Comparison of UAV–based camera data to multispectral sensor imagery for determining structural characteristics of a coniferous forest

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Abstract;

Sensors deployed on Unmanned Aerial Vehicles (UAVs) present unique opportunities for remote sensing of forest structural characteristics as images with high temporal and spatial resolutions can be collected over a specific site at a relatively low cost, making UAVs an attractive image collection platform. Sensor payload is often the limiting factor when working with UAVs, resulting in an emphasis on selection of an appropriate sensor. In this paper, pixel-based image classification accuracies for individual tree-level species and Leaf Area index (LAI) are compared between a consumer grade RGB camera and a broadband multispectral sensor, to determine which sensor is more appropriate for this application. UAV flights were conducted sequentially with a Sony WX220 RGB camera and a Sequoia Multispectral sensor at a height of 120m above ground level. Supervised pixel based classification accuracies based on spectral data resulted in overall classification accuracy of species for the RGB and multispectral sensors, at 50% and 61% respectively. Accuracies were attained for an initial LAI classification with overall accuracy of 24% and 31% respectively. Additional analysis of this dataset and investigations into the use of NIR-modified RGB cameras are suggested for future research, including object-based image classification and the use of more complex image variables such as texture derivatives, shape metrics, and 3D crown descriptors.

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Introduction;

Remote sensing classification of forested areas has a well-documented history (Pajares, 2015). While the majority of the literature refers to manned-aerial and satellite based remote sensing, Unmanned Aerial Vehicles (UAVs) are now increasingly used to collect remote sensing data (Rasmussen, 2016). Traditional image data products are used to create trajectory analysis and classifications of everything from global climate change to forest species classification and insect infestation mapping (Ahmed et al. 2017, Ewald et al. 2016, Gillanders et al. 2008). Typically, such traditional manned-aerial and satellite remote sensing images have proven to be quite reliable, and their systems and sensors rigorously designed and tested to ensure high quality data products are produced. Methods and procedures for interacting with these data in a scientifically meaningful way are well reasonably established (Omer et al. 2016). Technological advances of sensors have enabled manned-aerial and satellite platforms to collect data with sub-meter resolution with a high sampling repetition rate thus improving the ability of satellites to provide data for regional and local scale studies (Toth and Jóźków 2016). However, access to these highly-specialized datasets often come with a significant cost and the desired imagery may not be available during the time of interest. In such situations, Unmanned Aerial Vehicles (UAVs) are now a popular choice among remote sensing scientists as they can collect imagery with both a very high spatial and temporal resolution in a cost-effective manner (Pajares 2015. Reichenau 2015).

Unlike their manned-aerial and satellite counterparts, which often feature highly specialized and intensely engineered sensors, UAVs are often outfitted with consumer
grade RGB cameras, as these are lightweight and inexpensive to purchase. These consumer grade sensors do not undergo the same rigorous scientific testing as those which are mounted on satellites, as their intended use is usually restricted to casual or recreational photography. The suitability of such RGB cameras to extract quantitatively robust data for vegetation structural analysis and landcover classification has been investigated, and their reliability questioned in vegetation mapping applications (vonBueren 2015). vonBueren suggests that more comparisons between consumer grade sensors and more industrial grade sensors are necessary to determine what type of sensor is best suited for the application in question, noting that a lack of such sensor comparisons exist in the literature. Many different varieties of sensor exist that can be mounted on UAVs ranging from low to high megapixel consumer grade cameras and more industrial grade multispectral sensors which feature discrete bandwidths. With so many different options and benefits provided from each type of sensor, selecting the optimal sensor for the intended research is difficult. This study aims to compare a consumer grade digital RGB camera to a commercial grade multispectral sensor to determine each of these sensor’s respective abilities to sense structural characteristics of a forest.

Unmanned Aerial Vehicles fill a niche within the remote sensing platform ecosystem. Some lightweight UAVs can be flown at relatively low heights above the ground level, enabling them to collect imagery at an extremely high spatial resolution, in the order of centimeters per pixel in most practical applications. These lightweight UAV platforms can also be flown over an operator defined study with an ease of repeatability
that is unmatched by other platforms. While is it possible to fly manned airborne sensors over the same area multiple times in a short time span, or to program a satellite to acquire data at desired temporal resolutions these propositions can be extremely expensive. However, lightweight UAVs aren’t without their limitations, and their size is the biggest contributor to such limitations. The small size of such UAVs limits their payload, thus restricting their sensors to be very small and lightweight, leading numerous users to select a consumer grade digital camera to collect RGB imagery.

Data in the near-infrared (NIR) wavelengths of the electromagnetic spectrum have been demonstrated to contain valuable data regarding vegetation because of the interaction between photosynthesis and NIR wavelengths (Ewald et al 2016). The desire to collect NIR data has driven the spurred innovation of small and lightweight multispectral sensors as well as consumer RGB cameras to be modified to collect NIR data deployed from lightweight UAV platforms. Researchers have recognized that NIR data are valuable in vegetation studies; for example, numerous indices have been created using NIR and red reflectance wavelength data to model the health and growth of vegetation (Ewald et al 2016). This study aims to compare the ability of two different sensors, a consumer grade Sony DSC WX220 RGB camera to the Parrot multispectral sensor, to classify a coniferous forest by tree species and by Leaf Area Index (LAI).

