THE ESTIMATION OF BOREAL FOREST PROPERTIES USING SPECTRAL INDICES

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ABSTRACT

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The field of forestry has evolved to meet several objectives, including timber and other forest product production, tourism and recreation, habitat and wildlife management and climate change monitoring. As the field encompasses and affects several values, both public and private, the management of the forest and its properties needs to be efficient, timely, and accurate. As a result, there has been a lot of investment put into forest monitoring strategies, particularly with remote sensing. Several researchers have investigated the use of spectral indices to acquire certain forest attributes, such as biomass and characteristics of forest structure (age, basal area, species composition, etc.). Though spectral indices employed on multispectral images have been proven beneficial, other techniques such as texture analysis, hyperspectral remote sensing, RADAR, and LiDAR may be more useful in discriminating quantitative features of the forest and be favourable in certain applications, such as understory characterization. Studies of various spectral indices and other remote sensing techniques have been explored to determine their relatability and accuracy, to determine their usefulness in acquiring measurable properties in the forest. As technology and information advances, hopefully their capabilities will too.

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INTRODUCTION AND OBJECTIVE

The forests are a major part of many communities' way of life. Covering 42% of Canada's land acreage, these vast areas include several features of economical, social and ecological value to society, with examples being revenue, conservation of at-risk wildlife, and recreation (Isaev et al. 2002). With so many applications, forest characteristics such as tree species composition, basal area, biomass, etc. need to be readily available. Thus, remote sensing and the use of spectral indices is becoming more dependable on as a fast approach to get such criteria.

Spectral indices are mathematical formulae using different spectral bands from digital images (usually in the visible and infrared parts). By understanding how to use spectral indices with digital images and obtaining a high correlation with ground-truth sample data, the goal is that inventories and other forest structures are, in the future, interpreted and calculated without the need for time consuming, labour demanding and expensive field measurements - one can obtain the desired values directly from digital imagery. This thesis compares different spectral indices to determine which produce the highest correlation or r-squared value to the values obtained from the ground. Because some indices have been used and tested more frequently than others, one aim of this thesis is to further explore those new indices and see how well they compare to similar ones, or ones that are used for the same attribute, for example, amount of biomass. Thus, this thesis is intended to compare multiple spectral indices against each other to determine which produce the best correlation to ground data, as well as how well of a correlation it is to deduce if it is a worthwhile or useful index for future projects.

OBJECTIVE

An in-depth literature review will be used to determine the usefulness and accuracy of several spectral indices for acquiring forest properties. Alternatives will also be discussed with their benefits to certain applications.

LITERATURE REVIEW

Remote sensing techniques have provided many information products that are useful in many sectors such as forestry, conservation, agriculture and urban planning. This literature review will focus on publications examining the measuring of forest biomass, vigor, structure, and other forest attributes using remote sensing. Each technique will be examined for which tree species, age of trees, tree structure, and other forest characteristics the technique performs well and provides consistent useful information.

REMOTE SENSING FOR ESTIMATING FOREST BIOMASS

Biomass is biological material derived from living, or recently living organisms. In terms of forest biomass, also referred to as chlorophyll-based biomass, wood is the largest factor. The primary uses of forest biomass measurements is for monitoring forest growth and estimating energy content, with biomass now being more sought after as a possible renewable energy source (NRCan 2016).

A broad range of spectral ratios called vegetation indices (VIs) are effective algorithms for measuring relative amounts of green, chlorophyll-based biomass (Chen 1996). Many VIs have been widely explored for different applications, especially in forestry (Bannari 1995). To date, a wide variety of VIs are used to accommodate different sensors with different spectral bands and spatial resolutions. Therefore, customized algorithms have been developed for a variety of applications and environmental conditions.

Ratio Vegetation Index (a.k.a. Simple Vegetation Index)

The Ratio Vegetation Index (RVI) was originally described by Birth and McVey in 1968 (Silleos et al. 2006). It is calculated by simply dividing the reflectance values of the near-infrared band by those of the red band (Equation 1):

$$RVI = \frac{NIR}{Red} \qquad \text{Equation (1)}$$

This spectral ratio compares high red absorption by healthy plants to high reflection in NIR. The larger the difference in these two spectral regions, the larger the biomass estimate. In addition, because the index is constructed as a ratio, problems of variable illumination as a result of topography are minimized (Silleos et al. 2006). Studies have indicated that this VI is sensitive to atmospheric effects, and is often more effective when vegetative over is dense (greater than 50%) (Silleos et al. 2006).

Liu et al. (2006) presented the relationship between biomass and the RVI through linear and nonlinear regression analyses in northwestern China. The study area was 862,800 km^2, and consisted of a combination of agriculture and wilderness, covered by Pipa firewood wilderness, salt firewood class wilderness, and white sacsaoul wilderness, which include species such as loquat (*Eriobotrya japonica* (Thunb.) Lindl.), Chinese tamarisk (*Tamarix chinensis* Lour.), and sacsaoul (*Haloxylon ammodendron* (C.A. Mey.) Bunge). Images were gathered in 2003, using the MODIS sensor. This digital image had a spatial resolution of 250 meters. Accuracy assessments were based on 53 test sites in northwestern China, producing a regression model with an R^2 value of 0.656, using the linear model.

Das and Singh (2012) examined different vegetation indices and their correlation to biomass in part of the Konkan region, located in Maharashtra, India. The study area covers a geographical area of 5,087 km^2. The forest type is dominated by moist deciduous and semi evergreen forests, with the dominant tree species being Kokam (*Garcinia indica* Choisy), Ain (*Terminalia tomentosa* Wight & Arn.), Surangi (*Mammea suriga* (Buch.-Ham. ex Roxb.) Kosterm.), Kumbha (*Careya arbprea* Roxb.), Kinjal (*Terminalia paniculata* Roth), teak (*Tectona grandis* L.f.), Karmal (*Dillenia pentagyna* Roxb.), Jambha (*Xylia dolabriformis* Benth.), and Hadki (*Rauvolfia serpentina* (L.) Benth. ex Kurz). Imagery was acquired in 2009 using the Landsat TM sensor. Because this test site is quite susceptible to damage, the researchers were attempting to determine if the RVI was going to be accurate, and thus be able to be used in other studies with delicate ecosystems around the world. Regression models were built based on 33 test sites, with an R^2 value of 0.785 for the model predicting RVI values for biomass measurements in t/ha.

Normalized Difference Vegetation Index

The Normalized Difference Vegetation Index (NDVI) was introduced by Rouse et al. in 1974 in order to produce a spectral VI that better separates green vegetation from its background. This is done by using the differences in radiance values from the near-infrared and visible red bands. Its equation is listed below (Equation 2):

$$NDVI = \frac{NIR - Red}{NIR + Red} \qquad \text{Equation (2)}$$

NDVI is one of the most common indices as it minimizes topographic effects, and has been normalized with output values ranging from -1 to 1. Very low values of NDVI, usually 0.1 and below, correspond to unvegetated, barren areas such as of rock, sand, or snow. Moderate values, 0.2 to 0.3, represent shrub and grassland, while high values indicate temperate and tropical rainforests (0.6 to 0.8) (Weier and Herring 2000). Because of its characteristics, NDVI has been known to correlate well with leaf area index, crown closure, and other biomass-related parameters as well (Silleos et al. 2006).

