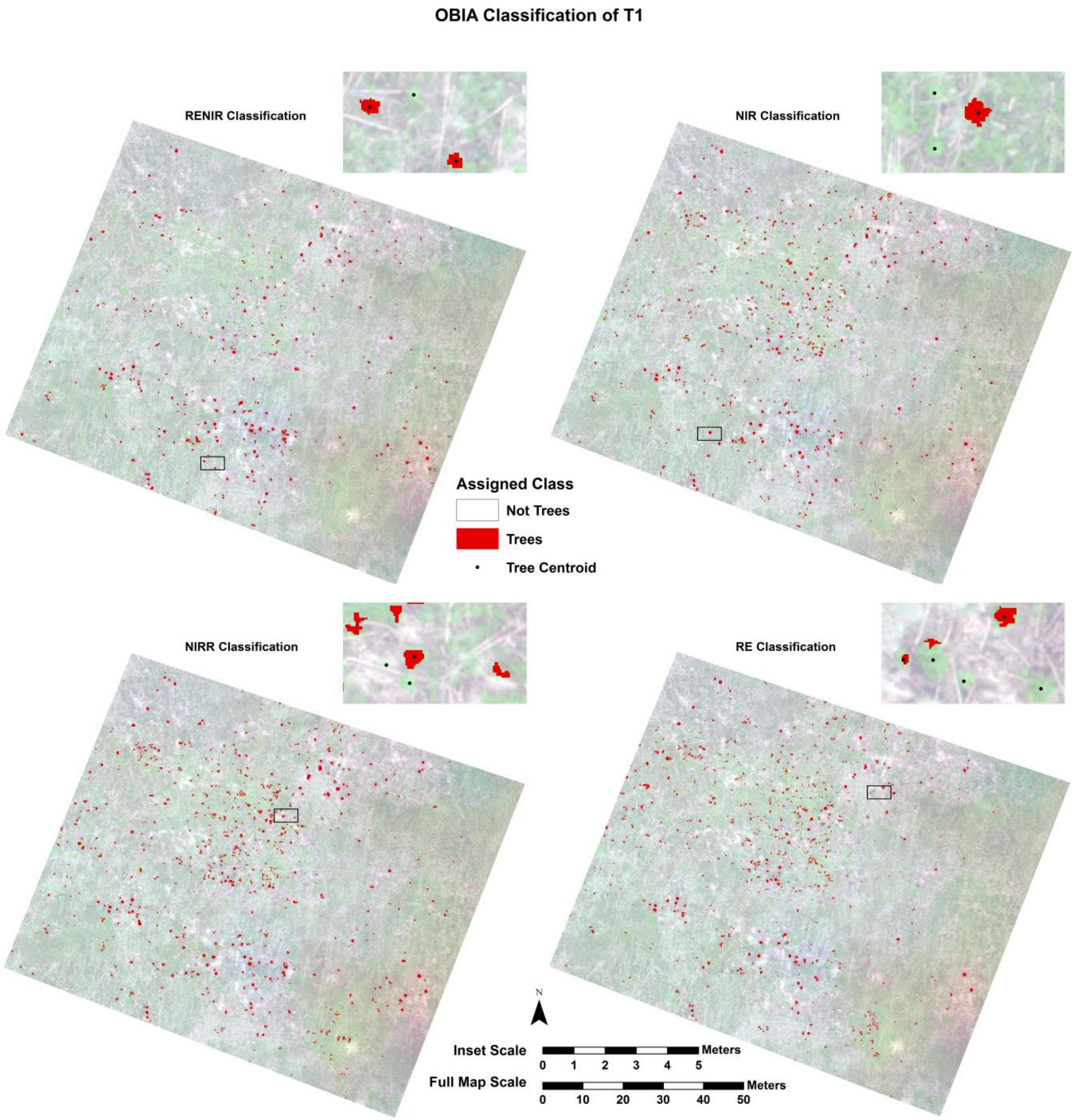

Figure 10: OBIA classifications for T_1 (Lowest accuracy)

4.1.3 Edge Similarity Accuracy Results

Plot - Time	Bands	Hausdorff Distance (m)	Plot AVG	Band AVG All Times
2-1	Both	.552	.548	.677
2-1	NIR	.545		.617
2-1	RE	.572		.619
2-1	NIRR	.526		.429
2-2	Both	.670	.637	
2-2	NIR	.670		
2-2	RE	.725		
2-2	NIRR	.486		
2-3	Both	.759	.652	
2-3	NIR	.762		
2-3	RE	.699		
2-3	NIRR	.389		
11-3	Both	.727	.504	
11-3	NIR	.494		
11-3	RE	.48		
11-3	NIRR	.315		