LAI is defined as the total one sided green leaf area per unit of ground and is dimensionless (Breda 2003). LAI is an important structural characteristic of forests as it gives insight into the energy transfer and the health of a forested ecosystem (Reichenau 2015). Leaf Area Index is sensed by determining the fraction of photosynthetically active
radiation that penetrates the forest canopy in relation to the total incoming amount of photosynthetically active radiation. This allows for insights into how much energy is being absorbed by the canopy for photosynthetic processes as well as how much radiation is available for understory vegetation processes (Guillen-Climent 2012). LAI is also an important variable for estimation of Net Primary Productivity (NPP), as the number of leaves and their photosynthetic activity controls NPP and other processes which are of climatological, and biophysical interest (Gonsamo et al 2011). Given the important nature of this characteristic, workflows have been established for the calculation and derivation of LAI from various satellite platforms such as MODIS and GEOV1 (Woodgate 2015). While LAI has been a cornerstone measure used by remote sensors for decades, its calculation is often cumbersome and requires significant calibration from accurate in situ measurements (Gonsamo et al 2011. Woodgate 2015). In addition, UAV based LAI mapping is covered more sparsely in the literature and is a gap that this study attempts to bridge.

The overall hypothesis for this study is that the UAV-deployed consumer-grade RGB sensor will have higher spatial resolution than an equivalently-deployed multispectral sensor, and that this higher spatial resolution will be able to outperform the higher spectral resolution multispectral sensor at separating different classes of Leaf Area Index. Spatial resolution of imagery is an important variable to consider when planning the collection of remote sensing data for forest structural applications, particularly when designing a using a lightweight UAV platform. Typically, a consumer grade RGB camera will have a higher megapixel sensor than multispectral sensors of an
equivalent form factor; this is a function of the camera’s radiometric and spectral
resolutions. Thus, when flown at the same height the true colour imagery collected by
the RGB camera will allow discrete objects, such as trees crowns, to be more clearly
delineated than the relatively coarser spatial resolution images collected by the
multispectral sensor. The effect of higher spatial resolution, theoretically, is to improve
object discrimination within the imagery. It is recognized that the same spatial
resolution could be achieved from both a RGB and multispectral sensor by lowering the
height at which the multispectral sensor is flown, in which case the benefits of an RGB
sensor would be less obvious. However, lowering the height to achieve the same spatial
resolution with both an RGB and multispectral sensor is often not feasible, as there may
be obstructions present at lower altitudes, and lower altitudes significantly increase the
amount of time required to image the study site. Given that it is often impractical to
achieve the same spatial resolution, RGB sensors benefit from an increased ability to
discern the heterogeneity of the object in question and can better discriminate between
similar objects. This spatial resolution creates more accurate shadowing phenomenon in
the sampled imagery and can lead to improved creation of objects of interest. However,
the trade-off is that while under similar conditions RGB sensors lack the same amount of
spectral data that can be collected by multispectral sensors.

Consumer-grade RGB cameras do not collect data in the near-infrared (NIR)
portion of the spectrum, which is known to contain important information on
vegetation biophysiology, such as LAI (Jannoura 2015). This absence of NIR data
suggests that RGB cameras would be a less appropriate sensor if one is interested in
determining LAI (Duan 2014. Reichenau 2015. Liu, 2016). However, Chianucci et al. in 2016 used an uncalibrated RGB camera to assess leaf area index in a beech forest, and their results demonstrate a good correlation \( R^2=0.59-0.70 \), depending on clumping technique used) between the UAV-derived LAI and fisheye canopy imagery that was collected in the field. This conclusion suggests that RGB cameras can be suitable for LAI estimation without NIR data. Efforts to improve RGB sensor calibration may serve to further improve the correlations observed by Chianucci et al. and the ability of RGB sensors to produce comparable LAI products to multispectral imagery requires further investigation.

In 2016 Ahmed et al. reported on UAV-based forest species classification and concluded that further research using multispectral remote sensing should examine the structural characteristics of forests. This conclusion is further supported by Pajares et al. 2015, who suggested that further investigations into the uses of multispectral images should be completed. A direct comparison between a RGB camera and a multispectral sensor to assess the LAI of a forest is therefore to be completed for the purposes of this research thesis. The conclusions from this research can serve to inform researchers on what sensor type is the most suitable for determining LAI, and tree species within forests, allowing for the potential of cost savings and increased sampling effectiveness. It is hypothesized that the higher spatial accuracy provided by the RGB sensor will increase the accuracy of species and LAI classifications than the higher spectral resolution multispectral sensor when analyzed with an object-based image classification approach.
Methods;

2.1 Study Site

The study area (44°21' N, 78°17' W) is a primarily coniferous, mixed age forest of 15 ha located on the Trent University Symons Campus in Peterborough Ontario, Canada (Figure 1). Within the bounds of the imaged area is the Trent University Promise Rock Nature Area, which is used by the University for educational and research opportunities, and by members of the public for recreation. White Cedar (Thuja occidentalis) is the most dominant species within the area, but White Pine (Pinus strobus) and White Spruce (Picea glauca) and various northern mixed-wood or boreal deciduous tree species are also common (Trent University Nature Area Committee n.d.).

Figure 1. Location of the study site at Trent University in Peterborough Ontario (Ahmed et al. 2017)
2.2 Aerial Data Collection

The aerial data were collected using a Sensefly eBee “mapping drone” on August 24th, 2016 between 10:00-14:00EST. The two sensors that comprised the payload for the eBee were a 4-band multispectral sensor, the Sequoia by Parrot and a Sony DSC-WX220 RGB camera (Table 1). Initial geolocations of imagery were derived from the eBee’s onboard GPS, and the Inertial Measurement Unit supplied angular offset data from the imagery. The flights were conducted using a grid pattern of parallel flight lines with 80% longitudinal overall and 60% lateral overlap. These flight conditions resulted in a ground sampling distance (GSD), or image spatial resolution, of 3.2cm for the Sony camera, and a GSD of 12.2cm for the Sequoia. The sensors were flown consecutively at height of 120m above ground level under variably cloudy conditions, and moderately windy conditions with temperatures of approximately 28°C. The sensors could not be flown simultaneously as there was insufficient space on the UAV to mount them, and the lightweight design of the eBee cannot support multiple sensors. The windy conditions negatively affected the overlapping of consecutive images, generating inconsistencies with image overlap that were noticeable in the dataset.

