INVESTIGATING THE POTENTIAL FOR HAZARD TREE IDENTIFICATION USING THERMAL IMAGERY FROM THE DJI MAVIC 2 ENTERPRISE DUAL

by

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ABSTRACT

Keywords: drones, hazard trees, management, thermal, sensors, aerial imagery

The Mavic 2 Enterprise Dual was recently released by DJI in December of 2018. It is a small compact device with enormous potential for field work in a variety of industries, one of which has been investigated in this undergraduate thesis report. Public parks and recreation areas are becoming an important part of our health and well-being during an increasingly technological and urban time. However, safety is always a concern with public participation in any activity, and one which wardens and managers are constantly trying to improve upon. Approximately 11% of deaths or injuries that occur during outdoor recreational activities have been the result of falling trees or tree branches (Brookes 2007). Trail inspections, in an attempt to identify hazard trees that are dead or rotting before causing issue, can be infeasible due to a number of conditions, making the rise in remote sensing and drone technology potentially revolutionary to this field.

The Mavic 2 Enterprise Dual is equipped with dual thermal and visual cameras. Thermal imagery is incredibly useful for identifying objects that are less visible with traditional imagery by using different heat signatures. Thermography has been used across a range of disciplines including engineering, medicine and perhaps most relevant, arboriculture. Although not thoroughly researched, numerous case studies have shown that zones of decay can be seen inside standing trees using thermal imagery at ground level (Catena & Catena 2008). Assessing individual trees in this manner may not be particularly useful for identifying hazard trees in large public parks but it begs the question of whether aerial thermal imagery could potentially be implemented in the same manner and if so, would the Mavic 2 Enterprise Dual be an appropriate tool for the task.

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This thesis would not have been possible without the support of thesis supervisor, Ulf Runesson as well as second reader, Alex Bilyk. A special thanks goes out to Ryan Wilkie as well, for extra assistance with data collection and image processing as well as Ryan Mackett from the Lakehead Region Conservation Authority (LRCA) for allowing us to collect images for this thesis on LRCA conservation grounds.

INTRODUCTION AND OBJECTIVE

Parks and greenspaces play an important role in the lives of many people around the world. Although there may be a lack of evidence to prove the connection between health and nature, much of the public perceives it as having a positive effect on their lives. This could be due to the calm and relaxing effect of spending time outdoors, or the fact that most of peoples time in natural environments is spent on activities such as walking or biking (De Vries *et al.* 2003). The perceived advantages to spending time outside are becoming seemingly more important in an increasingly technological and urban world.

Protected areas and parks often fill this desire for outdoor recreation by creating well maintained trail networks. However there is an inherent risk in participating in these activities. Approximately 11% of deaths or injuries that occur during outdoor recreational activities have been the result of falling trees or tree branches (Brookes 2007). These types of incidents are hard to prevent due to the sheer number of potentially hazardous trees and the variety of circumstances that surround their fall. Through an investigation by Andrew Brookes (2007) of incidents in natural areas since the 1960's it was observed that age and experience of the victims are not necessarily contributing factors to the incidents occurrence. Weather often plays the largest role in fallen tree incidents in the form of strong winds, snow and more. Most incident reports also cite the presence of rot or other damage to the tree prior to its fall. Unhealthy trees are more likely to fall and therefore more likely to cause injury or death when combined with other conditions.

In 2004 at Hamilton Ontario's botanical gardens, a 10 year old was struck and killed by a large tree branch. As a result of an investigation afterwards, the coroner's jury made 18 recommendations to improve the safety of the area. These included trail inspections every morning, and a thorough trail assessment every 2 years. However these recommendations are difficult to implement in large parks with extensive trail systems, treelined roadsides and campsites (Brookes 2007). It is simply impractical to inspect the entire area at an appropriate interval. Combined with the added backcountry routes and campsites that are even more rarely visited and it is nearly impossible.

Besides the obvious threat to human life, dead or dying hazard trees can cost organizations thousands of dollars. As an example, in 1993 a woman hiking in Toorongo Falls Reserve in Australia was struck by a falling tree. She was awarded $300 000 for damages from the Department of Natural Resources, despite the location of the incident being outside of any closely managed region of the park (Brookes 2007). She was exploring a riverbank away from any designated trail or campsite. The lawsuit was granted under the claim there should have been warning signs nearby. This enters into a grey area of snag management in which the line is blurred between managing parks and recreation sites for public safety or nature and conservation goals (Brookes 2007). I will not delve into the debate on what the intensity of snag management for public safety should be. However, the inherent risk of outdoor recreation activities, the impracticality of time-consuming trail inspections and the potential monetary costs of an incident, warrant the review of current methods of hazard tree identification.

The rising introduction of drone technology, their practicality and their speed has potential to revolutionize the identification of natural hazards from the air. In the last decade much literature has been published identifying possible techniques using LiDAR and Infrared images to identify hazard trees. These methods have produced variable accuracy rates between 70 – 80% (Yao *et al* 2012) (Polewski *et al* 2015) but can involve significant equipment costs and image analysis times, not to mention LiDAR systems often require winged aircraft to do the flyover which is a significant expense.

In conjunction with the Lakehead Region Conservation Authority (LRCA), I will investigate potential alternatives to traditional hazard tree identification, while keeping in mind cost-effectiveness and time. The LRCA is a community based environmental agency that is responsible for the management of renewable natural resources within the local watershed. The organization undertakes a broad range of duties including watershed management, erosion control, flood forecasting & warning, recreation, water level monitoring, environmental education and stewardship. The successful implementation of these commitments are partly achieved through providing Conservation Areas for semi-passive recreational and environmental educational opportunities. The safety of participants in these types of LRCA programs is the goal of the research involved in this thesis. My study area will be located in the Cascades Conservation Area located outside of the City of Thunder Bay Ontario, Canada.

OBJECTIVE

The goal of this project was to find an efficient method of identifying dead standing trees within the LRCA's managed Conservation Area, Cascades, using thermal imagery from the new DJI Mavic 2 Enterprise Dual which is a newly release mid-priced drone. The findings will aid in removal efforts to help keep visitors safe in high traffic areas of the park. The investigation will aim to determine the feasibility of using thermal imagery for hazard tree identification as well as whether the Mavic 2 Enterprise Dual is appropriate for such analysis.

LITERATURE REVIEW

There are many advantages to using remotely sensed data for dead standing tree identification. Ground surveys are often time consuming, financially expensive and challenging in remote areas. Also, in order to maintain the quality of ground surveys, high resolution data is needed. Satellite images from freely available sources are generally not a high enough resolution for this purpose (*e.g.*, Landsat imagery). Another problem with satellite imagery is the potential cloud cover during certain times of the year and in specific climates (Koh & Wich 2012). To address these problems autonomous unmanned aerial vehicles have risen in popularity through recent years. These devices are commonly known as drones but can be identified by many names including unmanned aerial vehicles (UAV), unmanned aircraft systems, or remotely piloted aircraft systems. Drones are self-propelled airborne devices that have no onboard pilot. They were first developed for military purposes in the Second World War. The increased use for other applications in recent years has been mainly due to the miniaturization and reduction in price of the cameras and sensors used on board. This has been largely driven by the smartphone industry.

Drones can take on many forms but the 2 main ones are fixed wing and rotary winged aircrafts. Fixed winged can often carry heavier loads and fly longer distances while rotary winged forms tend to be smaller with reduced range. For the purpose of hazard tree identification rotary winged devices are ideal because they are more maneuverable and take off and land vertically which is useful when working under forest canopies (Sandbrook 2015). Rotary winged drones are often used for more precision work such as agricultural and fire monitoring, which makes them ideal for conservation work as well.

Drones can offer flexible, accurate and affordable solutions to the technical challenges of conservation area monitoring. There are safety concerns to consider though when deploying this technology. These aircrafts are generally safer than piloted aircrafts mainly because there is no risk to the pilot in the event of a crash and the smaller size reduces risk to people on the ground as well. Most drones now have software to return them automatically to the takeoff location in the event of an emergency.

The history of these devices being used for military applications has raised a lot of concern over the ethical implications and possible infringements on privacy and civil liberties. This along with safety concerns has led to regulation on behalf of the government in many countries around the world. Drones have the potential to cause fear, confusion, and hostility among those on the ground who are uninformed of its presence. People who do not understand the practical uses for this technology can generate conspiracies and suspicions. Likewise, people may recognize the drone for what it is but have misconceptions about its purpose. Because of this, the potential conflict between drone research and the public must be considered for flying over public parks (Sandbrook 2015).

This being a relatively new technology, legislation governing the flying of drones is still in the development phase. The agency responsible for the implementation of drone laws in Canada is Transport Canada. Currently, as of May 2019 the laws surrounding the use of drones in Canada don't require any sort of training or license to fly as long as the drone weighs 35 kilograms or less. There are strict rules and conditions however governing how a drone must be flown: below 90 meters' altitude, at least 30 – 76 meters away from vehicles, or the public depending on the drone's weight, at least 3 miles from any aerodromes, 1 mile from heliports, away from restricted airspace, during the day, within sight or within 500 meters of the operator and many more. These restrictions limit the possible situations and locations where this technology can be implemented but are easily followed under most circumstances including this study (Transport Canada 2019).

As of June 1st 2019 Transport Canada is implementing new legislation which will define all drones as aircrafts, hoping to crack down on safety concerns from the public and other airspace users. This mainly effects who can fly, but also makes minor changes to original regulations restricting how and where a drone can be flown. The most significant change would be the introduction of a license requirement for all drone operators in the form of a drone pilot certificate. This creates a platform where each pilot is now fully responsible for his/her aircraft (drone) and also ensures each owner is fully aware and informed on all relevant laws governing it's use. These changes create a safer environment for drone operators and the surrounding public but will add an extra element of consideration for organizations hoping to implement this technology into their daily operations (Transport Canada 2019).

Despite the concerns and changing governance, the many advantages of drones have sparked a recent rise in remote sensing techniques attempting to identify hazard trees from the air so they can be dealt with appropriately before causing an issue. Recent advances in LiDAR technology has generated higher spatial point density and additional characteristics about the reflectivity and vertical structure of trees (Yao 2012). Mucke *et al* (2012), attempted to use this advance in LiDAR technology to identify dead standing trees. Using a specified area and the GPS locations of twelve known living and dead standing trees, a cylindrical extraction of LiDAR points within a 2.5 meter radius was analyzed. A full explorative point cloud analysis was carried out and the different representations of the dead and living trees were determined. The distinguishing features included, point distribution (number of echo's per certain height interval) and the FWF (Full Wave-Form) attributes echo width and amplitude. This was done for both leaf on and leaf off conditions to identify any differences (Mucke *et al* 2012). The finding was that echo distribution and echo amplitudes were the strongest indicators for the delineation between standing live and dead trees. Regardless of leaf presence, echo's from dead standing trees were more equally distributed than live trees. This was likely due to the dead standing trees used in this study not having a live crown. Live trees showed a significantly higher amplitude in the top 30% of echo's with leaves on versus leaves off. This experiment suggests that with further refinement, it may be possible to recognize and identify dead standing trees based on full waveform LiDAR data by using a measure of point distribution and penetration depth during leaf on conditions (Mucke *et al* 2012).