Das and Singh (2012) acquired images from the Landsat TM sensor in October 2009 to determine forest biomass in an extremely fragile ecosystem in the Sindhudurg district, India. This region is experiencing rapid change due to climate change and human activities. The types of forest include semi-evergreen and deciduous, with common Indian tree species such as Kokam, Kumbha, Ain, Jambha, Hadki, Sagwan, Surangi, and Kinjal. The accuracy assessment of this analysis, derived from a stratified random sampling method of 33 plots in different homogenous strata, produced an R^2 value of 0.750.

Lui et al. (2006) mapped the forest biomass of oasis ecosystems in Fukang, Xinjiang, China using NDVI. The imagery was obtained from the MODIS sensor, specifically its near-infrared and visible spectra bands, with a spatial resolution of 250 meters. The landscape consisted of both wilderness and farmland, with predominant forest species being in the *Tamarix* genus such as the Chinese tamarisk, as well as sacsaoul and loquat. Results showed an R^2 value of 0.743 correlating NDVI with biomass measurements at 53 sampling sites.

González-Alonso et al. (2006) studied the statistical relationships between satellite-derived NDVI data from the SPOT and NOAA-AVHRR satellites and field measurements including biomass estimates from the Spanish National Forest Inventory. The study area included the entire territory of Spain. Spanish forest ecosystems cover around 26 million hectares, with 15 million ha covered by trees in coniferous, broadleaved, and mixed forests assemblages (González-Alonso et al. 2006). The main broadleaved species in forested areas are evergreen oak (*Quercus ilex* L.), Pyrenean oak (*Quercus pyrenaica* Willd.), cork oak (*Quercus suber* L.), eucalyptus species (Eucalyptus spp.), and European beech (*Fagus sylvatica* L.), while Aleppo pine (*Pinus halepensis* Mill.), maritime pine (*Pinus pinaster* Ait.), and Scots pine (Pinus sylvestris L.) are the main coniferous species. Because their study was so large, they used NOAA-AVHRR imagery with a spatial resolution of 1000m. The images analyzed were collected between 1998 and 2004. Results showed a significant result for the NDVI values from both sensors, with a high coefficient of determination (R^2) of 0.96.

Difference Vegetation Index

The Difference Vegetation Index (DVI) is very sensitive to changes in soil background, which makes it beneficial for monitoring the vegetation and forests. The DVI is also called Environmental Vegetation Index (Silleos et al. 2006). Its equation is as follows (Equation 3):

$$DVI = NIR - Red \qquad \text{Equation (3)}$$

Only one study was found to explore DVI and its correlation to biomass estimation. Liu et al. (2006) mapped this relation in an 862,800 km^2 test site in the city of Fukang, China. This area consisted of vegetation types, from sacsaoul wilderness to Pipa firewood. Such forest types include species such as loquat, Chinese tamarisk, and sacsaoul. The MODIS sensor was used to take images of the ecosystems in 2003, collecting bands in near-infrared and visible spectra with a resolution of 250 meters. After analysis, an R^2 value of 0.651 was produced, in a regression model based on 53 sampling sites.

Renormalized Difference Vegetation Index

This index, the renormalized difference vegetation index (RDVI), is a modification of NDVI. It was developed to combine the advantage of

Difference Vegetation Index (DVI) and the NDVI (Das and Singh 2012). Its equation is listed below (Equation 4):

$$RDVI = \frac{NIR - Red}{\sqrt{NIR + Red}} \qquad \text{Equation (4)}$$

Das and Singh (2012) compared the relationship between forest biomass and RDVI in the Konkan region of Maharashtra. Several forest types were looked at, with species such as Indian laurel, Kokum, Indian rose chestnut, wild guava, tropical almond, Karmal, and Indian snakeroot. These assemblages consist of both evergreen and deciduous species. Images were acquired in 2009 from the Landsat TM sensor. Results were based off of 33 random test sites, with an accuracy of R^2 of 0.762.

Soil-Adjusted Vegetation Index

The Soil-Adjusted Vegetation Index (SAVI) was proposed by Huete in 1988 (Silleos et al. 2006). The intention with its creation was to minimize the effects of exposed soil background on the vegetation signal, through the use of a constant soil adjustment factor L. The L varies with the reflectance of the soil background (such as its colour and brightness), and is chosen depending on the density of the vegetation being analyzed (Silleos et al. 2006). In very low vegetation cover, the use of an L factor of 1.0 is suggested, for intermediate 0.5, and for high densities 0.25, with the general equation shown below (Equation 5):

$$SAVI = \frac{NIR - Red}{NIR + Red + L}(1 + L) \qquad \text{Equation (5)}$$

Araujo, Santos, and Shimabukuro (2000) conducted a study in the central-north of the Roraima State, in Brazilian Amazonia, to verify the potential application of SAVI derived from Landsat TM data from 1996 to relate with biomass values of forest and savanna formations. Several tree species were present in this area with the most common ones being the Andpapper tree (*Curatella americana* L.f.), maricao cimun (*Byrsonima crassifolia* (L.) Kunth), and locustberry (*Byrsonima coccolobifolia* Kunth). The digital imagery was collected in 1996 with the Landsat TM sensor. With the construction of simple regression model, a high relationship of SAVI values with biomass of forest formation was obtained, with R^2 equating to 0.80. There was a poor correlation with savanna formation, with an R^2 of 0.16.

Zhang et al. (2009) did a similar themed study on above-ground biomass for vegetation in coastal areas in Hangzhou Bay Zhejiang Province, China. Vegetation included grasses, sedges and tree species such as Chinese tamarisk (*Tamarix chinensis* Lour.) and the Chinese willow (*Salix matsudana* Koidz.). Hyperspectral images were used, provided by China Center for Resource Satellite Data and Applications during May of 2009. The imagery had a 10 m spatial resolution, with 115 spectral channels collected from 450 to 950 nm with a 4.4 nm spectral-resolution. The results showed that above-ground biomass was strongly related to the soil adjusted vegetation index with a value of 0.81 for R^2 (Zhang et al. 2009).

Optimized Soil Adjusted Vegetation Index

Optimized Soil Adjusted Vegetation Index (OSAVI) is a soil-adjusted vegetation index, based on the original SAVI, often used for agricultural monitoring. However, there are some examples of its use in biomass estimation for forests (Xue and Su 2017). Its Equation (6):

$$OSAVI = 1 + 0.16 \left(\frac{NIR-Red}{NIR+Red+0.16}\right) \qquad \text{Equation (6)}$$

Das and Singh (2012) attempted to examine OSAVI in relation to other VIs for biomass estimation of deciduous and semi-evergreen forests in the Sindhudurg district in India. Images were collected with a Landsat TM sensor in late 2009. The test sites are fragile ecosystems due to human damage and climate change, containing species such as Surangi, Kinjal, Hadki, Jankha, Ain, Kokam, Sagwan, and Kumbha. In correlation to 33 test sites in this area, the results showed an R^2 of 0.750.

Modified Soil Adjusted Vegetation Index

The Modified Soil-Adjusted Vegetation Index (MSAVI) is based on a modification of the L constant of the SAVI. This modification is intended to better correct, or minimize, the effect of soil background brightness (especially bare soil) in different low vegetation cover conditions (Silleos et al. 2006). MSAVI uses a preliminary L factor to correct values greater than 1 that SAVI may have. Thus, its use is limited for high vegetation density areas. The equation is listed below (Equation 7):

$$MSAVI = \frac{2NIR+1-\sqrt{(2NIR+1)^2-8(NIR-Red)}}{2} \quad \text{Equation (7)}$$

Lui et al. (2006) examine the relationship between biomass field data and MSAVI in oasis ecosystems within China, consisting both of farmland and forested wilderness. Digital imagery of the area were taken in 2003, at a 250m spatial resolution, using the MODIS sensor. After analysis, the R^2 coefficient of determination was 0.726, which was based on a correlation with field biomass measurements taken in August of 2003 at 53 sites.