Table 3: Edge similarity for Plots 2 and 11

In Figures 11 and 12 the yellow digitized tree outlines are compared to the red polygon area which is the classified tree area. The comparison of these features edges resulted in the Hausdorff distance values. Figure 11 is showing this comparison for the NIRR band combination on both plots 2 and 11for T_3 of data collection. As seen in Table 3 above this band combination resulted in the best edge similarity or lowest Hausdorff distance values. In all cases, in both images, the red polygon is completely contained within the yellow tree outline. This relationship of one completely contained within the other is how the best edge similarity was achieved. In contrast in Figure 12, there are red polygon features that spill over or are not completely contained within the yellow tree features. This spilling over results in the worst edge similarity accuracy and occurs in both plot 2 and plot 11.

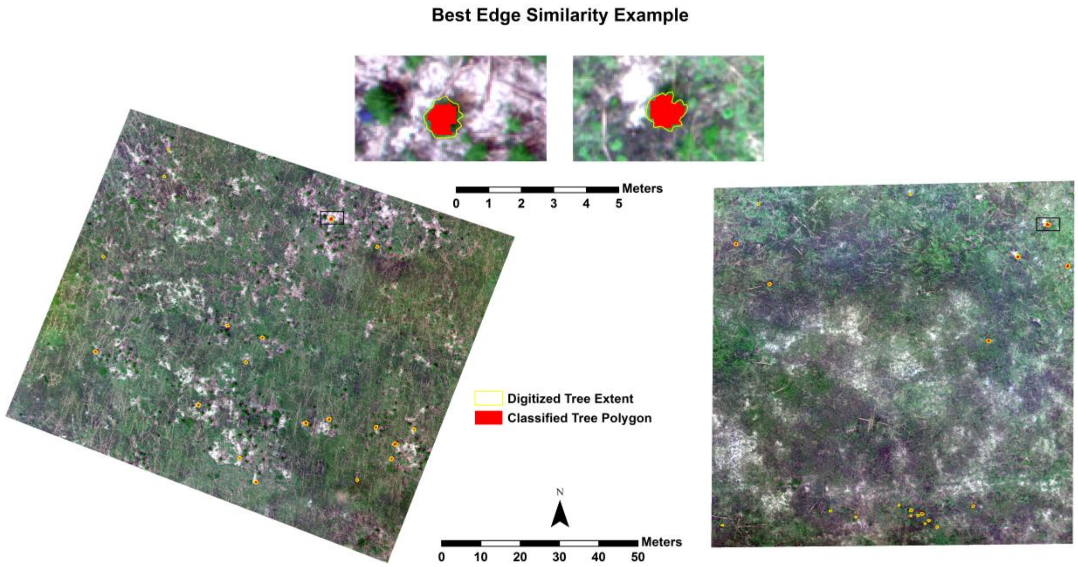

Figure 11: NIRR edge similarity for T_3 (Best similarity)