Other methods of possible dead tree identification may be by using colour infrared aerial imagery (Polewski *et al* 2015). This method uses single colour infrared images as an input with no image correspondence or 3D elevation information necessary. However a set of training samples must be used which comes in the form of polygons that delineate individual snags and their location. This is the basis for developing shape and prior intensity information. The first step is to use this intensity prior information to find regions in the image that are most likely to contain snags. Within this narrowed region, the second step uses the intensity and shape algorithm derived from the training data to classify likely dead standing trees. Finally a grid of circles is overlaid on the image. The circles are ranked based on the intensity algorithm to determine the probability of containing a dead standing tree. For the high probability circles, a level-set segmentation using the mean shape of a snag tree determines whether or not there is enough evidence to support the existence of said tree. The accuracy of this type of identification varied but generally averaged around 71 – 77%. Some issues that arose from using only colour based images were difficulties in distinguishing between open ground, lying dead trees and snags. The loss of fine detail was also observed because of the transformation from image intensity values into probability values (Polewski *et al* 2015).

Something that has not been thoroughly investigated as a possibility is using thermal imagery as a way of identifying dead standing trees. There is potential for success using this technique based off previous research on the thermal properties of dead trees. Large or living trees tend to heat and cool more slowly which creates more stable temperatures beneath the bark of the tree trunk. On the other hand smaller or dead trees tend to fluctuate more with the temperature of the surrounding environment (Coombs *et al* 2010). Bark is not very efficient with the transfer of heat and therefore has the ability to keep the wood inside at a significantly different temperature than the outside air. This is accomplished with the help of tiny air pockets within the bark that have very efficient insulating properties. The result is a small microclimate within the wood beneath the cambium of a living tree trunk (Nicolai 1986).

In order to measure the amount of thermal radiation being emitted from the tree, this thesis will utilize thermal sensors mounted on a drone. A thermal camera is a passive sensor that captures the infrared radiation emitted by all objects above absolute zero. Similar to drone technology these sensors were originally developed for military applications, for uses such as surveillance and night vision.

The development of automatic vision systems such as thermal sensors has increased dramatically in recent decades. In the beginning, standard images were captured either in grayscale or RGB (red, green, blue) colour bands. The problems with this image capturing technique is that an external energy source is needed to reflect colours and visibility, meaning nothing can be captured in total darkness. To improve the process, 3D and near infrared sensors were developed in the 1940's and 50's which could actively emit radiation and measure the reflection back. This allowed remote sensing to occur regardless of light conditions. Over time this idea was improved by creating a passive type of sensor which measures mid to long wavelength infrared spectrum radiation (3-14 um). This new sensor used the dominant wavelength emitted based off of temperature to measure the thermal properties of an object while being independent from any kind of external energy source. The development of this technology has led to its application in a range of industries and has led to a lower price range which makes the technology more affordable to more users.

The basic premise behind the sensor is that infrared radiation is constantly being emitted from objects based on their temperature. This radiation is located between the visible and microwave spectrum which has a wavelength range between 0.7 micrometers (700 nanometers) to 1 meter. The peak of radiation intensity emitted shifts more towards the visible light spectrum with increased temperature which is why extreme heat such as a red hot iron can be visible to the human eye. This peak is what is measured by the sensor to determine temperature (Gade & Moeslund 2014).

Thermal sensors are used for many different purposes in conservation and vegetation health. By using active thermography, (adding thermal energy to an object and measuring its temperature) sensors can detect a bruised fruit before allowing it to hit the market. Thermal imaging of wheat fields can also identify fungal infected wheat plants (Gade & Moeslund 2014). Airborne tests of the common thermal sensor brand FLIR, have also been used to show thermal variations in peach orchards based on irrigation levels. Peach trees that were under water stress were shown as warmer than those that were fully irrigated (Berni *et al* 2009). In some jurisdictions within the United States, stream temperatures are actively monitored using remotely sensed thermal images in order to protect endangered and threatened aquatic biota. This is very important as it can identify water temperatures that exceed the thermal tolerances of native species and make corrective actions to assist those (Torgersen *et al* 2001). FLIR thermal sensors have even been used in Australia to identify active termite infestations inside buildings (Reynolds & Riley 2002). These are just some examples that can be used to highlight the diverse number of applications that the FLIR thermal sensor can be utilized for.

As important as collecting the thermal imagery is, the ability to convert it into tangible information that can be utilized in conjunction with other data sets in GIS (Geographical Information Systems) programs is critical. This can be accomplished through image classification and analysis. As long as the pixel size within the images remains coarser, or of a similar size to the object of interest then general pixel based analysis is often sufficient. However if increased accuracy is warranted then object based classification is more appropriate. The recent advance of extremely high resolution imagery has made this method much more important since often the object of interest is made up of several pixels in the image. In 2007 the first 0.5 meter resolution satellite became operational and in the years since the diversity of applications for security, urban planning, conservation planning and more, has only increased the rate of improvement. When using object based image classification, the first step is to divide the image into segments generated by one or more criteria of homogeneity in one or more regions respectively. By doing this, each segment will have more spectral information available such as mean values per band, median values, minimum and maximum values, mean ratios, variance and more. This additional information is highly valuable for increasing the accuracy of classification. Object based analysis provides a new critical bridge between a spatial concept applied in multi scale landscape analysis and GIS and the synergy between image objects and their similar radiometric characteristics (Blaschke 2010).

As with all natural areas around the world, forest canopies are constantly changing. Another method of classifying these changes is to use an image analysis method known as change detection. This is accomplished by using repetitive image coverage at short intervals and identifying changes in the radiance values between multiple images. This will produce a final image showing where land cover has changed based on the spectral values. This is generally a pixel based analysis produced by the subtraction of 2 images. Pixels that show no change within the time period will be distributed around the mean, while the pixels with significant spectral change (*e.g.*, a tree that has died) will appear in the tails of distribution and therefore be highlighted as a changed area. This can be a very effective way of identifying forest canopy and vegetation changes as well (Mas 1999).

MATERIALS AND METHODS

The flights and data collection used in this thesis were conducted in conjunction with the Lakehead Region Conservation Authority within a high traffic conservation area that the organization maintains outside of the city of Thunder Bay, Ontario (Figure 1). Cascades Conservation Area is located north of the city within a 15 minute drive for most residents. Cascades is extremely popular for its spectacular rapids along the Current River which runs through the 162 hectare park. There are 5.5 kilometers of trails on the property including a popular 775 meter loop which is paved to be accessible to all abilities. There is also a pavilion area with BBQ's and interpretive displays highlighting the geological, hydrological and botanical features of the area. (LRCA 2016).

Our focus on Cascades Conservation Area is based on not only the presence of large volumes of visitors but also on the history of human interference in natural processes when preserved for protection. The Lakehead Region Conservation Authority is located within the Boreal Forest. In this biome, forest fires are the primary mechanism for stand replacement which creates new young stands while eliminating older dead or dying timber. This rotation is generally around 70 years naturally (Lee *et al* 1997). Inside protected land such as our focus area though, fire suppression is often practiced to maintain the aesthetics of the area for visitors and protect infrastructure. While this can result in major shifts in ecosystem structure and function, the real concern with respect to this study is the possible over-maturity of the forest, resulting in more potential dead standing trees. Fire exclusion eliminates the ability of nature to thin out dead or dying trees (fuel for the fire) within the natural fire cycle (Covington & Moore 1994). This highlights the importance of finding new innovative ways to identify these hazards.

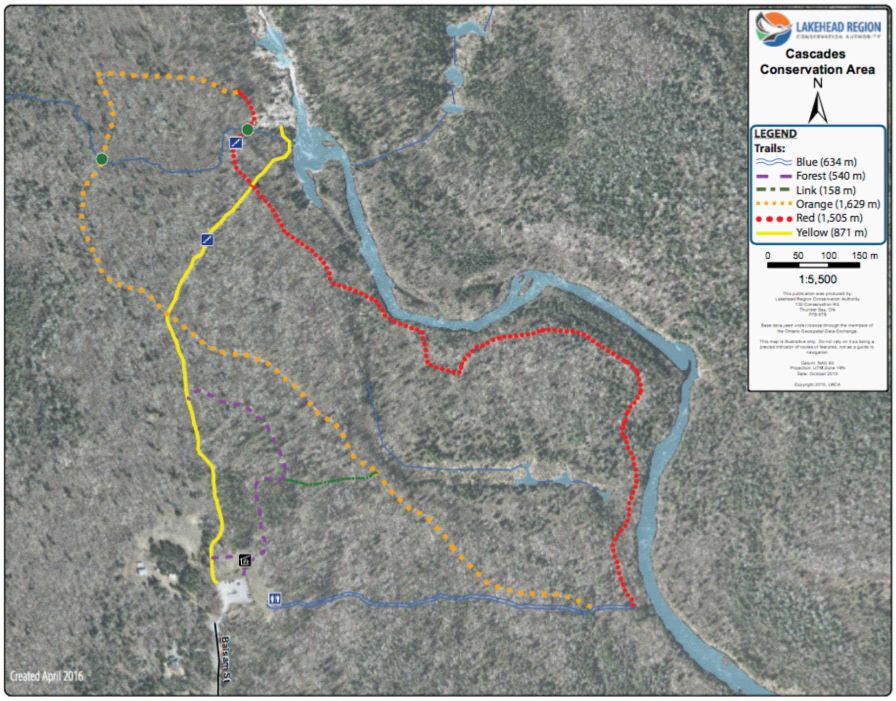

Figure 1. A map of the trail network at Cascades Conservation Area.

Since the focus of the hazard tree identification is on public safety, the flight path will attempt to follow and capture only the area surrounding the high traffic areas within the park, mainly the pavilion areas and trails. Table 1 lists the trails to be used in this study.

Table 1. A summary of trails in Cascades that should be captured for the purpose of this study.

Trail Name	Distance (km)
Forest Trail	0.775
Blue Trail	0.634
Orange Trail	1.629
Red Trail	1.505
Yellow Trail	0.871

Due to limitations, (see also the Discussion section below), the data was flown manually resulting in minor errors. If autonomous flight was possible we would've used a buffer imposed around the specific trails and areas of interest and clipped the imagery down to this smaller focus area for the analysis. The buffer would be 30 meters, which is above the average tree height in the park (Figure 2). Any tree in this buffer would therefore be at risk of landing on a trail if it were to fall.