Das and Singh (2012) obtained similar results for its R^2 for the relationship between MSAVI and forest biomass in a study that was conducted in the forest region of Konkan, Maharashtra, which consisted of common Indian species such as Indian laurel, Kokum, Indian rose chestnut, wild guava, tropical almond, Karmal, and Indian snakeroot. In late 2009, images were obtained using the Landsat TM sensor. The regression model of this analysis, based on 33 randomly sampled plots, revealed an R^2 value of 0.676.

Modified Simple Ratio

The Modified Simple Ratio (MSR) has been demonstrated to be sensitive to various biophysical parameters. MSR is a derivative of SVI = NIR/Red, which has proven useful in defining biophysical parameters of vegetation (Das and Singh 2012). Its equation states (Equation 8):

$$MSR = \frac{(NIR/Red)-1}{\sqrt{NIR/Red}+1} \qquad \text{Equation (8)}$$

The only study that was found to use MSR as a means of biomass estimation in a forest landscape was conducted by Das and Singh (2012). The purpose of the study was to compare several VIs to determine which has the best correlation to forest biomass on a sensitive ecosystem found in the Konkan region, within southwestern Maharashtra. They acquired images in October of 2009 from the Landsat TM sensor. The results indicated a fairly decent correlation with a coefficient of determination of 0.703, based off of ground data from 33 random plots within the region.

This vegetation index is most commonly used for crops rather than forests. Agricultural fields tend to be a lot more uniform and allows for VIs to be more precise, typically (Chen 1996). Though MSR was found to be used on only one forest-related study, it proved to have a good correlation, which means with further research it may be able to be used for more studies of a similar nature.

Estimating aboveground forest biomass is critical for many purposes such as responses to climate change, anthropogenic disturbance, and global carbon storage (Ni-Meister et al. 2010). Biomass is also now increasing in importance as it is being considered as a source of renewable energy worldwide (Markham 2015). Furthermore, with such valuable applications, its estimation must be done efficiently and accurately. Currently, the method most commonly for biomass estimation is through ground surveys and forest inventory. This is tedious and costly, which is why the use of remote sensing and vegetation indices are now becoming more popular for such purposes.

REMOTE SENSING FOR ESTIMATING FOREST STRUCTURE

Identifying forest structure properties such as age class, species composition, and vertical structure is important for several professionals. Such information is needed not only for current management practices such as timber or habitat management, but for dealing for issues in the future such as climate change mitigation. As technology advances, remote sensing will become more developed and used in a growing number of fields (Fiorella and Ripple 1993).

Enhanced Vegetation Index

The Enhanced Vegetation Index (EVI) was developed by the MODIS Land Discipline Group to be used with MODIS data (Silleos et al. 2006). It is a modification of the NDVI vegetation index, containing 4 variables: L, G, C_1, and C_2. L is the canopy background or soil adjustment factor, with its value commonly being 1. C_1, and C_2 are the coefficients for atmospheric aerosol scattering. Their values are 6.0 and 7.5, respectively. G is the gain factor and is often 2.5 in magnitude. This VI has improved results in areas that are high in biomass and altered by atmospheric effects (Silleos et al. 2006). EVI has shown to be more responsive to biophysical properties of the forest such as canopy architecture and plant physiognomy. Being a modification of NDVI, the two vegetation indices complement each other in vegetation studies when detecting changes and characteristics in forest attributes (Matsushita 2007). The formula for EVI is stated below (Equation 9):

$$EVI = G * (\frac{NIR - Red}{NIR + (C_1 * Red) - (C_2 * Blue) + L})(1 + L) \qquad \text{Equation (9)}$$

Rankine et al. (2017) wanted to investigate how well NDVI and EVI could represent the differences in phenology of tropical dry forests in different successional stages. The study area was located in the southeast of Brazil where deciduous trees dominate. The images collected had a 500 m spatial resolution, were collected with the MODIS sensor, and the vegetation indices were derived from atmospherically corrected blue, red, and near-infrared bands. After analysis, R^2 values were determined for different successional stages of the forest: abandoned pasture site at 0.78, early stage at 0.75, intermediate stage at 0.76, and late stage at 0.73 (Rankine et al. 2017).

Matsushita et al. (2007) also looked into the same two indices to compare spatial distribution in a high-density Japanese cypress (*Chamaecyparis obtusa* (Siebold & Zucc.) Endl.) plantation. Though specific values were not necessarily stated, it was concluded that the reflectance images of the single channels and the EVI image all show a greater variation than the NDVI image does in terms of spatial distribution.

Transformed Normalized Difference Vegetation Index

The transformed normalized difference vegetation index (TNDVI) has been used to evaluate vegetation conditions in a variety of landscapes. TNDVI is highly correlated to NDVI. The formula of TNDVI has always positive values and the variances of the ratio are proportional to mean values. TNDVI indicates an estimate of the amount of green biomass that is found in a pixel (Akkartal 2004). This index has been used many applications, including both biomass and biophysical properties of the forest. The equation is listed below (Equation 10):

$$TDVI = \sqrt{0.5 + (\frac{NIR-Red}{NIR+Red})} \qquad \text{Equation (10)}$$

Only a few studies explored this vegetation index, with the only forest structure example explained below.

Alrababah et al. (2011) wanted to estimate east Mediterranean forest parameters using Landsat ETM imagery. Its aim was to identify the best predictors of crown-cover percentage (C) using Landsat Enhanced Thematic Mapper (ETM) imagery and TNDVI, and then further determine if TNDVI is a good predictor of above-ground biomass (A), volume (V), Shannon diversity index (S), and basal area (B). The study area is 81,400 ha in Jordan. The major forests in the study area are of two types: evergreen oak forests and evergreen pine forests. The Landsat ETM image was resampled to 70 m resolution using nearest-neighbour resampling so that the block size of the field survey matched the pixel size of the image (Alrababah et al. 2011). The results indicate that crown-cover percentage was significantly correlated to TNDVI, which means it can be used as a predictor for it. The R^2 for this correlation was calculated to be 0.8. The index was then used to generate a C map, which was used to estimate A, V, S, and B. This resulted in coefficients of determination values of 0.56, 0.58, 0.50, and 0.43, respectively, based on a sample size of 64 plots.

Infrared Index

The Infrared Index (IRI), also known as the Normalized Difference Infrared Index, was developed by Hardisky et al. (1983) using values of different infrared red reflectances – near infrared reflectance (NIR) and short wave infrared reflectance (SWIR). This index was initially studied for its correlation with seasonal foliage changes and biomass estimation, as it is capable of analyzing amount of water in the leaves and canopy, particularly in Amazonian forests (Sriwongsitanon et al. 2016). More recent studies have discovered its association with forest structure and composition (Feeley et al. 2005). This index can be calculated using the following Equation (11):

$$IRI = \frac{NIR-SWIR1}{NIR+SWIR1} \qquad \text{Equation (11)}$$

As a by-product of determining water levels in vegetation, this index will be able to detect water stress of vegetated areas to allow for new prescriptions or efforts to rectify this issue (Sriwongsitanon et al. 2016).