Table 1. Characteristics of the Sony DSC-WS 220 and Parrot Sequoia sensors

<table>
<thead>
<tr>
<th>Sensor Name</th>
<th>Wavelengths</th>
<th>Sensor Megapixels</th>
<th>Weight</th>
<th>Ground Sampling Distance (120m AGL)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sony DSC-WX 220</td>
<td>Red, Blue, Green</td>
<td>18.2</td>
<td>105g</td>
<td>3.2cm</td>
</tr>
<tr>
<td>Sequoia</td>
<td>Green, Red, Red-Edge, Near-Infrared</td>
<td>1.2</td>
<td>72g</td>
<td>12.2cm</td>
</tr>
</tbody>
</table>
2.3 Field Data Collection

In addition to the GPS data from the eBee’s onboard GPS unit, ground control points were identified throughout the study site prior to data collection to aide in more precise image orthorectification. Five white 1m x 1m tarpaulins were placed throughout the study site in open areas, as they are easily discernable in the imagery and can also be used for radiometric calibration of the imagery. Georeferencing of ground control points was completed with a Trimble R-10 RTK GNSS unit, with sub-centimeter accuracy. In addition to these targets, other permanent features within the study site were georeferenced, such as a bench, to increase the number of ground control points and therefore improve image orthorectification procedures.

Two 120m transects were established through the forested area of the study site. Along transect A, measurements of below canopy photosynthetically active radiation was recorded using a Decagon Leaf Ceptometer at 4m intervals. The same process was followed for transect B except with a 2m sampling interval. A second Leaf Ceptometer was placed in an open unobstructed area and used in continuous sampling mode to collect the average incoming radiation at five-minute intervals. These below canopy measurements of photosynthetically activate radiation were later converted into values of Leaf Area Index (LAI). In addition to the Ceptometer measurements, tree species was also recorded at each sampling site. Species were determined empirically and recorded as the species that represented the dominant canopy cover at that location. The geographic location of the sampling points were also recorded with the
same Trimble R-10 RTK GNSS unit, however the accuracy was decreased to 5m as a result of poor satellite connection due to forest canopy interference.

Radiometric calibration was completed using an Analytical Spectral Devices (ASD) FieldSpecPro Spectroradiometer. The Spectroradiometer collects spectra between 350nm and 2000nm, with a sampling interval every 1.4nm within the visible spectrum and every 2nm in the NIR spectrum, allowing for a near continuous representation of target spectra. The spectroradiometer was used to collect a reflectance measurement every 34ms (integration time), and spectra samples were saved based on an average of the 20 most recent spectra collected. Reflectance spectra were collected once the spectroradiometer was calibrated to a target with nearly 100% reflectance. This was achieved using the “white reference” function within the ViewSpec software program. This function sets the maximum reflectance that all consequent samples will be compared against until another white reference calibration is completed. White referencing was completed using a pure white Spectralon Panel, with known reflectance of near 100% across all wavelengths before each set of samples were collected. Samples were taken of the white tarps that were also used for georeferencing, as well as strategically-deployed coloured plastic bags (black, green, red, yellow, approx. 1m square) to capture a wide range of reflectance signatures to improve radiometric calibration accuracy. Each sample was taken at nadir from a height of approximately 1m, with five spectra being collected for each target, one in each of the four corners and a fifth sample in the middle, while maintaining the same viewing geometry at all points. The samples of each target were then averaged and standard deviations determined.
2.4 – Data Processing

Aerial imagery was pre-processed using Pix4DMapper and Datamapper. Pix4DMapper is the leading industry standard software package for UAV-based image pre-processing and is easily integrated with aerial imagery collected from an eBee drone. Pix4DMapper was used to generate an orthophoto and a digital surface model (DSM) for all the datasets. However, the orthophoto and DSM from the Sony RGB camera flight did not cover the desired spatial extent due to errors of image position registration. To fill in this area of absent data another software package called Datamapper was used. Datamapper is an online cloud based orthorectification software by PrecisionHawk that uses the Pix4DMapper process, but with a unique proprietary set of optimizations. Using the Datamapper package, an orthophoto and DSM were created from the Sony sensor imagery that covered the full extent of the study area as desired.

Table 2. Comparison of image geolocation error from the mosaicking process.

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Root Mean Square Error from image mosaicking</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Geolocation Error X</td>
</tr>
<tr>
<td>Sony DSC WX220 RGB</td>
<td>0.52m</td>
</tr>
<tr>
<td>Parrot Sequoia</td>
<td>0.94m</td>
</tr>
</tbody>
</table>

Radiometric processing involved image calibration and conversion from RAW digital numbers to reflectance values. Radiometric calibration was completed using the empirical line method calibration function within the ENVI software package. The empirical line method removes the effects of atmospheric scattering and other incident
light altering phenomenon to calibrate images to the actual incoming radiance.

Calibration was completed by comparing the reflectance of the field targets to the spectra of those targets that were collected by the ASD. Conversion to reflectance from digital numbers was completed for the RGB image by dividing those digital numbers by 255. Given the 8-bit radiometric resolution of the data, the digital numbers of the imagery ranged from 0-255, with the 0 representing the darkest areas with no discernable light reflection, and 255 representing the brightest areas with the highest amount of measured reflectance. The conversion results in a relative image reflectance between zero and one for each of the three bands.