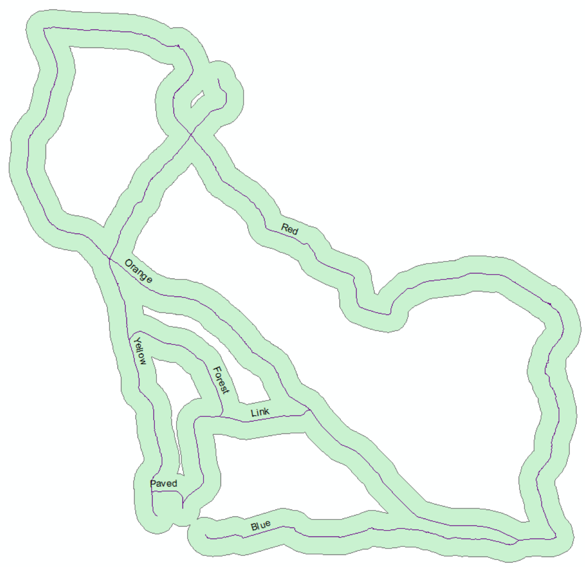

Figure 2. An example of the 30 meter buffers surrounding the trails at Cascades

The data collection was flown during the winter season in the target areas partly due to the timing of this thesis project but also because this is when we expect to see the biggest thermal difference between dead and living trees. This is hypothesized because the lower temperatures are likely to accentuate the effect that water inside the living trees trunk has on its overall temperature, as opposed to dead hazard trees which are more likely dry. However, this brought about a significant number of challenges, the most limiting issue being the battery life under cold weather conditions. The most common type of battery used in these devices are lithium ion batteries which have a significantly reduced capacity under cold weather conditions. To combat this, strategies were employed to maintain the batteries temperature above the recommended limit (usually about 10 degrees celsius) pre-flight until the moment before takeoff. Once in the drone, the battery will be able to maintain most of its heat with the help of energy losses from the drawn current. Efforts to accomplish this are not difficult and can be as simple as keeping the battery in the inner pocket of a jacket or inside a polystyrene casing. Another possible issue with winter flights was icing on the wings. Generally however if the sky is clear this is not a major concern. The only exception being when the temperature is around 0 degrees Celsius, which is when humidity in the air could cause ice issues (Ader & Axelsson 2017).

Our imagery was collected with the Mavic 2 Enterprise Dual which was released by DJI in late 2018. The Enterprise Dual is a compact unit that folds up to fit with all its gear (batteries, remote, etc) into a small carrying case making it ideal for field work. The second generation of the original Mavic drone includes advances in autonomous flight through obstacle avoidance and alerts to any nearby aircrafts which makes the device incredibly simple to fly regardless of experience level. The real advances with respect to this project though is the built in dual camera system. It includes a standard visible spectrum camera as well as an integrated radiometric FLIR thermal sensor. These video feeds can be seen separately or used in conjunction for an enhanced thermal display using object detection from the visible camera. This makes identifying ground features easy from the air even while filming using the thermal sensor.

The data collected for use in this research was collected over 2 days of field work on February 27 2019 and March 9 2019. Advanced notice was given to the Lakehead Region Conservation Authority and appropriate signage was posted to inform park visitors of our work.

Because the Mavic 2 Enterprise Dual is brand new technology, the appropriate software needed to program autonomous flights using the trail shape files from Cascades is still being developed. As a result, all the imagery used, was flown manually. This proved to be quite difficult as without the trail routes preprogramed, we had to visually identify them from the air using the camera footage as we flew. Our data collection method consisted of 4 base locations from which we took off and landed. From each location we were able to capture the forest area surrounding all sections of trail in the immediate vicinity. Once the battery range was exhausted, we moved to the next site with a new battery to collect from there.

As a result of the uncertainty surrounding processing imagery from such as new drone, the data was collected both in video and still photo format. The intentions of collecting the video was to then separate it into photo frames for stitching and analysis using an ESRI ArcPro extension named Full Motion Video. The video multiplexer within it is designed to extract frame by frame still images from the video which are automatically georeferenced for analysis. The resulting thermal imagery layer would then be clipped to reflect the buffer zone surrounding each trail. This would reduce the amount of un-needed data and therefore would also reduce processing time. Unfortunately due to software difficulty working with this drone model the plan was not realized. Instead a less detailed approach had to be taken due to technology and time constraints.

The video had to be ignored all together in favour of using individual photos for analysis. A set of 3 photos taken at various locations along the trails were used for analysis to attempt the identification of dead standing trees. The 3 images used, were chosen, as they appeared to provide the best thermal variance between trees, therefore giving the best chance of identifying differences between dead and living. Additionally, 6 more photos all from the same location were analyzed to determine if there is an optimal flying height to identify individual trees. Image locations and launch sites can be seen in Figure 3.

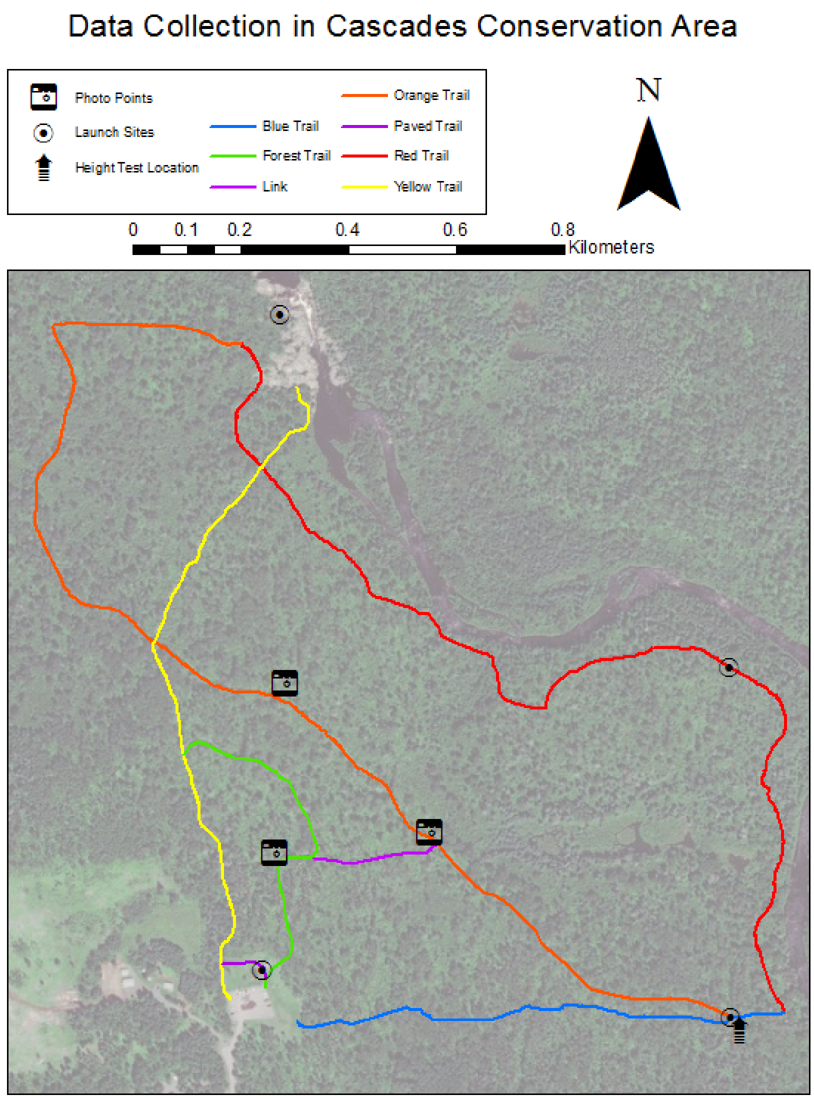

Figure 3. A map showing the GPS points of the 4 launch sites, 3 picture points and location of the height test photos

With the absence of fully georeferenced thermal imagery, identifying and pinpointing dead trees on the imagery for classification reference was not possible. As a result, there was no baseline to start the classification. Instead, a series of ground photos were used to identify sample trees in each image for prior thermal information which is needed for classification. Different classifications were done including a pixel based unsupervised classification and a supervised classification both done in ERDAS Imagine as well as a supervised object based classification done in eCognition on each of the 3 single images. All types of classifications were compared as best as possible to the ground truthed trees using a series of ground photos collected at the location each image is geotagged to. The ideal method of analysis would be to have ground truthed dead trees marked directly on the images for a comparison of spectral properties but this was not possible with the Mavic 2 Enterprise Dual Drone. Using the ground photos as a reference for the presence of dead trees in the aerial thermal image, a visual assessment of the difference in classification between individual trees was used to determine feasibility.

The second part of the analysis was to determine whether the height the imagery is flown at significantly affects the accuracy of a classification scheme. This will be done in a similar manner by classifying all 6 images from heights ranging from 20 - 70 meters. For this analysis, identifying dead hazard trees is not the priority. Instead focus was placed on simply identifying individual trees from different altitudes. This was because the largest effect height will have on the image is increased ground representation in each pixel meaning decreased resolution at higher altitudes. This could make identifying individual trees for assessments such as this much more difficult.

Our final analysis is hoped to conclude whether or not thermal imagery possesses the possibility of hazard tree identification in the future and if so, whether or not the Mavic 2 Enterprise Dual is appropriate for such analysis.

RESULTS

The 3 images used to assess the feasibility of using thermal imagery for hazard tree identification are referred to as 078, 112, and 136 which correspond to the image identification numbers on the original photographs. Identifying dead standing trees using computer classification requires a baseline to determine what spectral properties within the image represent a dead tree versus a living one. In the absence of photo georeferencing, visual assessments of the aerial thermal image compared to visual images taken using the Mavic 2 Enterprise's Dual camera system, and photos taken from the ground were used to identify dead trees from each image. 2 dead trees and 2 living trees were chosen in each image for use as samples for classification, they were circled respectively red and green to represent dead and living and then given unique identification numbers. This process can be seen in Figures 4 - 6.

Once a baseline was established we were able to complete 3 different classification tests. The first was an unsupervised classification using the image classification software ERDAS Imagine. The process of completing an unsupervised classification was the simplest of all the methods undertaken but generally results in the least accurate result. The steps consist of uploading the photos into the software and then simply instructing the program to conduct an unsupervised classification of the images. This involves specifying how many classes to create and then letting the software determine for itself the appropriate ranges of values for each class. The program was instructed to create 3 classes, one for living trees, one for dead trees and one for everything else. The results of this first rudimentary classification were predictably unsuccessful as each tree in the image was classified the same way with no difference between the dead and living trees. The results can be seen in Figures 7 - 9 with the reference trees circled and identified as well in each.