Feeley at al. (2005) conducted a study to examine the utility of the infrared index (IRI) against comparable indices such as the mid-infrared index (MIRI) and the normalized difference vegetation index (NDVI) for measuring various forest parameters in the semi-deciduous tropical dry forests of Lago Guri, Venezuela. A total of 5769 stems of 178 different species were identified from the study sites (Feeley et al. 2005). The study analyzed the relationships (both of the mean and variance) of spectral index values with measures of forest structure (annual woody increment, canopy closure, stand density, stand basal area) and composition (tree species diversity, tree community composition) collected in the field (Feeley et al. 2005). Relative diversity and species composition was collected using species lists from subsamples of canopy trees (>10 cm DBH) on each of the study islands. Composition was characterized using a Nonmetric Multidimensional Scaling ordination (NMDS) based off of a Bray-Curtis dissimilarity matrix, which used the relative abundances of tree species within the sites (Feeley et al. 2005). The correlations of the three indices are outlined below in Table 1.

Table 1. Correlations of spectral indices to the 4 studied forest properties (Feeley et al. 2005).

	Structure					Composition	
	Annual Woody Increment	Canopy Closure	Stand Density	Basal Area	Fisher's Alpha	Nonmetric Multidimensional Scaling axis 1	Nonmetric Multidimensional Scaling axis 2
NDVI							
Mean	0.6	0.49	0.08	0.14	0.63	-0.54	-0.26
CV	0.37	-0.08	-0.34	-0.28	-0.23	0	0.55
IRI							
Mean	0.17	0.45	0.1	0.2	0.33	-0.1	-0.54
CV	-0.19	-0.06	-0.18	-0.16	-0.19	0.2	0.03
MIRI							
Mean	0.1	0.44	-0.52	-0.47	0.57	-0.52	-0.17
CV	0.33	0.51	-0.05	0.06	0.37	-0.22	-0.14

As is shown, IRI had a poor correlation with the forest structure components, with the highest correlation with canopy closure at $R^2 = 0.45$. The index performed a little better with forest composition, with the highest correlation value being $R^2 = 0.54$ in terms of species composition (Feeley et al. 2005).

A second study, done by McMorrow (2001), tested the same spectral index. The purpose of the study was to investigate the performance of the spectral index when estimating age of forest stands. The study was particularly focused on African oil palm (*Elaeis guineensis* Jacq.). Images of this commercial plantation were captured using Landsat Thematic Mapper, with the site located in Selangor, Malaysia, consisting of blocks ranging in tree age from 4 to 21 years old (McMorrow 2001). Aerial images of the area were acquired using a Landsat TM image taken on March 6, 1996. This study found that IRI had a nonlinear positive relationship with tree age. The study also compared other indices such as NDVI and MIRI and was determined that when squaring the indices, the relationships were linearized. When squared, IRI had the strongest relationship with age with an R^2 of 0.607 (McMorrow 2001).

Not a lot of research has been done using this VI on forest stands or plantations, with the only examples done on tropical species. As shown in the previous studies, this VI did not have a high correlation with forest structure. If studied more, this index may have the potential to acquire better correlations with stand structure, both on tropical species and more northern assemblages as well.

Mid-Infrared Index

The Mid-Infrared Index (MIRI) has been used as a measure of greenness, correlating to the moisture content of plants, forest biomass, and canopy closure (Feeley et al. 2005). Like IRI, spectral indices using short-wave infrared (SWIR) bands are often used because studies have indicated their correlation to age is quite strong (McMorrow 2001). Its equation is as follows (Equation 12):

$$MIRI = \frac{SWIR1 - SWIR2}{SWIR1 + SWIR2} \qquad \text{Equation (12)}$$

Few studies have been found to use this correlation, with the only examples found done on tropical species.

McMorrow (2001) conducting a study to investigate the relation of MIRI to stand age. Images and field measures were done on sites in Malaysia, collected in March 1996 using the Landsat TM sensor. The area of study consists of a palm plantation, with tree blocks ranging from 4 to 21 years old. The field visits indicated that the area consisted primarily of African oil palm (*Elaeis guineensis* Jacq.) (McMorrow 2001). This study illustrated that MIRI had a very poor relation with age, compared to the other indices the study was testing. When squared, MIRI had a measured R^2 of 0.09 to block age.

Feeley et al. (2005) also did research on this index to measure different forest components on the semi-deciduous tropical dry forests of Lago Guri, Venezuela. A total of 178 species were identified in the study area, offering good variation in the test results (Feeley et al. 2005). The study analyzed the relationships of the spectral index values with stand density (SD), basal area (BA), annual woody increment (AWI), canopy closure (CC), tree species diversity (FA), and tree community composition (NMDS1 and NMDS2). The study indicated that MIRI had modest R^2 values, equating to 0.10, 0.44, -0.52, -0.47, 0.57, -0.52, -0.17 for AWI, CC, BA, SD, FA, NMDSI, and NMDS2, respectively (Feeley et al. 2005).

Many studies have not been done investigating this spectral relationship, probably because its relation to age and other forest parameters is quite poor. Though this index has performed badly on deciduous species, it may have applications on conifer-dominated stands if ever explored.

Normalized Burn Ratio

The Normalized Burn Ratio (NBR) was developed to estimate burn severity of an area. This index is determined through the use of imagery collected before and after a fire has occurred in an area (Anon 2015). There are usually two steps to determine significant and applicable results. First, the NBR ratio is collected for both the before and after images (using Equation 13), and then the change of NBR values is determined (using Equation 14) to indicate the presence or lack of vegetation following a fire event (Anon 2015).

$$NBR = \frac{NIR - SWIR}{NIR + SWIR} \qquad \text{Equation (13)}$$

$$\Delta\text{NBR} = NBR_{(pre-fire)} - NBR_{(post-fire)} \qquad \text{Equation (14)}$$

Imagery that has been collected before a fire will usually have very high near infrared values and very low mid infrared band values. Images collected after a fire will have the opposite: low near infrared values and high mid infrared band values (Anon 2015). When interpreting the change of NBR, a higher change often indicated more severe damage. If the change is negative, this suggests that there is increased vegetation productivity following a fire. Images and field work is often collected directly after a fire burns and the following growing season to assess vegetation survival or mortality (Anon 2015). The resulting ΔNBR values can be categorized into classes based on ranges (e.g. unburned, enhanced regrowth, low, moderate, high severity) (Karl 2012). Table 2 displays these ranges below:

Table 2. Severity classification scheme for NBR values (Karl 2012).

ΔNBR	Severity Classification
< -0.25	High post-fire regrowth
-0.25 to -0.1	Low post-fire regrowth
-0.1 to +0.1	Unburned
0.1 to 0.27	Low-severity burn
0.27 to 0.44	Moderate-low severity burn
0.44 to 0.66	Moderate-high severity burn
> 0.66	High severity burn

In addition to severity of the burn, the ΔNBR method can indicate levels of regrowth post-fire, to determine how different species regenerate or how well planning methods work after a fire (Karl 2012). This index and the subsequent maps produced can aid in determining restoration efforts and plans following a fire.

Cocke et al. (2005) conducted a study surveying the 2001 Leroux fire in the Coconino National Forest in Arizona. This area is dominated by conifers and other evergreen plants (Anon 2018b). Within the forest, there were several plots already established and measured prior to the fire. Landsat 7 ETM+ imagery was used to map the fire into four severity classes both right after the fire (in July 2001), and one year later (June 2002) (Cocke et al. 2005). Ground measurements were completed around the same time to determine differences in the forest structure. Correlation was conducted between the results from the spectral index and the field measurements, and the scatter plots of ΔNBR showed a relatively strong relationship (R^2= 0.706) for both 2001 and 2002 (Cocke et al. 2005). Several different forest parameters could be correlated to NBR and different burn severity levels including tree density, basal area, snag density, and fine fuel accumulation.