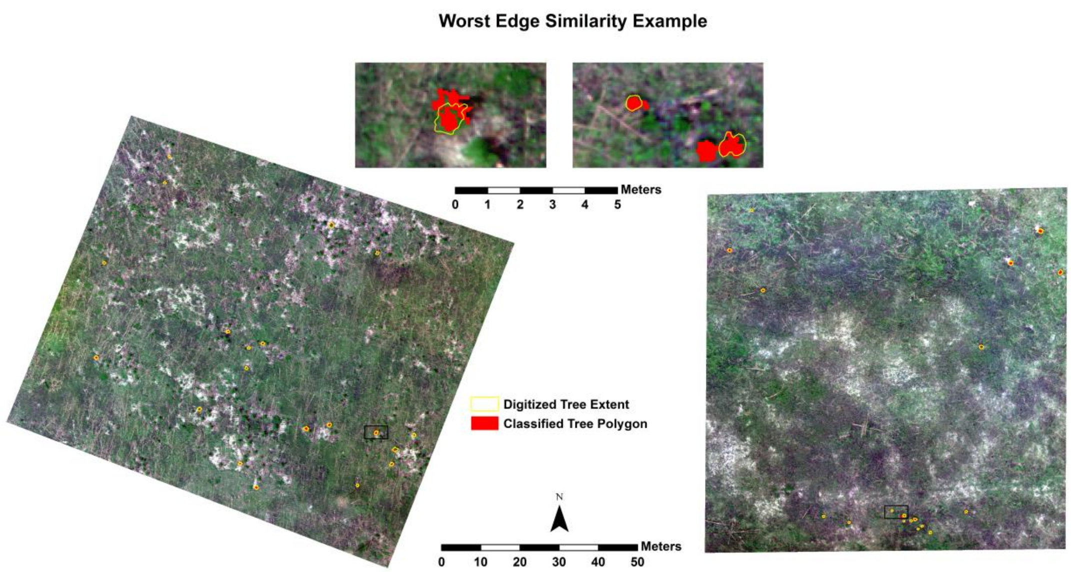

Figure 12: RENIR edge similarity for T_1 (Worst similarity)

5. Discussion

Like any research, this project had its share of limitations and unforeseen circumstances. Challenges in study design, data collection, data quality, the GEOBIA process and accuracy assessments all presented challenges in this study. Many of the challenges and limitations discussed in detail below are unique to this study but also applicable and could occur in any post-fire forest assessment. Evidence of study flexibility and adaptation are demonstrated in the following section leading to successful completion of the study goals.

5.1 Accuracy Assessment

The accuracy assessments used in this study are not the traditional wall to wall thematic assessments. A thematic accuracy assessment was not feasible because the ratio of tree to not tree area in the images is so large. When random points were generated throughout the images, the number placed on trees versus not trees were very uneven causing high accuracies >95%. There were few times that the assessment could recognize a misclassification because the majority of points were generated over not tree areas and also classified as not tree. To correct this problem and achieve a more accurate and realistic assessment more points needed to be generated over known tree locations and the number of points over not tree locations needed to be reduced. This methodology could potentially lead to a bias or make it appear as if the assessment data was being manipulated to achieve higher accuracy results, however, making the relationship between the two classes one to one removed that potential bias. The one to one relationship provided a much more accurate assessment because unlike the thematic method it is not biased or skewed by having one class with many more points than the other. This methodology and thought process is the reasoning behind there being 369 tree and not tree points in plot 2 and 21 tree and not tree points in plot 11 for conducting the accuracy analysis.

5.2 Band Combination Accuracy

Literature regarding both pixel-based and GEOBIA approaches to imagery classifications has shown that the RE band often enhances classification accuracy especially when dealing with plant species identification and separation (Kim and Yeom (2014); Schuster et al. (2012); Adelabu et al. (2014)). From reading these and other studies, it was expected that the RE band would improve classification results and likely show the highest accuracy of all the band combinations in this present study. Surprisingly this was not the case, in fact, the RE band resulted in the lowest accuracy overall as well as for most of the individual classifications run (see Tables 1&2). A likely explanation for this is the narrow portion of the electromagnetic spectrum chosen as the RE band used by the sensor in this study. The RE band in this study was 10nm wide centered at 717nm which is a rather narrow window considering that other RE sensors capture 40nm or even 150nm on some satellite sensors. This hypothesis is backed up by the use of the NIR-R combo which in theory should be the same as the RE band because the RE lies between and is the transition from the red to NIR band. The NIR-R equation results in a wavelength of 147nm (820-672nm) a broader window than the 10nm captured by the sensors default RE band. This larger window allows the classifier to see more significant variation in vegetation signatures, in turn increasing its capability of differentiating between them and increasing the classification accuracy.

It is entirely possible that the unique spectral signature of jack pine saplings lies mostly or entirely outside of the narrow 10nm window of the RE band used here resulting in misclassification and low accuracy. The relatively good accuracy of NIR band combination is to be expected as the NIR band is traditionally used for vegetation mapping, in particular, NDVI calculations. The NIR band in this study was a 40nm width centered at 840nm. Although this window is narrow, the classification results show that it captured enough spectral variance to differentiate vegetation species reasonably well. The NIR and RE combination performed as would be expected given the RE results of this study. The lack of added spectral information from the RE band as discussed above results in essentially a second NIR band combination producing very similar results as the first.

Although the RE band did not perform as expected, it did provide further insight into its limitations or usefulness depending on how it is configured. In its entirety, which in this study is the NIR-R combination, the RE band shows promise for species identification and separation and supports the other studies that have seen similar results and recognize the benefit of this additional band for GEOBIA analysis.