Image 078

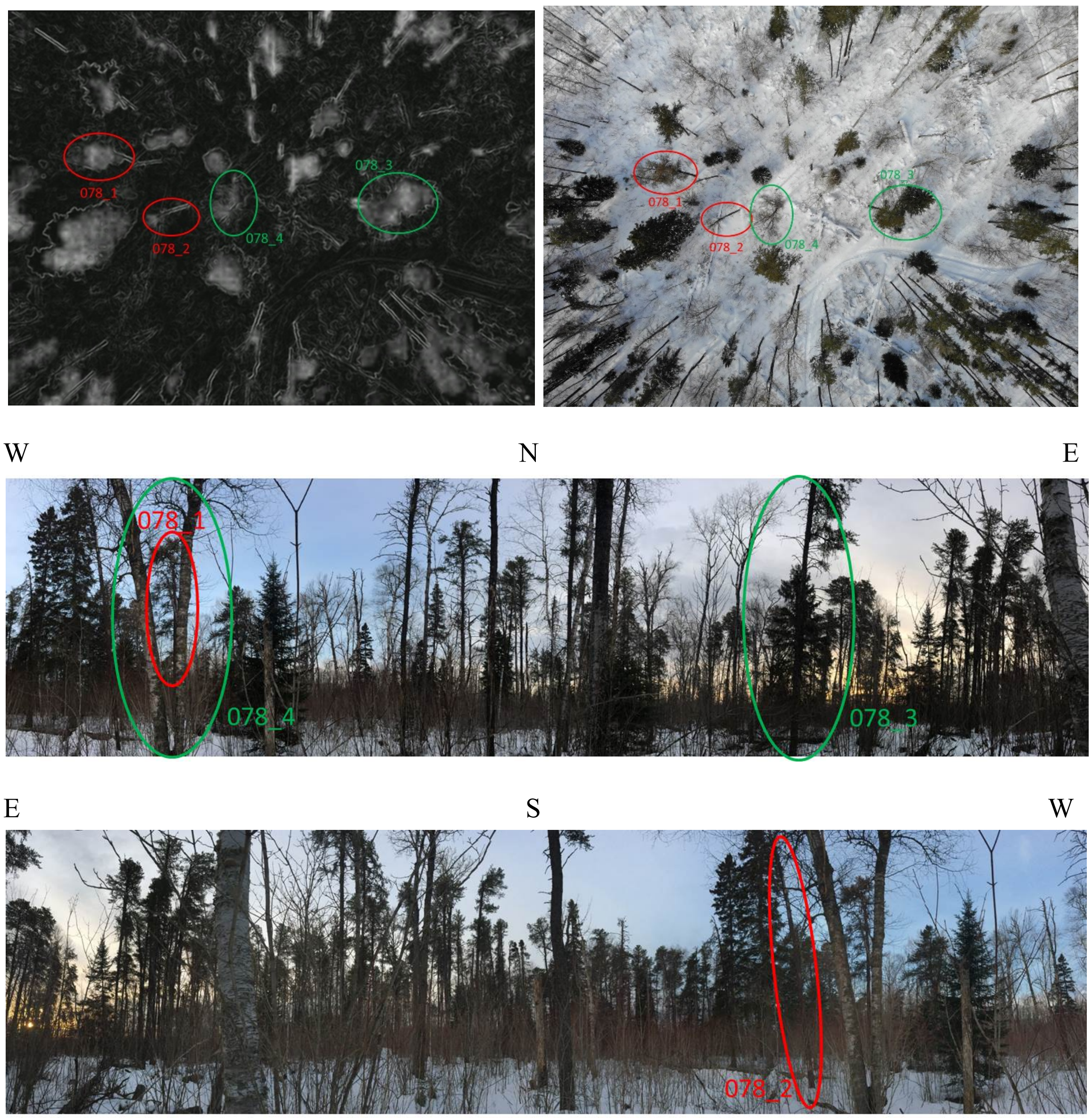

Figure 4. A comparison of the thermal image 078 with a spectral image of the same location and a 360 degree view from the ground at the same location.

Image 112

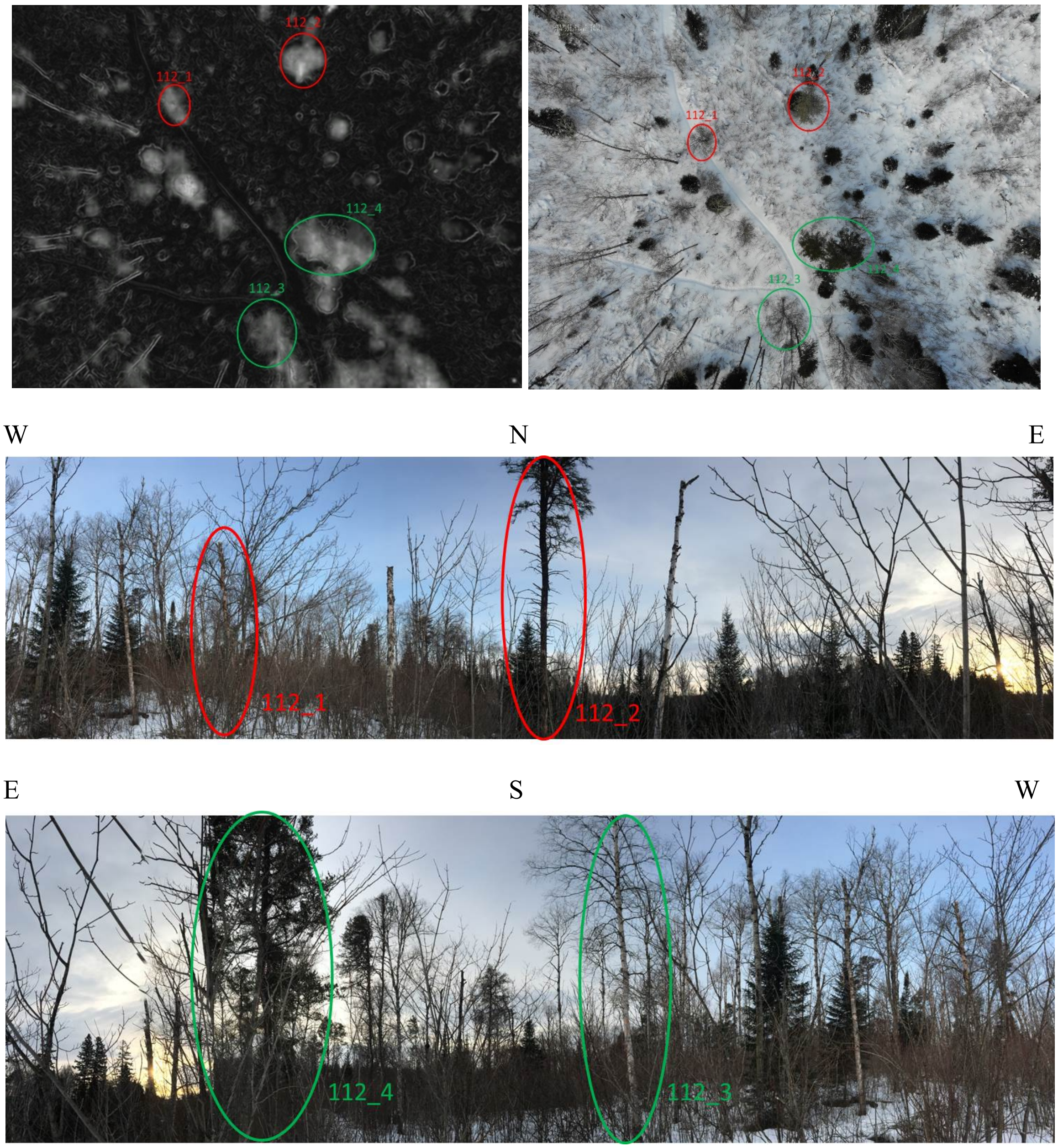

Figure 5. A comparison of the thermal image 112 with a spectral image of the same location and a 360 degree view from the ground at the same location.

Image 136

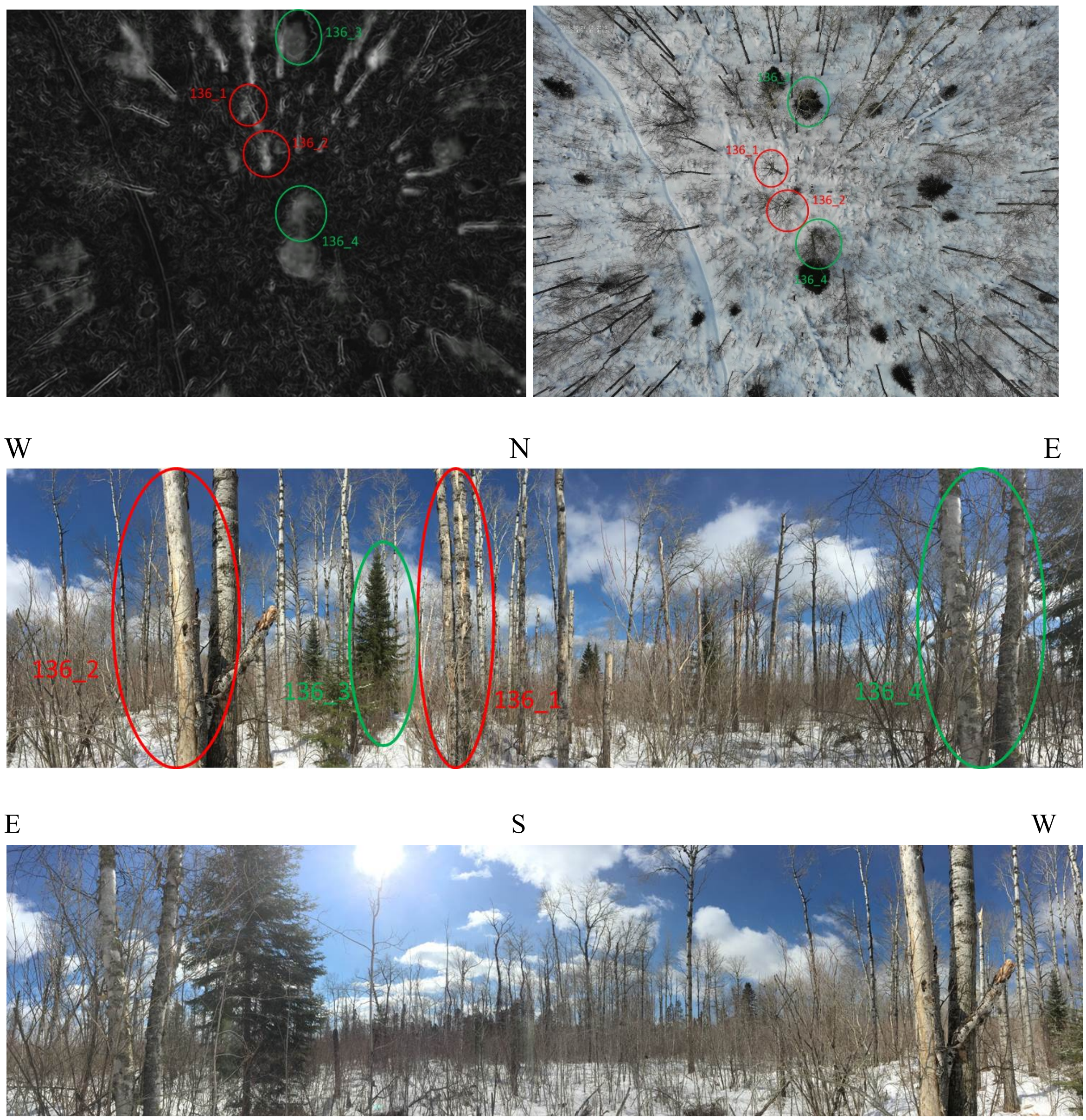

Figure 6. A comparison of the thermal image 136 with a spectral image of the same location and a 360 degree view from the ground at the same location.