Hall et al. (2008) conducted another study to test the relationship between composite burn index (CBI) plots and ΔNBR index, across recently burned areas of the Western Canadian boreal which has not been extensively explored. The CBI is used to attempt to quantify the burn severity on the ground by assessing the magnitude of different biophysical parameters that have been altered by fire (Hall et al. 2008). The study authors were particularly interested in determining if this CBI-ΔNBR relationship could produce significant results which could be applied to modelling, fire behaviour prediction (FBP) fuel type, and how field assessments could be incorporated into the burn severity mapping process to get more accurate results (Hall et al. 2008). It was calculated that CBI and ΔNBR were statistically significant, with R^2 values of 0.87 in the Saskatchewan boreal, 0.85 in NWT, 0.87 in the Yukon, and a value of 0.86 overall for all sites in the boreal.

In the past, the normalized difference vegetation index (NDVI) has been a frequently used method to detect burn severity for its high significance to biomass, however, different studies have indicated it performs poorly in areas with sparse vegetation. Current studies have began using Landsat TM bands 4 and 7 (NIR and SWIR areas of the spectrum) as they have proven successful at assessing burned areas in a wide range of forest stands and species assemblages (Hall et al. 2008).

Forest Structural Index

Distinguishing old-growth from mature forests has been difficult because both successional stages tend to have large trees, and high basal and leaf areas. Often, the differences between these two categories are determined by both overstory and understory factors acquired from ground surveys (Fiorella and Ripple 1993). Few authors have explored spectral indices and band transformations that contrast near-infrared values with middle infrared values. Indices like these, such as the forest structural index (FSI), also known as the forest structure index, have in theory been tested to eliminate topographic shadowing and thus allow better detection of spectral differences in older age classes (Fiorella and Ripple 1993). The structural index equation is listed below (Equation 15):

$$SI = \frac{NIR}{MIR} \qquad \text{Equation (15)}$$

Fiorella and Ripple (1993) first explored this index on the H.J. Andrews Experimental Forest, in the Central Cascade Range of Oregon. The study area falls within several species assemblages, with the dominant tree species consisting of western hemlock (*Tsuga heterophylla* (Raf.) Sarg.), Douglas-fir (Pseudotsuga menziesii (Mirb.) Franco.), a subclimax species. Western hemlock (Tsuga heterophylla (Raf.) Sarg.), Pacific silver fir (*Abies amabilis* (Dougl.) Forbes), and noble fir (*Abies procera* Rehd.) (Fiorella and Ripple 1993). Fiorella and Ripple wanted to determine how well the structural index compares to other remote sensing techniques to measure forest structure, particularly stand age. Cohen and Spies (1992) determined that wetness was the best Tasseled Cap feature compared to greenness and brightness for distinguishing old-growth from mature forest stands (Fiorella and Ripple 1993). It was also illustrated that wetness was also better than all other single TM bands and most simple spectral ratios. Fiorella and Ripple determined that SI had a similar correlation in comparison to wetness, with correlations between SI and stand age resulting in an R^2 of 0.92, higher than all individual bands and multiband transformations, including Tasseled Cap wetness (unpublished data). With such a high correlation, this index has the potential to be used to distinguish between forest stand ages (Fiorella and Ripple 1993).

There was only one other mention of this index being used in a real-world application. Malthus et al. (1993) were exploring how to estimate foliage cover independently of the effects of variations in canopy color and soil background brightness. Their main focus was on indices relating near-infrared parts to red parts of the spectrum, however, they did mention that using the mid-infrared (MIR) region instead of red may provide improved contrast between vegetation and soil, and allows for reduced atmospheric interference to provide more accurate measures (Malthus et. al 1993). Thus, though this paper did not suggest its usefulness in determining forest structure, this spectral index may be better applied to other applications to acquire more significant results.

It has been suggested that the Tasseled Cap wetness index performs the best in determining forest structure parameters, particularly age. This index contrasts between TM bands 1 through 4 versus TM bands 5 and 7 (Fiorella and Ripple 1993). However, when studied more in-depth, the most significant comparison when distinguishing between old-growth and mature forest appeared to be the contrast between TM 4 versus

TM 5 (NIR versus MIR). Therefore, using the structural index rather than the Tasseled cap wetness parameter is the simpler method to calculate and interpret (Fiorella and Ripple 1993).

Texture Measures

Remote sensing is continually being explored as a way to classify forest structure and identify species composition. It has been used in several applications to forest scientists, managers, and practitioners with the objectives to achieve significant accuracies acquired from aerial photography of different forest parameters (Franklin et al. 2001a). Often, spectral indices have been used with traditional classifiers, however, it has often related to poor accuracies at the individual tree level. Instead of relying on multispectral indices solely, digital classification of forest structure and composition should be supplemented with texture measures (Franklin et al. 2001a).

Texture is often measured at a per-pixel basis, measuring the distribution of tones across these pixels on aerial images (Creutzbrug 2013). This is a common method at providing tonal variation within the image, allowing users to analyze the variations in brightness and other spectral properties from surface features to be used in textural analysis or texture mapping. This variation is measured within a window of a particular size (i.e. 3 by 3, 5 by 5, etc.) that is applied over the image to assign each pixel a value based on the spectral properties of its neighbouring pixels (Creutzbrug 2013). These windows are designed to extract features from images that show a connection between a pixel and its neighbor; ones that contain variation in different criteria. Common methods used for this technique includes statistical methods such as spatial co-occurrence matrix and variogram (i.e. a gray-level co-occurrence matrix (GLCM)) (Li et al. 2015). Texture mapping has proven applicable in mapping vegetation heterogeneity and other ecological features to be used in several fields, such as in forestry which can be applicable in delineating different forest structure and composition parameters, including tree density, biomass, canopy cover and species, basal area, stem volume, and spatial arrangement of vegetation (Creutzbrug 2013).

Kayitakire, Hamel, and Defourny (2006) conducted a study to improve estimation errors of forest structure variables. Their study focused on very high spatial resolution images that have been shown to reduce these errors, especially in forest landscapes (Kayitakire et al. 2006). The study used 1-m resolution IKONOS-2 imagery to estimate the five main forest structure properties: age, top height, circumference, stand density and basal area within even-aged spruce stands. Original images were acquired on October 26, 2001, and then reprocessed using texture analysis. The texture features were derived from the grey-level co-occurrence matrix (GLCM) (Kayitakire et al. 2006). Three texture measures were used for this study, variance, contrast, and correlation, as previous studies have illustrating their benefits in forest type and age-class delineation. The coefficients of correlation (R^2) for circumference, top height, stand density, and age variables were 0.82, 0.76, 0.82, and 0.81 respectively. Basal area was found to have a weak correlation to texture variables, with an R^2 of 0.35.

Franklin et al. (2001) also explore the use of image texture on different aged Douglas-fir stands in the Sooke River watershed of British Columbia. Other dominant tree species besides Douglas-fir, included western red cedar and hemlock. These researchers used textural separability tests obtained by first- and second-order texture methods on IKONOS panchromatic imagery June 3, 2000 (Franklin et al. 2001b). Their measures included a second-order (spatial co-occurrence homogeneity) texture measure and a first-order (variance measure). It was established that the second-order measure was better at distinguishing between age classes, than the first-order measure, however no coefficients of determination were stated (Franklin et al. 2001b). The study also compared different sized windows in the texture analysis, and it was found that small windows sizes were not as effective as larger windows sizes in separating stands.