Figure 2. A comparison of the multiresolution image segmentation object products (left) to the manually delineated cedar tree crown outlined in red true colour Sony DSC WX220 imagery (right)


2.5 – Data analysis

The hypothesis of this research is based on an analysis of the imagery using object based image classification. The Object Based Image Analysis (OBIA) paradigm was outlined by Blashcke (2010). OBIA involves the automatic creation of image objects derived from a multiresolution image segmentation algorithm. These image segmentation algorithms require considerable operator expertise and computational power to create accurate image objects. Typically, a multi-resolution segmentation approach is best; such an approach was used by Ahmed et al (2016) in their analysis of tree species classification from similar UAV imagery to those used in the present study. However, after numerous attempts at image segmentation, the created objects did not accurately represent the individual tree crowns found within the study area and instead were fragmented into numerous smaller objects that were not considered meaningful for the goals of this study (Figure 2). Because of these complications, manually delineated tree crowns were created for the purposes of an initial test of image classification performance. The study then required an initial pixel-based approach to classification, with the training objects represented by the manually-delineated tree crowns digitized by the analyst.

To create objects that represented individual tree crowns, easily discernable tree crowns along the transects were digitized manually within ArcGIS. These objects were created using the orthophoto from the RGB camera, as it had the greatest spatial resolution, allowing the analyst to more accurately map out the extents of each individual crown. In total fifteen cedar crowns, seven pine crowns, four deciduous
crowns and seven spruce crowns were created. These species crowns were then divided into categories of low, medium and/or high leaf area depending on the variability of LAI values found within each species. As previously described, the LAI values were calculated from field measurements of below canopy photosynthetically active radiation and above canopy photosynthetically active radiation using a LAI calculator spreadsheet supplied with the Leaf Ceptometer.

Four of the digitized crowns did not have an LAI value directly associated with them due to the nature of the field sampling protocol. Therefore, LAI values were assigned to these crowns using an Inverse Distance Weighting interpolation method. There was a very high correlation (>95%) between the interpolated LAI values and the actual LAI values for all the actual sampled crowns, leading the analyst to determine that the IDW method was sufficient for predicting LAI values for the missing crowns for the purposes of this thesis analysis.

For each tree crown, mean and standard deviation of the pixel reflectance values were calculated using zonal statistics to determine a mean reflectance for each crown. These crown characteristic data were then input into a Microsoft Excel spreadsheet for both the Sony and Sequoia sensors. Upon creation of the crowns an exploratory analysis of the data was completed to determine if any trends were present between the parameters of interest, such as the relationship between species and LAI, species and reflectance across the different bands, and species to LAI. Pearson’s correlation coefficients and regression coefficients were calculated for the different relationships within Microsoft Excel.
Once the data had been compiled, multiple classifications were run on the datasets to determine the accuracy with which the pixel-based machine classification could classify the imagery. Unsupervised classifications were carried out in the ArcGIS software package using the EVNI tools “Classify without Training” tool. This classification algorithm uses the ISODATA approach, which calculates class means then uses minimum distance algorithms to iteratively cluster the image pixels. Class means are re-calculated at each iteration and pixels reclassified until the change threshold of 5% was met or ten iterations completed. This unsupervised approach classifies the image based solely on the spectral properties of the image and does not reflect any spatial relationships. The number of classes that were created are user defined and were varied, starting with 5 classes and then increasing the number of classes by five up to a maximum of twenty.

Supervised image classification was completed using a K-means Maximum Likelihood Classifier (MLC) algorithm in PCI Geomatica. The digitized tree crowns were used as the training samples for the classification. The input bands for the classification corresponded to the number of bands that were present in the sensor. A supervised classification was completed for both the species and the LAI classes within each species for all the tree crowns. All classifications were MLC with a null class, to eliminate the forced classification of other features in the image such as the bike path, which could potentially skew the classification results.

It is recognized that the use of a pixel-based classification approach, which averages the reflectance characteristics of the crown – the shadowed areas, branches, the full leaf and partially-obscured canopy – would likely not support the main thesis
hypothesis that higher spatial resolution RGB imagery would outperform lower spatial resolution (but higher spectral resolution) multispectral imagery. However, the results of a pixel-based image classification could be considered viable as an initial classification approach that would be useful prior to committing to the more complex object-based image classification.

**Results;**

3.1 Exploratory analysis of dataset

Prior to classification of the datasets, exploratory analysis was conducted to determine the suitability of these data for classification. This analysis involved the determination of Pearson’s correlation coefficients and regression coefficients for multiple relationships between the image data and the field data. Comparisons of species to LAI, and average reflectance detected for each species, were explored from each sensor.

Results from the investigation of the relationship between Leaf Area Index value and reflectance in the red, green, blue and NIR bands revealed weak correlations from both sensors. A tree crown with a high LAI value indicates that the tree is “more green” than a tree with low LAI. A tree with a higher LAI would have more leaves in its crown, which would then translate into higher reflectance values in the NIR and green portions of the electromagnetic spectrum and increased absorption in the red band as photosynthetically active vegetation is known to highly reflect in the NIR and green
wavelengths and absorb in the red wavelengths (Ustin et al 2004). In both datasets, the
R² values of the relationship were less than 0.21 in the red band, except for the
deciduous species with an R²=0.69 and 0.99 in the RGB and multispectral data
respectively. This trend of relatively poor R² relationships for conifers is persistent in all
wavebands from both sensors, and the relationship between deciduous LAI and
reflectance was consistently the highest R² value.