5.3 Edge Similarity

The edge similarity assessment across all 16 classifications showed a range of values from .75m to .31m or approximately 2.5 and 1ft, respectively. The majority of the higher values were due to the inside or classified polygon spilling over the outside or digitized polygon. This means that in most cases the most significant error or lowest accuracy for the classification is a result of over-classification of tree objects, not under-classification. Some examples of this observed in the classification results were when two classified tree polygons are close enough or have a classification error that join them into one large polygon. The large two tree polygon gets compared in size to a one tree digitized polygon, and that additional classified tree area leads to a significant error or value in Hausdorff distance.

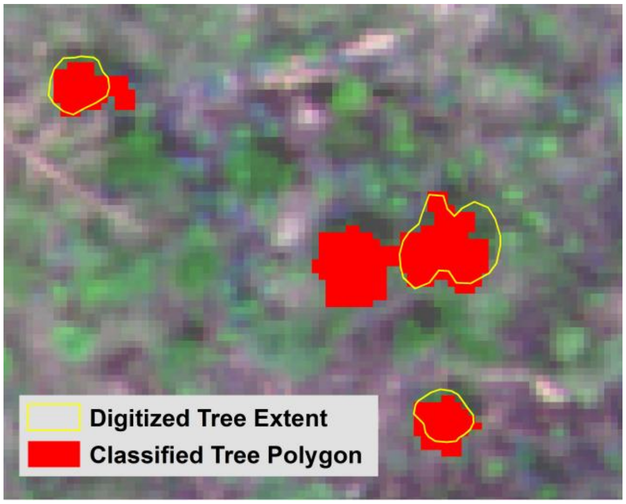

Figure 13: Classification error leading to worst edge similarity values

Another example of over-classification was when dense vegetation was in close proximity to a classified sapling, and that vegetation was classified as tree along with the actual tree, again leading to a large Hausdorff distance. There were very few instances where a tree being under-classified led to a large Hausdorff distance.

A logical hypothesized pattern of the Hausdorff distance was that as the identity classification accuracy increased so did the Hausdorff distance accuracy. This is an inverse relationship meaning that as the identity accuracy increases the Hausdorff distance decreases. The NIR-R band combination which showed the best accuracies for both assessments across all images supported and clearly illustrated this hypothesis. Although this edge analysis may not be crucial with the goal of identifying saplings it does show potential for additional functionality in GEOBIA that can be utilized when using UAS imagery.

5.4 Seasonality Effects on Identity and Edge Similarity Accuracy

Each type of vegetation has a unique spectral signature. During the growing cycle of a plant these signatures change as water content, and chemical composition fluctuate. These fluctuations are unique to each plant species and are often most noticeable in the spectral signatures of the red, RE and NIR bands. At the beginning of the growing season (March-June) spectral signatures of plant species can look quite similar but as the growing season progresses the signatures become more distinct and distinguishable. This is true across all plants whether in a forest setting (Nikopensius, Pisek and Raabe 2015) or in an agricultural setting (Wilson, Zhang and Kovacs 2014), or anywhere in between. The results of the temporal identity analysis in this study follow this pattern as well. As the summer months progressed an increase in identity accuracy is evident, likely due to better separation in spectral signatures between the jack pine saplings and surrounding vegetation. At T_1 (6/30/17) in the study area, it was still spring in the

UP with lots of rain and cool temperatures. The grasses and blueberry bushes were in early stages of growth, and the jack pines were also starting to show new growth. This early growth stage resulted in more similar signatures, making it more difficult for the GEOBIA classifier to distinguish between jack pine and other vegetation. At T_2 (8/5/17) it was the middle of summer with warmer temperatures and the vegetation was close to or fully grown. Ample amounts of rain kept their water content fairly similar, which is most easily observed in the NIR band, but the signatures were starting to become more unique. By T_3 (8/19/17) many of the grasses were withering and turning brown, and the blueberry bushes, which are broadleaf plants, were drying out due to high temperatures (which can be seen in the flight record). The jack pine, which have a deeper root system and lose water less quickly to evaporation, were green and healthy showing very high reflectance in the NIR band, which can mostly be attributed to a higher water content than the other plant species. These differences in water content, health and life stage of the plant species resulted in more unique and better separated spectral signatures increasing the ability of the GEOBIA classification process to identify the jack pines correctly. An even better classification accuracy could potentially be achieved in late fall when most all species other than conifers are dormant due to cold temperatures. The jack pines would be quickly identified, and classification error due to spectral signature similarity would be minimal or possibly nonexistent.