There has been little work done on how and where texture measures can be applied to be an effective tool in forestry applications (Franklin et al. 2001a). Further research has to be conducted to determine their performance and ability at retrieving forest properties in different conditions (Kayitakire et al. 2006).

There were several other vegetation indices stated in literature that could be used for biomass estimation and forest structure, however, sources defining their accuracies and methods were unable to be found. These equations are listed in Table 3.

OTHER SPECTRAL INDICES USED IN REMOTE SENSING

Many algorithms and methods have been developed from remote sensing for applications in several fields including agriculture, urban planning, and forestry. Several involve the use of spectral data from aerial images captured of an area, with information then extracted and analyzed for a particular purpose. In terms of forestry, many of these algorithms revolve around use of visible and near-infrared reflectance bands, in the form of mathematical equations as spectral vegetation indices. These indices have been studied to save time and money for forestry companies to estimate biomass and other forest structure characteristics to be used for silviculture, operations, and even conservation. Vegetation indices have proven to be an asset in the industry, and with more research conducted every year, their accuracies and uses continue to increase.

Several vegetation indices have been explored above, however, there were many others that were stated but did not have sufficient research done to determine their accuracy and use. Some of these indices are listed below on the next page (Table 3).

Table 3. Other vegetation indices used to determine various forest properties (Rewucki 2017).

Vegetation Index	Abbreviation	Equation	Citation
Weighted Difference Vegetation Index	WDVI	$WDVI = NIR - aR$ a = slope of soil line	Silleos et al. 2006
Green Atmospherically Resistant Index	GARI	$GARI = \frac{NIR - [Green - \gamma(Blue - Red)]}{NIR + [Green - \gamma(Blue - Red)]}$ γ is a weighting function that depends on aerosol conditions in the atmosphere (often recommended at 1.7)	Xue and Su 2017
Green Difference Vegetation Index	GDVI	$GDVI = NIR - Green$	Xue and Su 2017
Green Normalized Difference Vegetation Index	GNDVI	$GNDVI = \frac{(NIR - Green)}{(NIR + Green)}$	Barati et al. 2011
Green Ratio Vegetation Index	GRVI	$GRVI = \frac{NIR}{Green}$	Aeroeye 2017
Infrared Percentage Vegetation Index	IPVI	$IPVI = \frac{NIR}{NIR + Red}$	Xue and Su 2017
Non-Linear Index	NLI	$NLI = \frac{NIR^2 - Red}{NIR^2 + Red}$	Barati et al. 2011
Visible Atmospherically Resistant Index	VARI	$VARI = \frac{Green - Red}{Green + Red - Blue}$	Xue and Su 2017
Chlorophyll Vegetation Index	CVI	$CVI = \frac{NIR * Red}{Green^2}$	Aeroeye 2017
Extended Normalized Difference Vegetation Index	ENDVI	$ENDVI = \frac{(NIR + Green) - (2 * Blue)}{(NIR + Green) + (2 * Blue)}$	Aeroeye 2017

These are only a few others, with several others explained by Aeroeye (2017) and Xue and Su (2017).

IMAGE TRANSFORMATIONS FOR ESTIMATING FOREST PARAMETERS

Forest structure usually refers to the way in which the attributes of trees are physically distributed – vertically and horizontally – within a forest ecosystem. It refers to various physical and biological components of an ecological system, such as age, height, basal area, diameter at breast height (DBH), and other related criteria (Gadow et al. 2012). Many properties within a forest are affected by forest structure. Some include biodiversity and habitat requirements, biomass production, and other ecosystem services. These properties further affect other practices such as forestry and conservation (Gadow et al. 2012).

As stated previously, the use of remote-sensing techniques allow for the estimation of biomass, however, many researchers have explored methods to determine other forest stand features as well, such as age, basal area, species diversity, and canopy structure (Lu et al. 2004). Many vegetation indices that use NIR and red bands, such as several of the ones explored above, have been analyzed and determined to be weakly correlated with selected forest stand parameters, as opposed to biomass estimation. Studies have concluded, though, that mid-infrared bands and linear transformed indices such as principal component analysis, tasseled cap transformations, and albedo are most strongly correlated with forest stand parameters (Lu et al. 2004). Below are a few methods that have proven successful at determining some biophysical attributes of a forest.

Tasseled Cap Index

The Tasseled Cap transformation is an adjustment of the viewing perspective so the data which one is trying to obtain is more easily observed. It is a guided principal components analysis, which results in a fixed transformation where the 6 reflectance bands are transformed into the brightness, greenness, and wetness spectral indices (Cohen and Species 1992). Brightness is a weighted sum of the six reflectance bands of the TM imagery, greenness is a contrast between the near-infrared band and the three visible bands, and wetness is a contrast of mid-infrared bands with the other four bands (Cohen and Spies 1992).

Cohen and Spies (1992) attempted to determine 16 forest stand structural attributes in Douglas-fir (*Pseudotsuga menziesii* (Mirb.) Franco) and western hemlock (*Tsuga heterophylla* (Raf.) Sarg.) forests in Oregon and Washington. Forest attributes included tree bole diameter at breast height (DBH), tree crown diameter at maximum crown width (CD), tree height (HGT), tree density (DNY), basal area (BA), and time since a major disturbance or age (AGE). The spectral data was derived from two sensors, the SPOT HRV with a 10m spatial resolution (panchromatic) and the Landsat TM sensor (multispectral data) in June 1989 and July 1988, respectively. The analysis was correlated with 41 representative sample plots, which indicated that the relationship to the HRV data was strongly related to several stand attributes evaluated, whereas TM imagery was weakly related to the attributes. The results (correlation coefficients) are shown below (Table 4). Subscripts mn and u represent mean value for all trees and mean value for trees in the upper canopy only (dominant, codominant, and emergent positions), and O and T referring to measures derived from the original and the texture images.

Table 4. Absolute values of correlation coefficients for the relationships of stand structural attributes with tassel cap indices from the satellite data (Cohen and Spies 1992).

Stand Variable	HRV_T	BRT_O	GRN_O	WET_O
DBH_{mn}	0.55	0.44	0.44	-0.6
DBH_u	0.88	0.43	0.47	-0.87
CD_{mn}	0.67	0.33	0.35	-0.69
CD_u	0.88	0.42	0.27	-0.88
HGT_{mn}	0.45	0.37	0.37	-0.51
HGT_u	0.86	0.35	0.43	-0.85
DNY	-0.62	0.49	0.51	0.69
DNY_u	-0.84	0.39	0.51	0.87
BA	0.73	0.53	0.52	-0.69
BA_u	0.73	0.47	0.53	-0.71
AGE	0.87	0.55	0.63	-0.9

Cohen et al. (1995) presented the similar findings as the study above. The purpose of the study was to use several techniques to estimate the age and structure of a conifer-dominated forest area on the west side of the Oregon Cascade Range, and essentially extend the research done by the Cohen and Spies in 1992. Spectral data for this 1,237,482 ha, forest was a single Landsat TM image collected in 1988, which was resampled to a 25m cell size using nearest neighbour rules and was transformed into the three axes of the TM Tasseled Cap (Cohen et al. 1995). The major forest types of this area included the western hemlock/Douglas-fir, Pacific silver fir (*Abies amabilis* Douglas ex J.Forbes), and mountain hemlock (*Tsuga mertensiana* (Bong.) Carr.) forest zones. 106 closed canopy conifer stands were sampled for ground-referencing, and led to an overall accuracy of 82% for estimating forest cover classes (Cohen et al. 1995).