Table 3. Maximum likelihood pixel based species classification accuracy from the Parrot
multispectral sensor

<table>
<thead>
<tr>
<th>Species Name</th>
<th>Null</th>
<th>Cedar</th>
<th>Pine</th>
<th>Deciduous</th>
<th>Spruce</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cedar</td>
<td>6.53</td>
<td>76.22</td>
<td>7.38</td>
<td>4.61</td>
<td>5.27</td>
</tr>
<tr>
<td>Pine</td>
<td>3.19</td>
<td>24.5</td>
<td>46.83</td>
<td>9.11</td>
<td>16.36</td>
</tr>
<tr>
<td>Deciduous</td>
<td>2.84</td>
<td>18.34</td>
<td>11.12</td>
<td>44.6</td>
<td>23.1</td>
</tr>
<tr>
<td>Spruce</td>
<td>3.84</td>
<td>24.14</td>
<td>10.06</td>
<td>9.81</td>
<td>52.16</td>
</tr>
</tbody>
</table>

Average accuracy = 54.95 %
Overall accuracy = 61.21 %

Regarding the mean reflectance by species, the trends were different for the two
sensors in the two common bands i.e., the red and green bands. Overall, reflectance’s
were higher when measured by the multispectral sensor. In the red band, the
multispectral sensor detected the highest mean reflectance by species to be the spruce
trees, and the RGB sensor detected cedar as the highest. Similarly, in the green band,
the multispectral sensor again detected the highest reflectance in the spruce class while
the RGB sensor detected the highest reflectance in the cedar class. Given the near coincident sampling by the two sensors, it would be expected that the results for the highest mean reflectance in each band would be consistent between the sensors, however this does not appear to be the case; this is likely due to the differences in spectral and radiometric resolution in the two camera systems.

Overall, separability between the different species spectrally was interpreted to be relatively low. The mean values of reflectance for all the species in all bands for both sensors fall within one standard deviation of the other species’ mean reflectance, suggesting that there will be low levels of distinction between the different classes based on spectral reflectance properties alone. The NIR band mean from the multispectral sensor showed the largest difference between classes, however the means still fall within the standard deviations of the other band means. This analysis suggests that the classification accuracies of both datasets will be low, as a pixel-based classification is based on the mean spectral qualities of the tree crowns, which are alike, thus providing no clear distinction between species.
These findings are not consistent with expectations and earlier studies (e.g., Ahmed et al 2016), and suggest that the validity of the dataset and its’ ability to be used in a scientifically robust manner is not operational. However, as noted previously, possible explanations for this relatively poor result includes: (i) inconsistent sampling of LAI and (ii) relatively poor matching of LAI values to the appropriate crown. The values of LAI determined in the field, although realistic in a relative sense, are questionable as absolute values: for example, LAI values of 9.00 are clearly not supported in boreal forests (Wulder et al 1998). Such a value would difficult to attain even in the densest canopies of the rainforest. Likely measurements of LAI should be re-obtained with a more careful field protocol, and perhaps these data would align more closely with the
expected and established trends of remote sensing observations of LAI (Boyd et al 2000, Wulder et al 1998). Another potential source of error is in erroneous tree crown delineation, resulting in pixels being assigned to a class in which they do not belong, which could explain the minimal spectral variation between species. More careful image processing methods, such as object-based image segmentation and classification would likely support a stronger quantitative analysis than a pixel based analysis as employed in this thesis research.

3.2 Classification accuracies

The supervised species classification of the RGB imagery resulted in an overall accuracy of 50%. Significant confusion was observed within all species classes, as the highest accuracy of an individual species was spruce trees with an accuracy of 67%. The lowest accuracy by species was the pine with only 38% accuracy which, was highly confused with the deciduous and spruce classes at 20% and 24% respectively. This result indicates the pine class spectral properties, when measured as a mean crown reflectance, are similar to the deciduous and spruce trees spectral properties. However, the other species exhibit less confusion with the pine class than with other classes, and there are higher classification accuracies and lower levels of error for the cedar, spruce, and deciduous classes. Such trees are less erroneously classified as pine trees. The pine class suffers from significant error of omission, but lower errors of commission. This means that more pixels that were classified as pine in the training set were erroneously classified as different species, but that fewer other species were erroneously classified as pine trees.
Supervised classifications of LAI using the RGB imagery, resulted in increased confusion compared to the species classification with an overall accuracy of 24%. Estimation of LAI in classes is known to be a difficult process when using mean tree crown reflectance (e.g., Wulder et al 1998 used mean tree crown reflectance and texture derivatives to increase accuracy in western conifers). Therefore, the results in the present thesis research are unsurprising; the spectral differences that existed between classes of LAI within the same species were smaller than the differences between the spectral response of different species, which themselves were not highly accurate. All classes of LAI were highly confused with one another highlighting the low separability between the various classes of LAI. The one exception is the high LAI deciduous class, which achieved an accuracy of 86%. In this classification, there were numerous instances such as with the high cedar, low pine, high pine, low deciduous, and low spruce where the errors of commission were so high, that they were classified more frequently in a different class than they were correctly classified in their own class.

The multispectral camera species classification achieved an overall classification accuracy of 61%. The cedar species achieved the highest classification accuracy of all the species at 76% with the confusion being evenly distributed between the other three classes. The lowest species accuracy was observed in the deciduous class at 44%, with confusion occurring primarily with the spruce at 23.1% omission error. The multispectral classification exhibits fewer errors of commission than the RGB classification which suggests that the data contained in the NIR band of the electromagnetic spectrum can be used to improve the distinction between the different species.
As was observed from the RGB dataset, classification accuracy of LAI was again lower than the accuracy of the species classification when using the multispectral camera data. The overall LAI classification accuracy from the multispectral sensor was 31%. Again, this result was expected as there is less distinction between LAI classes within species than there is between the actual species themselves. The highest individual classification accuracy was the high deciduous category with an accuracy of 86%, similar to the values determined by the RGB sensor. The low cedar, high cedar, and low spruce classes were also committed more to other classes than they were to their own class. It is important to again note that these results are based on mean tree crown reflectance. Therefore, spectral values of areas of the crown that are influenced by pixels that are brightly lit, shadowed, the understory, and even the branching characteristics of the individual trees. Even with this level of ‘generalization’, however, the estimation of LAI can be interpreted to be reasonable and provide a modest level of support for the use of these data in a more sophisticated image processing procedures, such as the texture-based analysis described by Wulder et al (1988), and the object-based segmentation and machine-learning classification described by Ahmed et al (2016).