This temporal analysis was made possible by the ability of an UAS user to collect high quality, high-resolution data at a relatively high temporal frequency often not achievable with other remote sensors.

5.5 Study Limitations

The original plan for this study was to use data from 15 study plots stratified according to area burned each day to conduct an overall assessment of vegetation health and other patterns across the study area. Due to several factors and circumstances beyond our control, only portions of the data were used, and the goal of project was revised.

5.5.1 Study Site Accessibility

Upon arrival at the study area for the first time, it was realized during marking and creation of the study plots that it would not be possible to access all of the proposed plots due to accessibility and time limitations. Many of what appeared to be roads in the Google imagery were two tracks or ATV trails some of which were no longer open for use. Dead timber, deep sand, and water blocked many of the open trails and made them impassible. For a number of the southern plots there was no trail access and hiking through swamp or marsh would have been required. These accessibility limitations lead to concerns about time, safety, and feasibility of collecting UAS imagery. Additionally equipment failure, lack of cellular service, and working in such a remote location lead to removal of the study plots further to the south and a focus on 10 study plots in the northern part of the study area.

5.5.2 Imagery Limitations

All RS data regardless of the sensor or platform it is collected with has limitations and imperfections. The data collected in this study was no exception. The imagery collection methodology and workflow was designed to eliminate as many data issues as possible and had been used on other previous projects with great success; however, this specific study area presented new challenges. Weather in this area is very unpredictable and changes rapidly especially being right next to Lake Superior causing fluctuations in cloud cover and wind speed. The amount of cloud cover effects spectral reflectance values of the earth’s surface changing the values in the imagery collected and causing inconsistency. On numerous occasions during data collection, one-half of the images collected for a study site were in full sunshine while the others were under cloud cover. Sun angle and time of the day also affected the imagery, creating shadows but could not be avoided due to threat of inclement weather and time limitations. Variations in wind speed and direction affected the ability of the UAS to keep the sensor nadir or 90 degrees to the ground. Slight differences in image capture angle caused object distortion and elongation in the images. Saved flight paths and consistent elevation of image capture assured similar image capture patterns but could not account for all possible flaws. Ground control points (GCP) were originally planned as a way to spatially correct and rectify the imagery to the earth's surface, but lack of cellular connection did not allow for the sub-cm acquisition accuracy of those points. To avoid further spatial distortion to the imagery, the GCPs were not used as in normal UAS data collection. These challenges and data inconsistencies lead to the use of only two of the ten study sites, plots 2 and 11.

5.5.3 GEOBIA Limitations

Creation of the rule set for the GEOBIA was one of the biggest challenges of this project. The eCognition Developer software is excellent in regard to versatility but is also challenging because there are so many different ways to accomplish the same objective. Many hours were spent trying different settings to achieve a sufficient image segmentation. Once the segmentation was acceptable, then the type of classifier (rule-based or automated) was decided, again through many hours of trial and error. Next, the training sample scheme was created assuring that enough samples were collected to capture the full spectral range of the objects but not too many leading to confusion. The individual parameters of the classifier were then adjusted to reach the best results. This work flow is no different than for any other GEOBIA project however in this study it was much more of a challenge. The greatest challenge was that the same master ruleset had to run 16 times on 2 plots with 4 different band combinations and 3 different time stamps while making sure the methodology, functionality, and results were consistent and reproducible for each analysis. This was done by leaving the ruleset for each analysis identical except for changing the spectral band combinations as well as the corresponding sample features that were used to train the classifier. A TTA mask or polygon shapefile that had the same sample polygons selected was used to increase consistency across the classifications assuring an accurate difference in classification accuracy across band combinations. Errors in spectral reflectance and overexposure on some bands of the imagery lead to poor image segmentation and misclassification of the polygons. The results from these images would have skewed the accuracy comparison between band combinations and were removed. Plots 2 and 11 had very minor to no errors or imperfections, so they were the main datasets for the GEOBIA. Aside from the errors in the imagery, Plots 2 and 11 were chosen because of time limitations as GEOBIA is time intensive and these data sets were sufficient to test the study's research questions and show quality results.