Overall, studies have shown that the brightness and greenness from tasseled cap transformations are highly sensitive to topographic variation, but also capture several spectral variations in cover types which is beneficial for describing many biophysical properties of the forest. The wetness component was an important spectral variable for distinguishing among age and structure, or classes, of closed-canopy coniferous forests (Cohen et al., 1995). Equations (16, 17, and 18) for Tasseled Cap transformations are presented below:

$$Brightness\ (KT1) = 0.3037TM1 + 0.2793TM2 + 0.4743TM3 + 0.5585TM4 + 0.5082TM5 + 0.1863TM7 \quad \text{Equation (16)}$$

$$Greenness\ (KT2) = -0.2848TM1 - 0.2435TM2 - 0.5436TM3 + 0.7243TM4 + 0.0840TM5 - 0.1800TM7 \quad \text{Equation (17)}$$

$$Wetness\ (KT3) = 0.1509TM1 + 0.1973TM2 + 0.3279TM3 + 0.3406TM4 - 0.7112TM5 - 0.4572TM7 \quad \text{Equation (18)}$$

Variables used include visible wavelengths TM1 (blue), TM2 (green), TM3 (red), and mid-infrared wavelengths TM5 and TM7.

Principle Component Analysis

Principal components analysis (PCA) is a method in which the original spectral data is transformed into a new set of data to better capture and visualize information. Often some variables are highly correlated with each other, so instead of having redundant information, such information is grouped together into a few variables called principal components. The concept of PCA involves transforming the data into a new coordinate system, where each observation, such as a tree, involving different variables (n amount of variables), such as DBH, height, etc., is considered as a point in an n-dimensional vector space (Watkins 2017).

It ultimately produces a new set of images or principal components that are uncorrelated to one another and ordered with respect to the amount of variation they represent from the original image set. Typically, the first component represents albedo (variation to soil background), and the second component often represents variation in vegetative cover (Silleos et al. 2006). This type of transformation has been shown to be strongly correlated with forest stand parameters with examples described below.

Lu et al. (2004) conducted a study to estimate forest stand parameters with PCA in three study areas, Altamira, Bragantina, and Ponta de Pedras, all in the Amazon basin. The dominant types of vegetation in Altamira are mature moist forest and liana forest, with the main tree species being the trumpet tree (*Cecropia palmata* Willd.), *Cecropia obtuse* Tréc, *Inga alba* (Sw.) Willd., and *Banara guianensis* Aubl. Bragantina consists of flooded forest, secondary growth forest, and cropland. The main forest species include bloodwood (*Vismia guianensis* (Aubl.) Pers.), *Croton matourensis* Aubl., maripa palm

(*Maximiliana maripa* (Aubl.) Drude), *Guatteria peoppigiana* Mart., and *Tapirira guianensis* Aubl. The Pedras study area is a transitional forest is located in the ecotone between forest and savanna, with the dominant tree species are *Croton matourensis*, maripa palm, *B. crispa*, and *Piriquiteira*. Landsat TM images were acquired in July 1991 for Altamira and Pedras and in June 1994 for Bragantina. There are several formulae are used to determine PCA with them outlined below (Equations 19 to 27):

$$\mathrm{PC1\text{-}A} \quad 0.054TM1 + 0.130TM2 + 0.143TM3 + 0.595TM4 + 0.709TM5 + 0.321TM7 \qquad \text{Equation (19)}$$

$$\mathrm{PC2\text{-}A} \quad -0.079TM1 - 0.121TM2 - 0.212TM3 + 0.787TM4 - 0.421TM5 - 0.372TM7 \qquad \text{Equation (20)}$$

$$\mathrm{PC3\text{-}A} \quad 0.230TM1 + 0.504TM2 + 0.616TM3 + 0.140TM4 - 0.472TM5 + 0.266TM7 \qquad \text{Equation (21)}$$

$$\mathrm{PC1\text{-}P} \quad 0.056TM1 + 0.079TM2 + 0.127TM3 - 0.845TM4 - 0.490TM5 - 0.143TM7 \qquad \text{Equation (22)}$$

$$\mathrm{PC2\text{-}P} \quad -0.052TM1 - 0.060TM2 - 0.162TM3 + 0.472TM4 - 0.745TM5 - 0.436TM7 \qquad \text{Equation (23)}$$

$$\mathrm{PC3\text{-}P} \quad 0.327TM1 + 0.617TM2 + 0.663TM3 + 0.233TM4 - 0.116TM5 - 0.079TM7 \qquad \text{Equation (24)}$$

$$\mathrm{PC1\text{-}B} \quad 0.140TM1 + 0.242TM2 + 0.313TM3 + 0.262TM4 + 0.739TM5 + 0.457TM7 \qquad \text{Equation (25)}$$

$$\mathrm{PC2\text{-}B} \quad -0.062TM1 - 0.026TM2 - 0.170TM3 + 0.952TM4 - 0.108TM5 - 0.222TM7 \qquad \text{Equation (26)}$$

$$\mathrm{PC3\text{-}B} \quad 0.276TM1 + 0.502TM2 + 0.674TM3 + 0.069TM4 - 0.439TM5 - 0.140TM7 \qquad \text{Equation (27)}$$

The attributes tested in this research included aboveground biomass (AGB), basal area (BA), average stand diameter (ASD), and average stand height (ASH). This study concluded that linear transformed indices such as PCA are more strongly correlated to forest stand structure than vegetation indices that use red and near-infrared bands (Lu et al. 2004). Pearson's correlation coefficients were used to interpret the relationships between the data and forest stand parameters, with the results for principal components analysis shown below (Table 5).

Table 5. Values of correlation coefficients for the relationships of stand structural attributes with principal component analysis variables derived from the satellite data (Lu et al. 2004).

VI	Altamira				Bragantina				Pedras			
	AGB	BA	ASD	ASH	AGB	BA	ASD	ASH	AGB	BA	ASD	ASH
PC1	-0.603	-0.562	-0.741	-0.79	-0.815	-0.809	-0.851	-0.876	0.815	0.811	0.816	0.867
PC2	-0.126	-0.132	-0.001	0.024	-0.797	-0.741	-0.751	-0.766	0.438	0.369	0.459	0.558
PC3	0.3	0.311	0.355	0.246	-0.058	-0.177	-0.355	-0.276	-0.742	-0.729	-0.735	-0.806

The correlation analysis was based on 20 sites for Altamira, 18 sites for Bragantina, and 14 sites for Ponta de Pedras. Though this research was done particularly for moist tropical regions, it can be used as a precursor for similar studies done for the boreal forest.

Albedo

The term “albedo” is often referred to as a measure of the fraction of incident radiation reflected from an object. When looking at different aerial images, it is easily observed that there are large differences in albedo for different landscapes such as soil and vegetation, for example (Climate Data Information 2017). However, albedo also varies with vegetation and cover, which may be used to determine forest characteristics between stands. Research was found to use albedo as a linear transformed index to determine forest structure characteristics such as basal area, stand height, and stand diameter (Lu et al. 2004).

Lu et al. (2004) conducted a study in the eastern part of the Amazon Basin to compare different forest characteristics to different linear indices, including albedo.