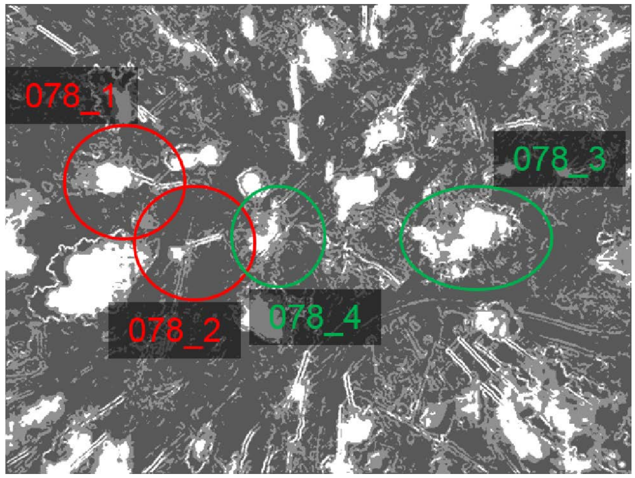

Figure 7. Image 078 with a 3 class pixel-based unsupervised classification, showing no difference between living and dead trees.

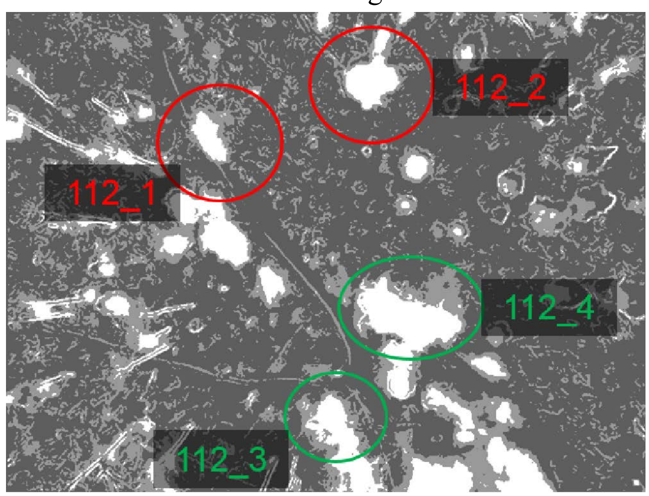

Figure 8. Image 112 with a 3 class pixel-based unsupervised classification, showing no difference between living and dead trees.

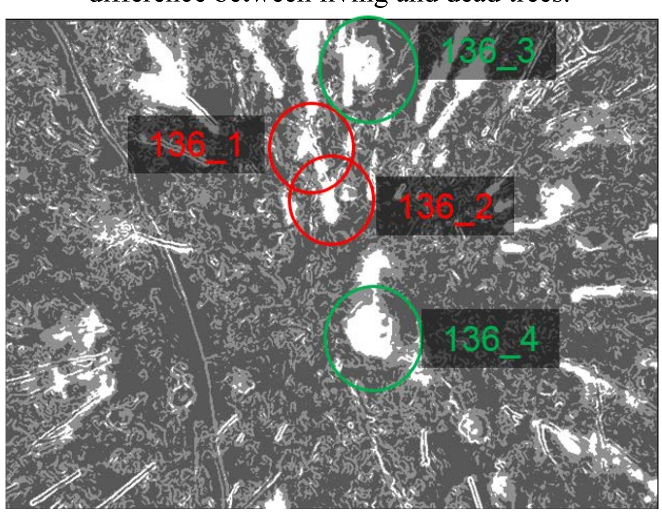

Figure 9. Image 136 with a 3 class pixel-based unsupervised classification, showing no difference between living and dead trees.

Using the same program, ERDAS Imagine, the next step was to create a new classified image this time using a supervised method. Once again the images were loaded into the software but this time around, I used a drawing tool to create polygons around the 2 dead and 2 living tree canopies identified as references in each photo, as well as a number of samples representing the forest floor. The thermal values within each polygon were then used by the computer as a reference to what constitutes the classification of each. Generally, this results in more accurate classification results, however as seen in Figures 10 – 12 this was not the case.

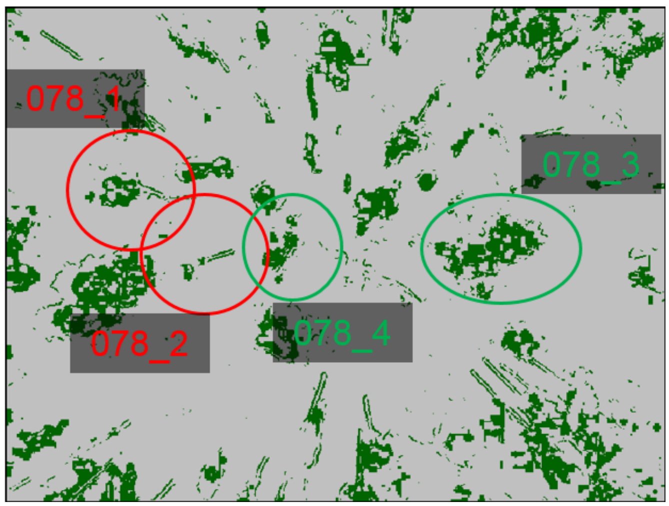

Figure 10. Image 078 with a pixel-based supervised classification using thermal values from referenced dead and living trees in the image.

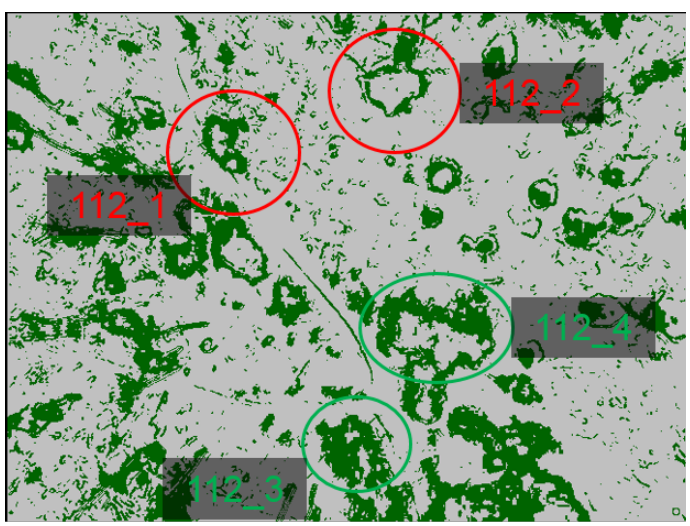

Figure 11. Image 112 with a pixel-based supervised classification using thermal values from referenced dead and living trees in the image.

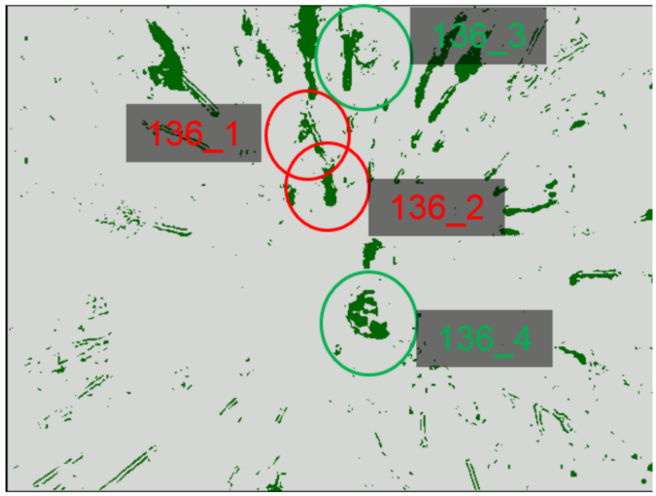

Figure 12. Image 136 with a pixel-based supervised classification using thermal values from referenced dead and living trees in the image.

Not only did the supervised pixel based classification fail to differentiate between dead and living trees, but the difference in thermal values between the two was so minuscule that all the trees were given the value of the same class (green for living tree) similar to the results of the unsupervised classification.

The third and final classification method was a supervised object based classification which involves more steps to complete and is therefore more time consuming for implementation, however it is often the most accurate of all 3 methods. The program used is called eCognition, in which you can upload individual images to first be classified into objects. The program uses the images thermal characteristics to separate it into small objects, essentially separating the trees from the ground before the primary classification even begins. By setting a high shape value during this phase, the program will also ensure that shape has a strong influence in the definition of objects. The result is an image separating the trees and surroundings into smaller objects each with averaged pixel properties from what lies within them. The averaged pixel properties in each object consists of characteristics such as standard deviation from the mean, brightness, maximum difference and more, which gives the program more values to use in the classification (Figure 13).

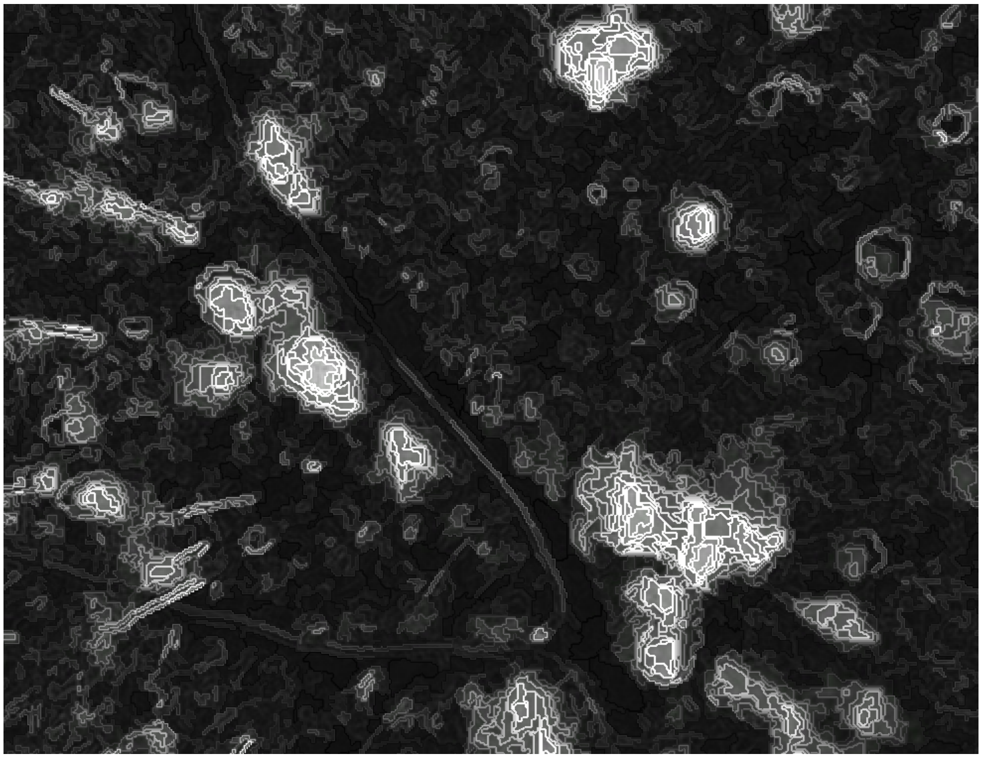

Figure 13. An example of an image (112) classified into objects, to create more consistency between pixels in the hopes of a more accurate classification.