While the overall accuracies for all the supervised classifications were low for the species and even lower for the LAI classes, they were an improvement over an accuracy that would equate to a random classification. This suggests that the spectral information derived from the various tree species can be used to obtain a meaningful classification. From these data, the multispectral sensor produced improved classification accuracy
over the RGB sensor accuracy, by 10% for the species and 7% for the LAI. This accuracy improvement would appear to indicate that at the tree crown level, the increased spectral resolution provided by the presence of the NIR band improves the accuracy of both species and LAI classifications. This conclusion is consistent with other studies in which species were classified by RGB and multispectral sensors mounted on an unmanned aerial vehicle (Ahmed et al 2017, Ahmed and Franklin 2016). To the extent of the researcher’s knowledge, at the time of this research, there are no papers published that directly compare the ability of two different sensors to estimate LAI in a similar manner to that completed in this study. However, studies highlighting the benefits of the NIR band to determining LAI are well documented (Berterretche et al 2005, Boyd et al 2000), suggesting that LAI in this study would also benefit from NIR data. Overall, these results indicate that meaningful classifications of LAI and species can be obtained from both RGB and multispectral sensors, with multispectral sensors providing increased performance due to their collecting of data in the NIR band of the spectrum.

Discussion;

4.1 Comparison of Spatial and Spectral Resolution

The higher overall classification accuracy of the multispectral sensor suggests that the data contained in the NIR band of the electromagnetic spectrum is more beneficial to both species and LAI classification studies than the benefits of increased spatial accuracy. This is almost certainly a result of the pixel-based analysis that was
conducted in this initial study; an object-based approach, as was originally planned, would need to be considered separately. In the exploratory analysis of the dataset, it was found that the relationship between mean NIR reflectance and species was the most varied compared to any other band to species relationship, indicating that the NIR band plays an important role in species class separation. The NIR band has been known to contain important data regarding the biophysical properties of vegetation and NIR data is frequently used in a wide range of vegetation classification and monitoring programs (Ewald et al 2016). NIR energy is highly reflected by photosynthetic processes that occur in green vegetation such as tree crown leaves, thus making vegetated surfaces easy to observe in NIR imagery. This finding indicates that there are significant benefits from the inclusion of NIR data into the analysis.

The benefits provided by increased spatial resolution, especially at the relative scale used in this project appear to provide less distinct benefits than the inclusion of the NIR band. Again, this finding would need to be analyzed at the object-level. The benefits of increased spatial accuracy from a RGB sensor include, better delineation of individual objects within an image and increased sharpness of image characteristics such as shadows. The higher the spatial resolution, the easier it is to discriminate between smaller features of interest and the more easily heterogeneity, or crown texture, can be represented (Wulder et al 1998). However, the benefits gained from a higher spatial resolution could outweigh the benefits that spectral resolution adds to the data (Moreno et al 2016). If the object of interest is a very large object such as a forest stand, a coarse spatial resolution can be used and the object will still be recognizable within
the imagery and can be easily delineated. That same coarse resolution would not be suitable if the object of interest was the individual tree crowns, as the averaging of reflectance within individual pixels prevents distinguishing between one crown and the next.

In this study, with the relatively coarser 12cm resolution of the multispectral sensor, tree crowns could be delineated with relative ease, as the individual crowns themselves were an order of magnitude larger than the pixel size. While the higher resolution RGB imagery of 3cm would have significantly more pixels within each individual tree crown, the benefit of the increased spatial resolution is marginal as the desired image objects could already be delineated at a lower resolution. The benefit of a 3cm resolution is that more within crown heterogeneity or texture could be resolved, such as shadows and the extent of the crowns easier to delineate. However, it appears that in this comparison of pixel size to desired object size, the benefits of increased spatial resolution are limited. If a texture algorithm were used in addition to mean reflectance for the crown, the increased heterogeneity conceivably would provide a significant improvement (as per Wulder et al 1998). This is consistent with results in the literature that suggest that a threshold exists based on the ratio of the pixel size to the size of the object of interest (Moreno et al 2016); at that point, the higher spatial resolution provides a significant benefit. While the ideal pixel size for this study was not determined, the results suggest that the 3cm imagery is perhaps too fine, unless a texture derivative is used to characterize the spatial variability within the crown.
Unfortunately, such texture processing was not available for inclusion in the analysis presented here.

Within the visible imagery collected during this study, the differences in the colour of the crowns of the different species were minimal and visual misinterpretation of individual crown species common. This lack of spectral distinction is consistent with the results of the exploratory analysis that was conducted, which demonstrates very little variation between the mean reflectance values of the different species. Theoretically, every species and type of vegetation is considered to have its own unique spectral response; in reality this difference can be very small and requires increasingly sensitive instrumentation to detect (Leckie et al 2017). The radiometric, spatial, and spectral resolutions of the UAV-based equipment used in this study were not high. Highly accurate sensors, such as hyperspectral sensors that contain hundreds of bands with bandwidths in the order of 1nm, the uniqueness of a target’s spectral response can be more easily determined (Ferreira et al 2016). At a bandwidth of 40nm in the multispectral sensor and even greater in the RGB sensor, the differences in such responses are not adequately measured or sensed. This coarse, broadband range of 40nm increases the spectral homogeneity between species, thus reducing the classification accuracy of the species when based on spectral information alone as was done in this study. Had a higher spectral resolution sensor been deployed in this study, it is likely that the accuracy of classification would be increased.