5.5.4 Ecological Implications of Study

The methodology used in this study should not be limited to only jack pine identification. Here it was shown to be useful for identifying jack pine saplings after a fire, but it could also be applied to other fire-tolerant tree species such as oak. Additionally, this identity GEOBIA could be used to identify or quantify other plant species in a landscape when fire isn't involved to conduct species distribution or composition studies. This high-resolution object-oriented type of analysis should be applied in ecological mapping or similar applications when fine-scale data is required, and object identification is the goal.

6. Conclusions

Despite some potential improvements to the methods for data collection in the future, explicitly regarding sensor configuration and lighting conditions to achieve better quality and higher quantity of usable data, this study verified the validity of aerial imagery collected via UAS to be a sufficient and adequate source of RS data for GEOBIA. It also clearly demonstrated the ability of GEOBIA as a viable method to produce good results for object identification and more specifically tree sapling identification, achieving accuracies of up to 97.5 percent. The edge similarity assessment also showed the ability of the GEOBIA in this study not only to identify the centroid of the saplings but classify the majority of their physical extent.

The surprising results of the RE band being the least helpful or effective for sapling identity contradicts much of the literature which showed the RE bands potential for increasing classification accuracy. As discussed above this is potentially sensor related due to the narrow 10nm window the sensor collects in; however additional research is needed to confirm that.

The results of this research confirm that UAS is an effective method of capturing RS data for use in connection with GEOBIA and identifying tree saplings on a small scale such as the 1ha plots used here. However, in future research, this RS data source and GEOBIA method should be tested on a much larger scale with the expectation that similar identification accuracy can be achieved. At a large scale, this methodology for tree sapling identification after a fire disturbance could help forest managers estimate and quantify natural regrowth and make more informed decisions on replanting, streamlining this aspect of forest management.

In the background section of this paper, there was no literature directly related to or showing methodologies to achieve the same goals as this study. This research will hopefully begin to fill this void in the RS and GEOBIA literature helping others in the field recognize and utilize the full potential of both UAS as a RS tool and GEOBIA as a relevant and very useful method for RS imagery analysis.

This study showed the ability of the UAS GEOBIA combination to accurately detect jack pine saplings post-fire. Aside from assisting forest managers in calculating sapling counts, this methodology could also be applied to assess habitat for wildlife that reside in these jack pine landscapes. One animal species that is exclusively reliant on jack pine, specifically young jack pine, is the Kirtland's Warbler a native and endangered bird species to Michigan. Without proper management of jack pine habitat, this species will go extinct. The detection of low branch nesting areas which are vital to the Warblers' existence could be achieved using this methodology.

This methodology is not specific to Michigan and could be utilized in states such as Wisconsin, Minnesota, and Iowa or even in the southern portions of Canada where these same jack pine forests are found. Additional landscapes and forest types could also be evaluated after fires with this workflow. Oak savannahs that contain fire-tolerant tree species such as burr oak (*Quercus macrocarpa*) exist throughout the Midwestern United States. The often sparse distribution of fire-tolerant trees throughout these grasslands makes them ideal for induvial tree identification after a fire disturbance.

The applicability of this research and methodology is only limited by the managers and overseers of these unique, fire tolerant, forested landscapes. The opportunity to aid in post-fire forest management and habitat evaluation for endangered species across different landscapes has been clearly illustrated here. The full potential will not be realized unless it is implemented.

APPENDIX

Date	Plot #	Time Start	Time End	Temp °C	RH%	Wind (m/s)	Sky	Altitude (m)	Battery	Persons Present	Data Used/Not Used
6/29/2017	1	3:40 PM	3:49 PM	22.3	72.9	3.2	Cloudy	80	I1	M.Bomber R. White J. Hupy P. Menet	Not Used
6/30/2017	7	10:56 AM	11:12 AM	22	56.1	1	Cloudy	80	I5	M.Bomber R. White J. Hupy P. Menet	Used
6/30/2017	10	11:29 AM	11:38 AM	21	62.3	0	Cloudy	80	I3	M.Bomber R. White J. Hupy P. Menet	Used
6/30/2017	8	12:00 PM	12:07 PM	21.6	60.1	0	Cloudy	80	I6	M.Bomber, R. White J. Hupy P. Menet	Used
6/30/2017	9	12:45 PM	12:51 PM	20.9	65.8	0	Cloudy	80	I4	M.Bomber, R. White J. Hupy P. Menet	Used
6/30/2017	5	1:16 PM	1:23 PM	21.1	60.4	0	Cloudy	80	I1	M.Bomber R. White J. Hupy P. Menet	Used
6/30/2017	12	3:20 PM	3:26 PM	19.2	70.9	2.2	Clear	80	I4	M.Bomber R. White J. Hupy P. Menet	Used
6/30/2017	2	3:45 PM	3:52 PM	18.7	72.8	4.4	Clear	80	I5	M.Bomber R. White J. Hupy P. Menet	Used