Once the objects are created, the supervised classification was similar to the pixel based method, except that since the sample objects are automatically classified as what they are identified as, I only used one of each tree as a sample to see if the second would end up being classified correctly. Figures 14 - 16 show the results of the supervised classification with the dead sample tree pointed out, since dead tree identification specifically was our goal.

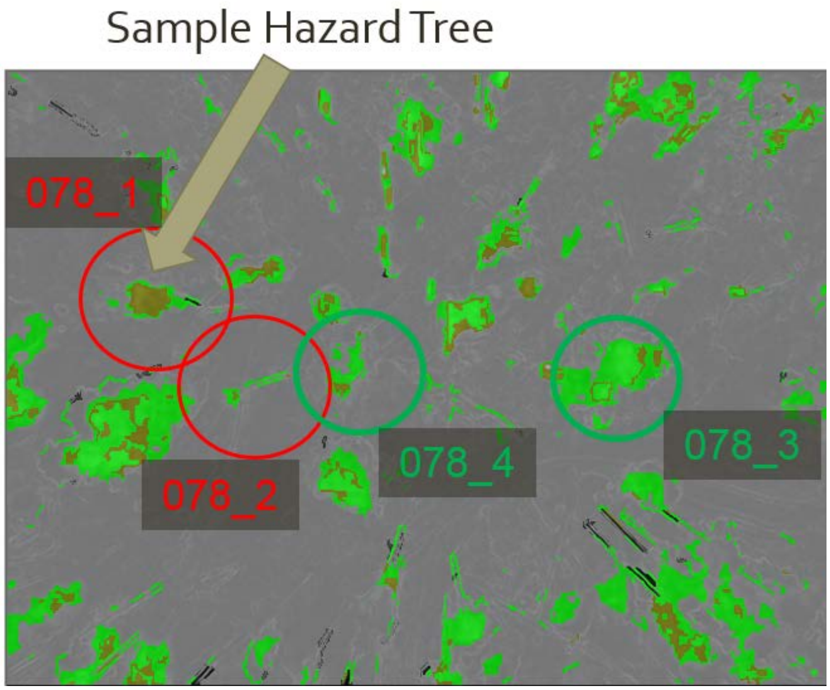

Figure 14. Object based supervised classification for image 078 with the dead tree used as a sample pointed out. Brown objects are classified as dead and green represents living.

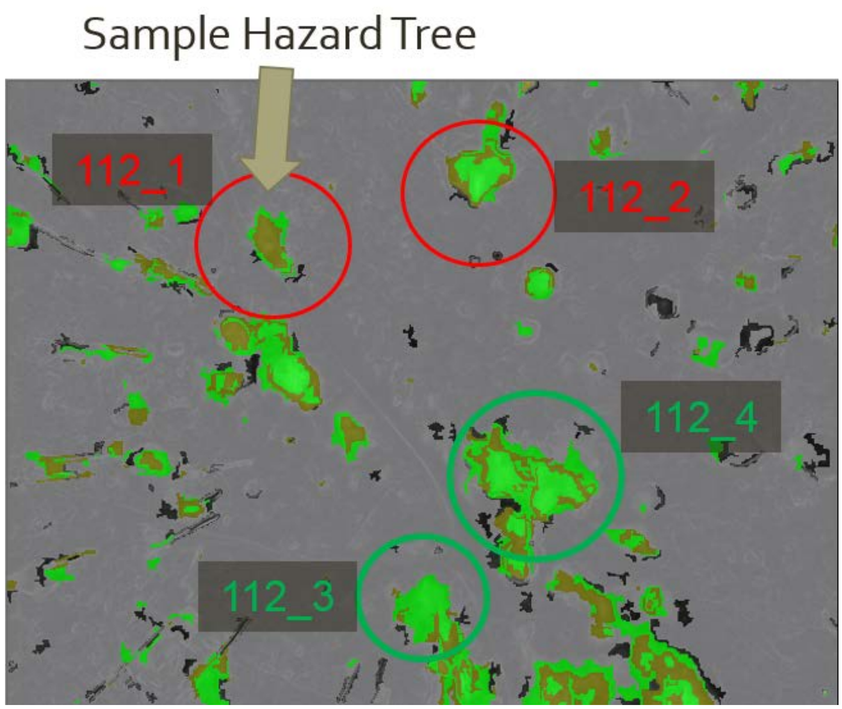

Figure 15. Object based supervised classification for image 112 with the dead tree used as a sample pointed out. Brown objects are classified as dead and green represents living.

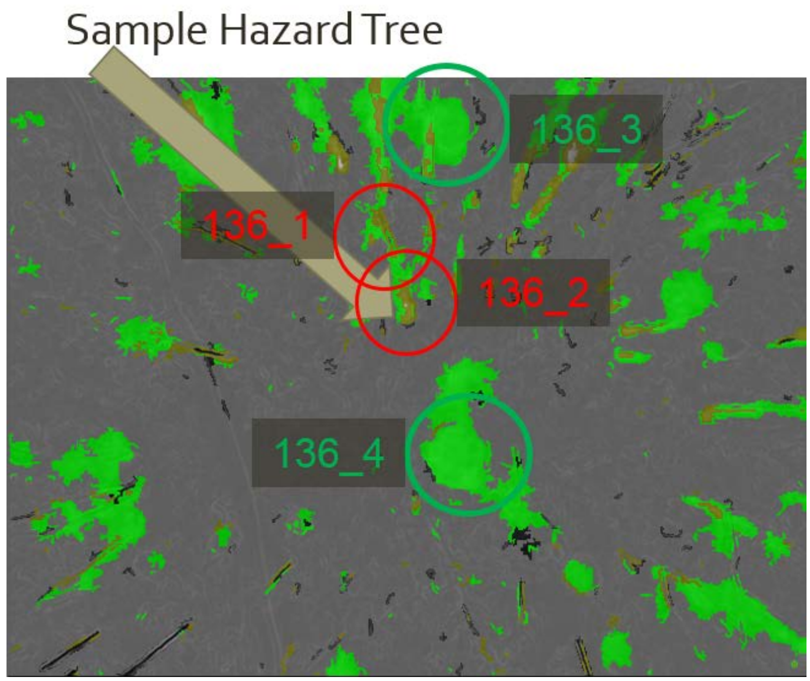

Figure 16. Object based supervised classification for image 136 with the dead tree used as a sample pointed out. Brown objects are classified as dead and green represents living.

The final of the 3 classification methods tested produced the most promising results with the second dead tree in 2 of the 3 images being classified as dead (when looking at the center of the tree).

The imagery for this analysis was flown at 50 meters' elevation, but given the importance that resolution plays in classification and image processing, a series of aerial images were taken of the same area at 10-meter height intervals between 20 meters and 70 meters to determine if there was an optimal height above ground to fly for this type of analysis. Using the images in Figure 17, an object classification was done on each one to see which appeared to allow the easiest identification of individual trees.

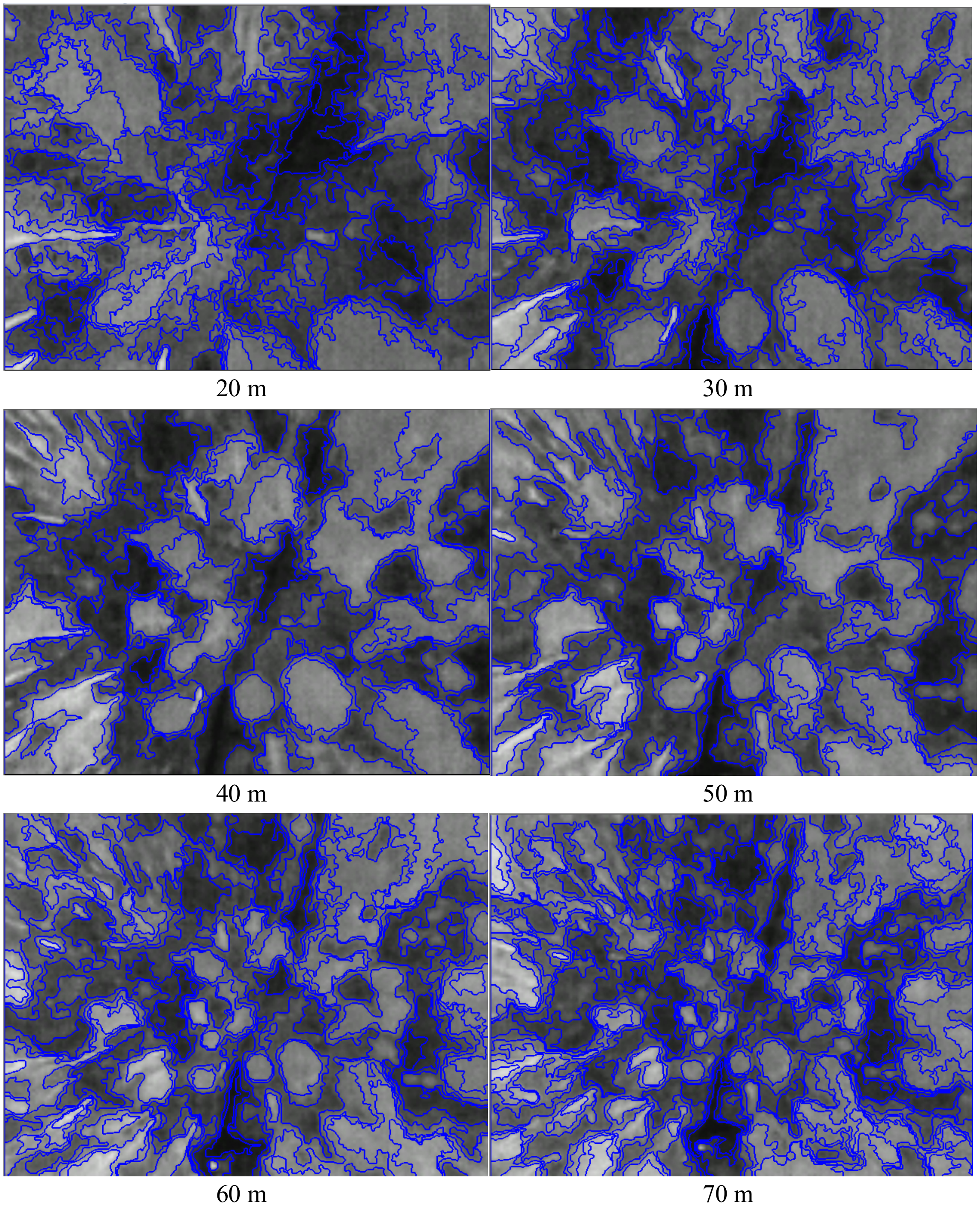

Figure 17. An object classification of individual trees at different heights to determine if there is an optimal flying height for hazard tree identification.