Lower accuracies of LAI were expected when compared to the broader species classification, as the differences between the LAI classes were less distinct than the
differences between species. Hierarchical classification studies such as this one tend to result in lower classification accuracies the more similar the targets become, as the ability to differentiate specific classes based on mean crown reflectance are less than in the broad class (Ahmed et al 2017). In a mature largely closed canopy forest such as the one found in this study site, differences in LAI are difficult to discern from aerial imagery as only the top of the crowns were viewed. Thus, leaves that are present in the canopy which contribute to increased LAI would not be recorded by the sensor, as other layers of leaves cover them. Therefore, a saturation of the signal – especially at lower radiometric resolution – will occur. Due to the two-dimensional representation of the scene, any factors that contribute to LAI in the vertical are not accurately represented in the canopy image and will not be accounted for during classification.

Since all specimens within a species share similar spectral reflectance characteristics and properties, discrimination by LAI is more difficult. Spectrally in the visible bands, the difference between a tree with a high LAI and low LAI are minimal and extremely difficult to determine empirically. However, the use of vegetation indices such as NDVI and GVI have been shown to correlate well with measures of LAI (Schlerf 2004). These band indices estimate the amount of “greenness” at a pixel, and are used heavily within forestry and agricultural applications to monitor primary productivity and plant health (Schlerf 2004, She et al 2016). Increased LAI means more leaves are present in a unit of area, which contributes to increased greenness and photosynthetic activity that NDVI and GVI represent. While NDVI was calculated for the multispectral data, it could not be determined from the RGB dataset as the NIR band is needed in the
calculation. It is likely that, had NDVI and/or GVI values been used in the classification that overall accuracies would improve for the LAI classes, at least with the multispectral data.

4.2 Implications of Preliminary Analysis

Issues with the usability of this dataset were noticeable from the very beginning, starting with the conditions in which the data were collected. Conditions during image collection were varied with respect to cloud cover and winds were forceful enough to force the UAV to quickly drain its battery and struggle to remain on its specified flight lines. The less than ideal presence of intermittent cloud cover resulted in shadows being cast across multiple different areas of the study site at the same time, resulting in fluctuations to incoming radiance, thus limiting the consistency of the illumination of the imagery. This not only affected the aerial imagery, but also impacted the quality and reliability of the LAI measurements that were being collected, as intermittent cloud cover would alter the continuous readings of above canopy radiation, thus skewing the relationship used to determine LAI. The relative LAI values used were likely consistent, but absolute values were clearly not correct.

In addition to errors at the time of data collection, the image processing stages also introduced significant errors that negatively affected the quality of the data. Tear lines and image artifacts are present in the orthorectified imagery, specifically the multispectral data as a result of poor orthorectification accuracy. Numerous iterations with various software packages were run in an attempt to minimize these errors, but
they could not be fully eliminated from the final image product. This resulted in individual tree crowns being warped or shifted between the two datasets, making the manually digitized crowns not perfectly align on both sets of imagery. Even though the images shared a common spatial reference, the crowns that were used for classifier training did not perfectly match the extent of the crowns in both datasets. The error adversely affects which pixels are included in the calculation of average reflectance for each tree crown and possibly results in the inclusion of pixels that do not represent the desired tree crown in the calculation of mean reflectance. Poor quality stitching over forested areas with continuous canopy cover is a result of the image processors poor ability to determine tie points within homogenous canopies, especially when extremely high spatial resolutions are used such as in this study (Xu et al. 2016). More efforts and research are needed in this area to improve the stitching of high spatial resolution imagery collected from airborne platforms such as UAVs.

4.4 Further Analysis and Next Steps

Compared to similar studies of species classification the accuracy results from this study were poor though reasonable, given the experimental conditions and image processing decisions based on limited testing. Ahmed et al. (2017) reported species classification results of 82% for deciduous tree species using similar sensors and platforms for aerial data collection. Chianucci et al. (2016) concluded that an uncalibrated consumer grade digital camera collecting data in the RGB wavelengths provided meaningful measurements of LAI. Those results and the results of the present intimal analysis suggest that if the methodology of this study were to be improved and
feature an object based image classification based on a more statistically advanced classifier, and variables such as texture, that higher classification accuracies could be achieved.

The relatively poor classification accuracies achieved by this study are interpreted to be improved by implementing the following; i) multiresolution image segmentation; ii) texture processing; iii) 3D shape analysis.

Unfortunately, the dominant remote sensing paradigm of Object Based Image analysis could not be followed in the present analysis, and instead a pixel based approach was used. OBIA is widely accepted to be a superior method of classification over pixel based methods for higher spatial resolution imagery for a variety of reasons (Blaschke 2014). Creation of image objects for an entire image allows for the classification algorithm to utilize the spatial relationships that are present between the objects. This enables inclusion of neighbourhood characteristics that serves to eliminate the “salt and pepper” problem created by pixel based classifications which cannot account for spatial relationships (Blaschke 2014). This leads to single pixels being classified as a class that does not at all belong to what the surrounding area is, a result of the lack of spatial context or texture in the classification. The creation of objects can also contribute to the reduction of errors due to manual crown digitization, allowing for objects to accurately represent the individual crowns in each of the different datasets.

In addition, further improvements to the classification could likely be attained from an increased sample size and the use of more sophisticated classification
algorithms and more variables. Ahmed and Franklin (2016) used a combination of 35 imagery derived variables in an object based species level classification to obtain an accuracy of 78%. The inclusion of shape variables, including texture, have been shown in numerous studies to contribute well to high classification accuracies, as the degree of discrimination between classes in increased by measures such as texture. Making use of these additional variables in a more sophisticated classification algorithm would clearly result in improved accuracy. Maximum Likelihood Classification is a relatively rudimentary decision rule when compared to a method such as Random Forests, or other machine learning techniques, as these methods are significantly more statistically complex and robust. Random Forest classification affords the analyst increased control over the input classification parameters and can be manipulated to achieve more accurate results.