Table 4: Aerial data collection flight log

Table 4 (cont'd)

6/30/2017	3	4:19 PM	4:25 PM	19	71.5	0	Clear	80	I1	M.Bomber R. White J. Hupy P. Menet	Used
6/30/2017	4	4:48 PM	4:54 PM	21.6	66.2	3.1	Clear	80	I6	M.Bomber R. White J. Hupy P. Menet	Used
8/5/2017	8	7:08 AM	7:15 AM	16.5	65.8	0	Cloudy	80	I3	M.Bomber R. White J. Hupy	Used
8/5/2017	7	7:27 AM	7:34 AM	17.5	64.2	1.5	Cloudy	80	I6	M.Bomber R. White J. Hupy	Used
8/5/2017	9	8:04 AM	8:10 AM	17.5	62.8	2.3	Cloudy	80	I5	M.Bomber R. White J. Hupy	Used
8/5/2017	5	8:27 AM	8:33 AM	15.8	69.7	3.6	Cloudy	80	I1	M.Bomber R. White J. Hupy	Used
8/5/2017	3	8:50 AM	8:57 AM	15.5	72.6	2.4	Cloudy	80	I4	M.Bomber R. White J. Hupy	Used
8/5/2017	10	10:40 AM	10:51 AM	21.8	57.7	2.6	Cloudy	80	I4	M.Bomber R. White J. Hupy	Used
8/5/2017	4	11:07 AM	11:14 AM	21	56.5	4.9	Cloudy	80	I1	M.Bomber R. White J. Hupy	Used
8/5/2017	2	11:31 AM	11:40 AM	19.6	63.1	5.8	Clear	80	I3	M.Bomber R. White J. Hupy	Used
8/5/2017	11	11:53 AM	12:00 PM	21.7	57.6	5.9	Clear	80	I6	M.Bomber R. White J. Hupy	Used

Table 4 (cont'd)

8/5/2017	12	1:20 PM	1:25 PM	22.4	56.8	4.7	Clear	80	I5	M.Bomber R. White J. Hupy	Used
8/5/2017	1	1:38 PM	1:46 PM	20.7	59.9	3.9	Clear	80	I4	M.Bomber R. White J. Hupy	Not Used
8/19/2017	9	8:45 AM	8:55 AM	17.9	73.7	0	Cloudy	80	I1	M.Bomber R. White J. Hupy	Used
8/19/2017	7	9:58 AM	10:08 AM	22.7	61.7	0.8	Cloudy	80	I6	M.Bomber R. White J. Hupy	Used
8/19/2017	10	10:41 AM	10:52 AM	29.7	42	0	Cloudy	80	I4	M.Bomber R. White J. Hupy	Used
8/19/2017	8	11:30 AM	11:37 AM	28.9	42.8	0.8	Cloudy	80	I3	M.Bomber R. White J. Hupy	Used
8/19/2017	5	12:15 PM	12:22 PM	32.7	34.8	1	Cloudy	80	I5	M.Bomber R. White J. Hupy	Used
8/19/2017	11	2:57 PM	3:05 PM	23.1	63.4	2.4	Cloudy	80	I4	M.Bomber R. White J. Hupy	Used
8/19/2017	3	3:23 PM	3:30 PM	25.8	54.6	1.2	Cloudy	80	I6	M.Bomber R. White J. Hupy	Used
8/19/2017	2	4:03 PM	4:13 PM	25.2	54.8	1.8	Cloudy	80	I1	M.Bomber R. White J. Hupy	Used
8/19/2017	12	4:39 PM	4:47 PM	24	60.4	0.8	Cloudy	80	I5	M.Bomber R. White J. Hupy	Used
8/19/2017	4	5:17 PM	5:25 PM	21.8	69	2.1	Cloudy	80	I3	M.Bomber R. White J. Hupy	Used

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