DISCUSSION

Despite the promising results seen in the third classification method (object based supervised classification; Figures 14 -16), significant technological hurdles must be solved before effective implementation of this method can be considered. The most significant factor holding back the use of the Mavic 2 Enterprise Dual for this type of field work currently is its release date. The Mavic 2 Enterprise Dual was only released on December 20th 2018 which was what led to this study investigating its potential for this type of analysis, however this also led to limitations. There is a distinct lack of software available that works with this drone for everyday flight and image analysis tasks. The DJI Pilot application, which is currently the only compatible flight app with the Mavic 2 Enterprise, has yet to release an update which allows autonomous flying for the Mavic 2 Enterprise Dual model. Autonomous flight would be ideal for hazard tree identification as a set of trail shape files similar to Figure 2 could be uploaded as a flight path and then the equipment could direct its self to ensure the area was covered. Autonomous flight and data collection could also ensure a more consistent overlap between images which is important for creating image mosaics and georeferencing later on. Without this feature though, we had to fly manually while visually following the trails of interest from the air, while simultaneously capturing photos as consistently as possible. This is much more challenging and nearly impossible to maintain centering overhead the trail while flying. It is because of this challenge that the original plan was to fly manually and record video instead, so we could keep focus on flying the correct path. However once again it was technological limitations that prevented us from implementing this method.

With the aerial video footage from most drones, a tool called a video multiplexer within the popular ArcPro computer program offered by ESRI can be used to create a compatible file for the Full Motion Video tool, which can then extract individual frames to georeference images on the landscape. To compute and display the relative corner points of the video image footprint on the map, a series of required metadata is needed from the drone. This includes, time stamp information, latitude. longitude, altitude, heading, pitch, roll, sensor relative roll, elevation, and azimuth as well as the sensors horizontal and vertical field of view. The majority of which is present in the Mavic 2 Enterprise Dual's flight log except for the sensor information, specifically the horizontal and vertical field of view. These camera specifications for the onboard thermal sensor are not readily available which makes displaying the images accurately, impossible. Many other popular drones have their camera specifications programed into the Full Motion Video tool however due to the recent release of the Mavic 2 Enterprise Dual, ArcPro has yet to update their software to be compatible with this new equipment. This was a major blow to our analysis and is what forced us to use the limited number of aerial photographs we took while manually flying.

Agisoft is a popular and common software used to stitch together a series of images into one georeferenced image using the metadata available to us, which included each images coordinates and altitude information. Unfortunately, as a result of technological limitations once again, creating an image mosaic using Agisoft proved impossible. Because of the lack of consistent image overlap (due to lack of autonomous flights) the program failed to identify matching features between images to combine and stitch together (Figure 18).

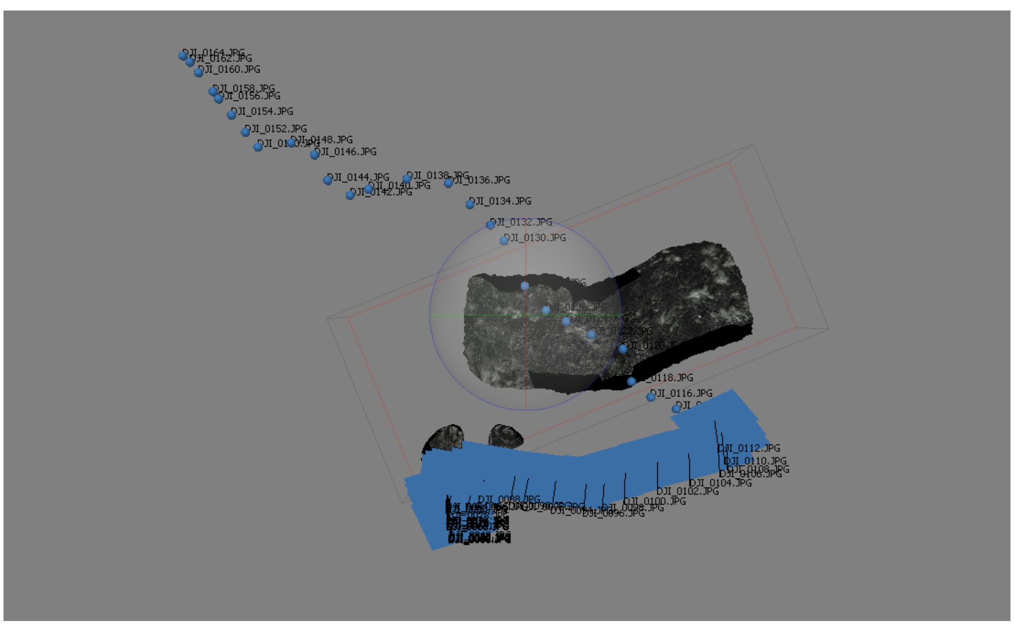

Figure 18. Screen capture from Agisoft showing only ½ the photos combined, based on overlap.

As a result, only about half of the set of images were combined (Figure 18). Of the limited photos that were successfully mosaicked and georeferenced, the low resolution of the thermal sensor resulted in significant distortion in the final image. The distortion made picking out individual trees, as is needed for this analysis impossible as shown in Figure 19.

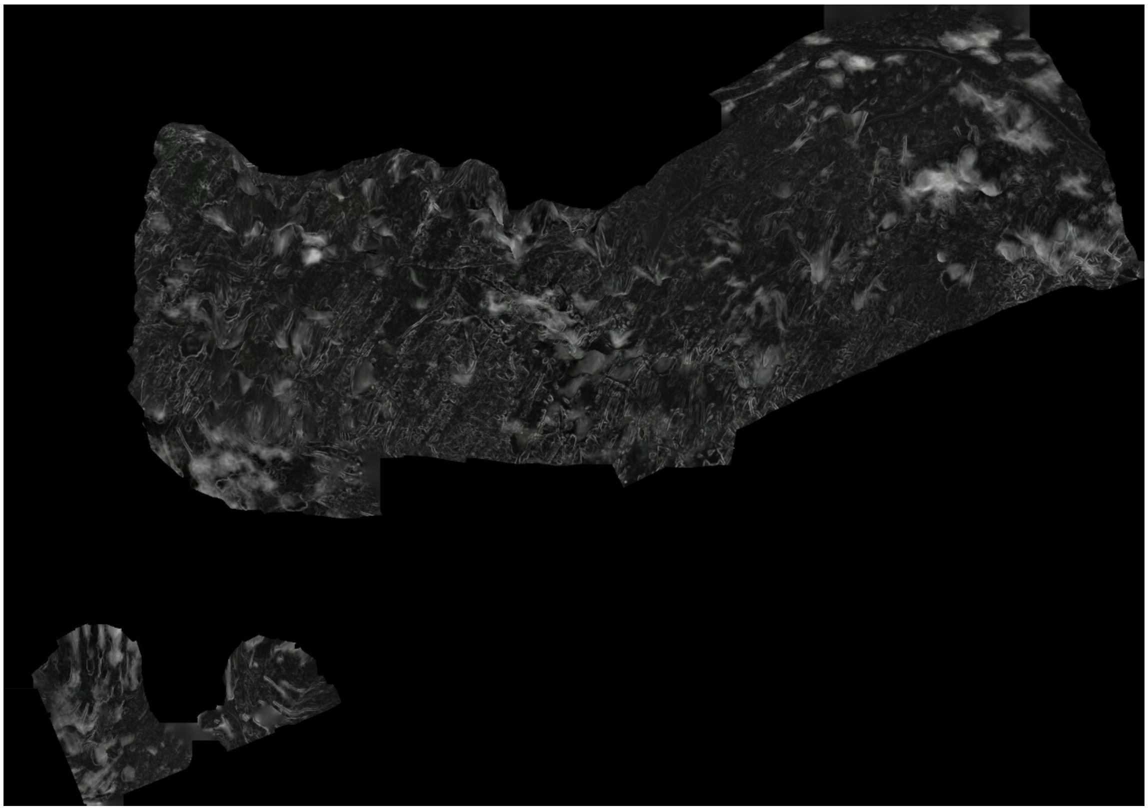

Figure 19. The final mosaic that was created using irregularly spaced images in Agisoft. There is significant distortion making the image useless for photo classification.

The failure of these standard methods for creating workable georeferenced images for classification, unfortunately meant the depth of this study's final results would be slightly compromised since all the classification would have to be done without the images being georeferenced. Instead we had to classify a number of individual images and use ground truthing and photos to pick out where trees of interests were located in each image. This meant that even if we did get meaningful success, the location of any additional dead trees that were classified would be difficult to point out in the field. However, using the individual images still presented us with an opportunity for an effective proof of concept study to determine the feasibility of this method should the technology improve in the future.

There are 2 main types of classifications used in all fields, pixel and object based. This study was no different, so we started with 2 pixel-based classifications, one unsupervised and one supervised followed by a supervised object based classification. The order of these classifications were strategic as they generally are progressively more accurate which is also shown with the increasing complexity of each one. We started with the pixel based classifications (Figures 7, 8, 9, 10, 11, & 12). As we expected with both, the results were relatively inaccurate. They did pick out the difference between what is a tree and what is not, however the difference in thermal characteristics between living and dead trees was too small to accurately pick out using this method.

An example of a histogram (Figure 20) from one of the images illustrates the sharp differences between thermal values. A very high number of pixels (14693) have a value very close to the average which in this case is 38.794, likely representing the value of the forest floor that covers most of the image. After that there is a sharp drop where the rest of the pixels have relatively high values with less separation. The large difference between the ground values and the vegetation values is much more obvious than the difference between individual living and dead trees, which explains why the pixel based classifications had no trouble with this differentiation. By using individual pixels for classification as well, it increases the likelihood of including forest floor values that show through the canopy of the trees in the samples for supervised classification, which would certainly decrease the accuracy of the final results.

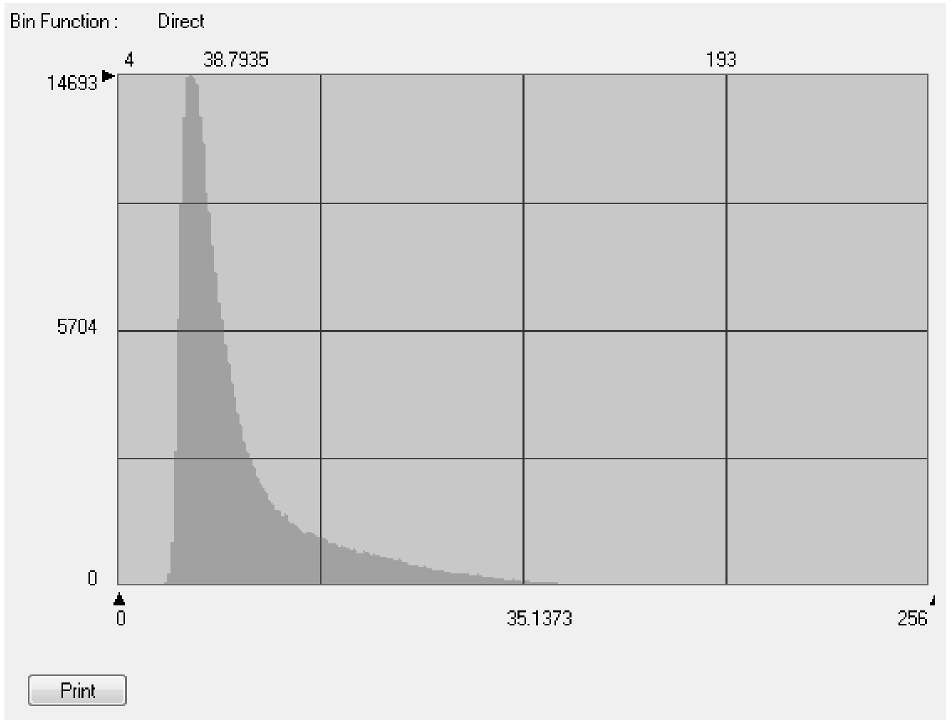

Figure 20. An example of a histogram from image 078 showing the sharp difference in thermal values throughout the image.