**Conclusion;**

An unmanned aerial vehicle mounted with a Sony DSC-WX220 RGB camera and a Parrot multispectral sensor were flown over a primarily coniferous forest in Peterborough Ontario, Canada. Field data were collected in order to calibrate the aerial imagery and tree species data collected as well as Leaf Area Index measurements. Using a pixel based Maximum Likelihood Classification algorithm, both datasets were trained on a set of manually digitized tree crowns and classified according to their spectral properties. Overall classifications were relatively low, with a five-species accuracy of 50% and 61% for the Sony and Parrot sensors respectively. A further level of
classification, Leaf Area Index within species, achieved still lower accuracy than the species classification with accuracies of 24% and 31% overall. Such results are lower than those reported in the literature but higher than those achievable through a random classification predictor. These results suggest that the collection of data in the NIR portion of the electromagnetic spectrum provided greater benefits to classification accuracy than increased spatial resolution. NIR data contains significant information on the biophysical processes occurring within tree species which can be useful for improving the distinction between targets which share a similar visible reflectance.

Future work on this dataset will include: i) implementing an Object Based Image Analysis approach, and ii) the addition of shape and texture variables and iii) the use of a more sophisticated classification algorithm. In addition, the use of a consumer grade RGB sensor that is modified to collect data in the NIR band of the spectrum would be of interest, as this type of sensor would feature both higher spatial and spectral accuracy than individual cameras used in this study.

Acknowledgements;

This study was funded by the Natural Sciences and Engineering Research Council of Canada (NSERC). I would like to thank Dr. Steven Franklin for his guidance and supervision throughout the course of this study, and Dr. Oumer Ahmed and Rachel Wasson for their assistance in image processing and field data collection and their all-around support.
**References;**


Boyd D, Wicks T, Curran P. 2000. Use of middle infrared radiation to estimate the leaf area index of a boreal forest. Tree Physiology. 20, p.755-760


Appendix I; Classification Accuracies

a) Pixel based maximum likelihood classification of species from the Sony DSC WX 220 RGB camera.

<table>
<thead>
<tr>
<th>Species</th>
<th>Null</th>
<th>Cedar</th>
<th>Pine</th>
<th>Deciduous</th>
<th>Spruce</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cedar</td>
<td>0.97</td>
<td>52.63</td>
<td>6.69</td>
<td>24.85</td>
<td>14.86</td>
</tr>
<tr>
<td>Pine</td>
<td>0.12</td>
<td>16.54</td>
<td>38.56</td>
<td>20.29</td>
<td>24.48</td>
</tr>
<tr>
<td>Deciduous</td>
<td>0.43</td>
<td>18.22</td>
<td>8.51</td>
<td>46.64</td>
<td>26.2</td>
</tr>
<tr>
<td>Spruce</td>
<td>0.14</td>
<td>6.01</td>
<td>9.85</td>
<td>16.87</td>
<td>67.14</td>
</tr>
</tbody>
</table>

Average Accuracy 51.24 %
Overall Accuracy 50.29 %

b) Pixel based maximum likelihood classification of species from the Parrot Sequoia multispectral camera

<table>
<thead>
<tr>
<th>Species</th>
<th>Null</th>
<th>Cedar</th>
<th>Pine</th>
<th>Deciduous</th>
<th>Spruce</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cedar</td>
<td>6.53</td>
<td>76.22</td>
<td>7.38</td>
<td>4.61</td>
<td>5.27</td>
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<tr>
<td>Pine</td>
<td>3.19</td>
<td>24.5</td>
<td>46.83</td>
<td>9.11</td>
<td>16.36</td>
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<tr>
<td>Deciduous</td>
<td>2.84</td>
<td>18.34</td>
<td>11.12</td>
<td>44.6</td>
<td>23.1</td>
</tr>
<tr>
<td>Spruce</td>
<td>3.84</td>
<td>24.14</td>
<td>10.06</td>
<td>9.81</td>
<td>52.16</td>
</tr>
</tbody>
</table>

Average accuracy 54.95 %
Overall accuracy 61.21 %
Pixel based maximum likelihood classification of Leaf Area Index classes from the Sony DSC WX 220 RGB camera.

<table>
<thead>
<tr>
<th>Percent Classification by Leaf Area Index in Classified Image</th>
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</thead>
<tbody>
<tr>
<td>Name</td>
</tr>
<tr>
<td>------</td>
</tr>
<tr>
<td>Low Cedar</td>
</tr>
<tr>
<td>Medium Cedar</td>
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<tr>
<td>High Cedar</td>
</tr>
<tr>
<td>Low Pine</td>
</tr>
<tr>
<td>High Pine</td>
</tr>
<tr>
<td>Low Deciduous</td>
</tr>
<tr>
<td>High Deciduous</td>
</tr>
<tr>
<td>Low Spruce</td>
</tr>
<tr>
<td>High Spruce</td>
</tr>
<tr>
<td>Average accuracy</td>
</tr>
<tr>
<td>Overall accuracy</td>
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</table>

Pixel based maximum likelihood classification of Leaf Area Index classes from the Sony DSC WX 220 RGB camera.

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<tr>
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<tr>
<td>High Spruce</td>
</tr>
<tr>
<td>Average accuracy</td>
</tr>
<tr>
<td>Overall accuracy</td>
</tr>
</tbody>
</table>
Appendix II; Exploratory Analysis Data

a) Sequoia multispectral data absolute reflectance compared to absolute field sampled Leaf Area Index

![Cedar LAI vs Red Refl](image1)

![Cedar LAI Vs Green Refl](image2)

\[ R^2 = 0.0886 \]

\[ R^2 = 0.1661 \]

b) Sequoia multispectral data mean absolute reflectance compared to tree species

![NIR Refl by Species](image3)

![Red Refl by Species](image4)
c) Sony DSC WX220 RGB relative reflectance compared to absolute field sampled Leaf Area Index
d) Sony DSC WX220 RGB mean relative reflectance compared to tree species

- **Red Refl by Species**
- **Green Refl by Species**
- **Blue Refl by Species**