The third and final method of classification attempted to fix this issue using object based classification. By classifying the tree canopies beforehand using the unique pixel characteristics and averaging the values within each object, the ground values would have less of an effect. It was also likely to create a more distinct spectral difference between objects for classification. Due to these factors, the object based classification (Figures 14, 15, & 16) of the 3 images produced much more promising results. In images 078 and 136 (Figures 14 and 16), the second dead tree (078_2 & 136_1) that was not used as the sample, was identified as dead (brown classification). Although not all the objects covering the trees canopy received this classification, the center of them did, which was different that the rest of the trees in the image. The only exception was in image 112 (Figure 15), dead tree ID 112_2 still appeared as living (green classification) in the center of the canopy. However, there is a likely reason for this, as can be seen by looking at the visual images and ground photos for image 112 in Figure 5, it can be clearly seen that there is a living conifer tree beneath the open canopy of the dead tree

(112_2). This could have potentially led to this anomaly. The partial success of this method of classification can most likely be attributed to the increased number of pixel characteristics including brightness, standard deviation from the mean and more, that are included in the definition of objects. Using objects also minimizes the effects that individual thermal readings from the forest floor can have through the canopy of individual trees. However, the method is far from perfect.

Figure 21 clearly shows how much overlap still exists between the object values of a dead tree versus an alive tree. It is an example from image 078, however image 112 was also very similar. Both dead and alive tree properties occupy the same range of values regardless of which image characteristic is being used and the overlap value is high for each. This demonstrates that there is still only minor differences between the properties of a dead and living tree in most cases, and also explains why none of the classified trees were shown as entirely dead or entirely living since the difference was so minor. However, there was an exception this pattern in image 136 which had a lot less overlap between the two (as shown in Figure 22). This was unexpected, given the limited range difference of thermal values we had been seeing in the other images. The most likely explanation for the significant difference is by looking at the trees stage of death. By looking at the visual ground images for image 136 in Figure 6, it can be seen that both dead trees have their bark falling off, if not already gone in a lot of places along the trunk. This indicates the tree has been fully dead for a long time period whereas others may still be hanging on with part of the canopy or a few solitary branches living.

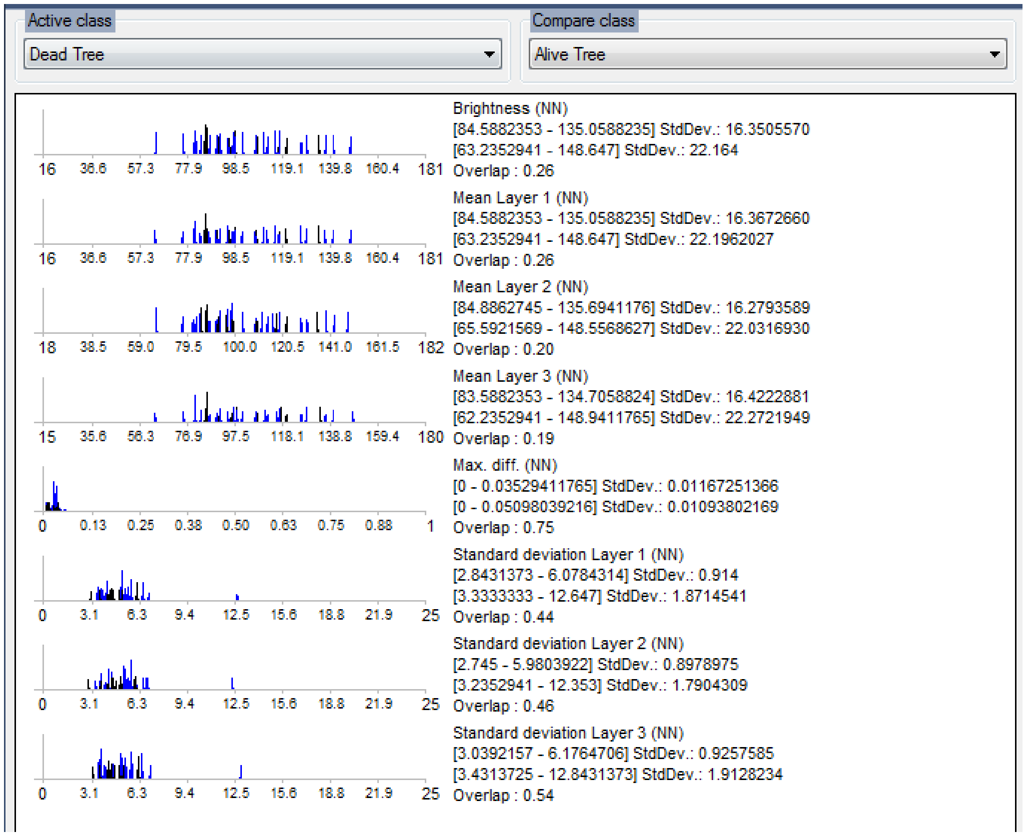

Figure 21. A screen capture showing the difference in object values between dead trees (blue lines) and alive trees (black lines) for image 078, using the sample trees from the supervised classification.

The object based supervised classification gave us the most promising results of the 3, it demonstrated that under certain circumstances, mainly the reduction of ground thermal values in the canopy and the introduction of more image characteristics, dead trees that pose a hazard to park users have the potential to be classified using thermal imagery. However, it has also become apparent that characteristics such as the stage of the trees death and the species (hardwood or softwood specifically) can drastically affect the accuracy of such classification.

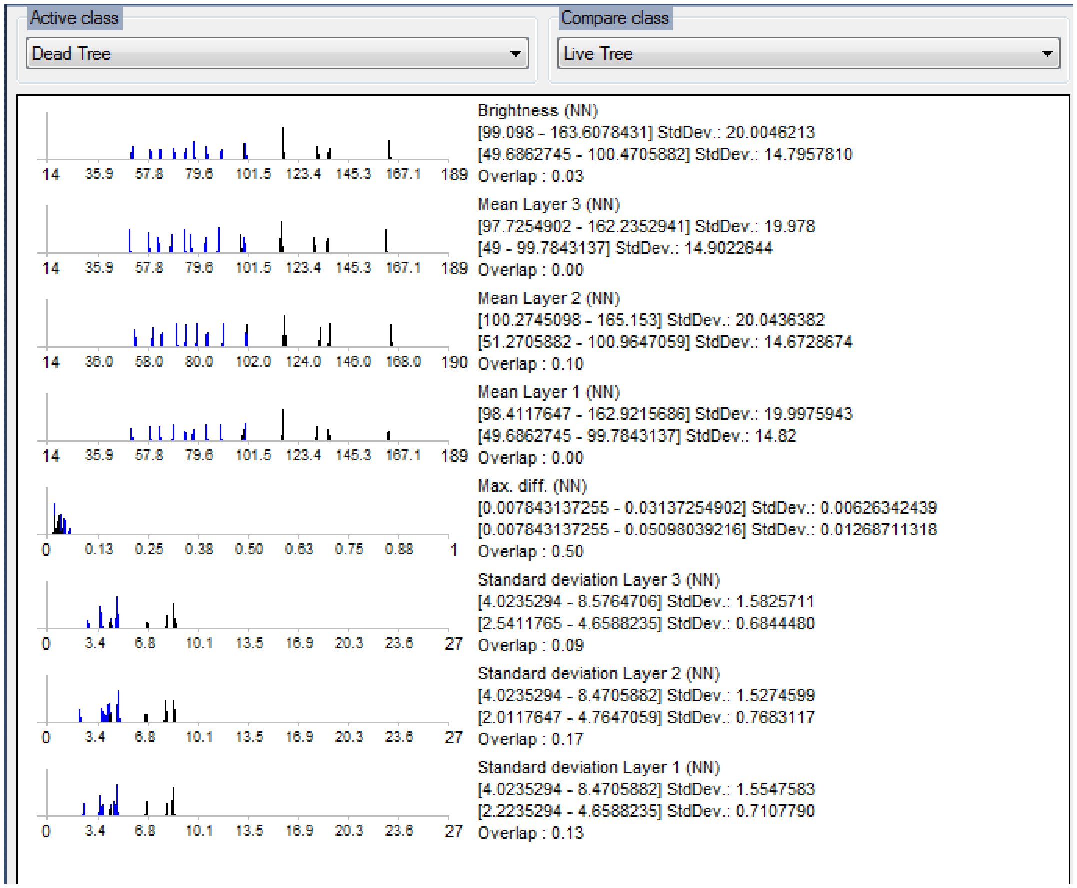

Figure 22. A screen capture showing the difference in object values between dead trees (blue lines) and alive trees (black lines) for image 136, using the sample trees from the supervised classification. Much less overlap between the two is seen.

By testing a variety of different flying heights as well, we were able to determine that a flying height of 40 - 50 meters was ideal with the current generation of thermal sensor on the Mavic 2 Enterprise Dual. The stark differences can be seen between the different heights in Figure 17. Between 20 - 30 meters, the sensors could pick out individual branches and ground features which makes identifying individual trees difficult. Between 40 - 50 meters, individual trees could easily be picked out and at an appropriate size for classification. At 60 meters or higher the classification was also able to identify individual trees, but they were much smaller which would make classification much more difficult. Not only that, but the thermal radiation from groups of trees in close proximity also begins to merge together due to reduced resolution at this height which further reduces the effectiveness of individual tree identification.

Therefore, we were able to conclude that if this study is revisited in the future, our flying height of 50 meters is ideal. Again, in the future with less technological limitations reducing the capability of this analysis, there is significant potential here for park managers to increase the safety of visitors in a time and cost efficient manner

CONCLUSION

There does appear to be slight differences between living and dead trees when it comes to thermal imagery. This is demonstrated in the rudimentary classification of all 3 test images using an object based supervised classification. It is apparent though that that are a variety of technological issues preventing large scale adoption of the assessment method. First and foremost was the lack of compatible software to georeference the video and photos into a workable format. The features of the drone itself is also preventing the Mavic 2 Enterprise Dual from having large scale success. We know from the use of thermography for identifying structural issues with trees at ground level (Catena & Catena 2008) that there should be thermal differences present between living and dead trees. These differences were partially present in the object based classification especially for image 136, which indicates that despite the overall poor quality of the results, a more sensitive thermal sensor may have greater potential. There is also a possibility of the misidentification of reference trees using ground photos without georeferenced information, which may have skewed the results. Regardless, based off the partial success that we saw with the technological limitations we faced, it is likely that this technique could be useful in the future once technological improvements are developed.

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