Major tree species within the study areas include the trumpet tree, *Inga alba* (Sw.) Willd., *Banara guianensis* Aubl., bloodwood, maripa palm, *Croton matourensis* Aubl., and *Guatteria peoppigiana* Mart. Landsat TM images were acquired in the summer months of 1991 and 1994. Four different parameters were studied: basal area (BA), aboveground biomass (AGB), average stand height (ASH), and average stand diameter (ASD). The equation used to determine albedo in this study was as follows (Equation 28):

$$Albedo = TM1 + TM2 + TM3 + TM4 + TM5 + TM7 \qquad \text{Equation (28)}$$

The correlation analysis was done for each study area in the basin, respectively being 18 sites for Bragantina, 20 sites for Altamira, and 14 sites for Ponta de Pedras (Lu et al. 2004). The correlation analysis resulted in Pearson correlation coefficients stated below (Table 6).

Table 6. Values of correlation coefficients for the relationships of stand structural attributes with albedo derived from the satellite data (Lu et al. 2004).

VI	Altamira				Bragantina				Pedras			
	AGB	BA	ASD	ASH	AGB	BA	ASD	ASH	AGB	BA	ASD	ASH
Albedo	-0.609	-0.56	-0.755	-0.819	-0.818	-0.813	-0.859	-0.881	-0.816	-0.798	-0.816	-0.89

For most variables, the relationship, though negative, was still quite high.

Though this index was only found to be used in that one study, it has the potential to be applied to several other studies which may prove to be successful. It needs to be further explored and used to determine if this index will be a valuable resource in the future.

HYPERSPECTRAL REMOTE SENSING FOR FORESTRY

The previous studies that have been discussed have often used the traditional form of imagery – ones acquired by RGB and/or NIR sensors. As illustrated, this type of imagery and associated analyses have been proven as an effective tool in many forestry applications. These traditional sensors, however, can lack the precision and spectral range needed to perform and be used in certain applications. This has led to a new method that uses high-resolution spectroscopy – hyperspectral remote sensing (Adão et al. 2017). This technique is still quite expensive though and restrictive due to logistics or availability. The future outlook of remote sensing has been demonstrated to shift from panchromatic/multispectral analysis to the hyperspectral, and then eventually ultraspectral (Adão et al. 2017). Several countries have been exploring applications with the use of hyperspectral sensors, and as the method becomes more readily available, its utility may be expanded over several fields (Tong et al. 2004).

The benefits of hyperspectral remote sensing is its ability to provide information across numerous contiguous spectral bands, rather than multispectral remote sensing which measures spaced spectral bands (Sekhar et al. 2017). Most projects, however, only require select frequencies according to what is being measured, and what the absorption and reflection properties of study area. The objects being observed have unique compositions and structures, allowing objects, such as vegetation to have spectral signatures. With hyperspectral remote sensing, these signatures can be used to provide more detail in several fields of study such as forestry or farming (crop classification) (Sekhar et al. 2017). Thus, the main goal of hyperspectral remote sensing is to obtain the spectrum, or spectral signatures, of objects captured in an image to find objects themselves, to delineate different areas, to identify subject matter, and to detect processes.

Spectral Mixture Analysis

Spectral mixture analysis (SMA) is one method that has used hyperspectral remote sensing as its basis. It is a sub-pixel classification technique which could be used to “unmix” different forest canopy measurements into respective categories. Currently, it has been more commonly used to differentiate soil, vegetation and non-photosynthetic vegetation. SMA “unmixes” a mixed pixel by determining the fractions of each spectral endmember which combine to produce the mixed pixel's spectral signature (Song 2005). SMA depends on the spectral response of the land cover, and is an advanced remote sensing technique used to detect material that are smaller than an image pixel. Mixed pixels tend to cause problems in traditional image classifications such as supervised or unsupervised (Song 2005).

Rogan and Franklin (2001) used SMA to map fire severity within several vegetation types affected by wildfire in southern California in June 1999. This process used Landsat ETM imagery of two areas, in Cleveland National Forest, San Diego County, to map the effects of fire on a wide range of vegetation including chaparral shrublands, shrub wetlands, oak woodlands, mixed riparian corridors, coastal sage scrub and annual grassland (Rogan and Franklin 2001). Five canopy consumption classes were defined: unburned vegetation (UV), bare soil (BS), mixed burned pixels with low

(<50%) vegetation cover (MBPLV), mixed burned pixels with high (>50%) vegetation cover (MBPHV), and severe burn (SB). Overall kappa classification accuracy results were quite high for the burned areas, using. Individual severity class accuracies ranged from 0.52 to 0.90 between both fire areas (La Jolla fire and Laguna fire) (Rogan and Franklin 2001). The La Jolla classification resulted in an overall Kappa accuracy of 0.85, with the Laguna fire being 0.71. In reference to accuracies of each class, the values are shown in Table 7.

Table 7. Kappa value accuracy results for La Jolla and Laguna fires (Rogan and Franklin 2001).

Classification	Kappa Values	
	La Jolla Fire	Laguna Fire
Unburned Vegetation (UV)	0.83	0.81
Bare Soil (BS)	0.80	0.75
Mixed Burned Pixels with Low (<50%) Vegetation Cover (MBPLV)	0.70	0.80
Mixed Burned Pixels with High (>50%) Vegetation Cover (MBPHV)	0.85	0.52
Severe Burn (SB)	0.90	0.67

Caetano at al. (1994) also studied this method for fire severity mapping. The study area is located in central Portugal, averaging to 19km by 12km in size. Several species were looked at in this area, including conifer (pine) stands, deciduous stands containing eucalyptus, the chestnut tree, and the cork oak tree (Caetano et al. 1994). Parts of the study area also included agricultural and brush lands. Three sets of Landsat 5 TM data was acquired for this study: pre-fire on November 9, 1989, two post-fire images on July 23, 1990 and November 12, 1990. This study did not provide an accuracy assessment, however, it was stated that the SMA was efficient at separating areas with abundant vegetation cover that was partially burned, to ones that were not burned (Caetano et al. 1994). Though this study has not given too much information, SMA has demonstrated its dependability at providing quantitative information on extent of burns, both aerially and severity.

Peddle et al. (2014) explored the use of Spectral Mixture Analysis and its applications in the Superior National Forest in Minnesota, USA. The 4800 km^2 study area comprised of stands of black spruce (*Picea mariana* (Mill.) Britton, Sterns & Poggenburg). Spectral data was obtained using a helicopter-mounted Modular Multi-band Radiometer (MMR) at Landsat TM parameters (bands, spatial resolution, etc.) The correlation was based on 31 test sites, with a full range of stand densities. Both data sets – aerial and field – were collected during the summers of 1983 and 1984. The paper concluded that this method has been shown to consistently provide better estimates of forest biophysical information such as biomass, diameter (DBH), stems/m^2, and leaf area index (LAI) compared to those provided by vegetation indices such as NDVI as others stated below (Table 8). When comparing SMA against other VIs, in all cases, SMA provided significantly better results, with a 40% improvement (Peddle et al. 2014). The results are shown below (Table 8).

Table 8. Comparison of coefficients of determination of SMA to other vegetation indices (Peddle et al. 2014).

	Biomass		NPP		LAI		DBH		Stems/m^2		Basal Fract.	
Approach	r^2	S.E	r^2	S.E	r^2	S.E	r^2	S.E	r^2	S.E	r^2	S.E
NDVI	0.4	3.26	0.47	0.11	0.47	0.85	0.28	2.51	0.15	0.19	0.44	0
SR	0.36	3.38	0.43	0.11	0.43	0.89	0.24	2.57	0.15	0.19	0.4	0
MSR	0.38	3.33	0.44	0.11	0.45	0.87	0.26	2.55	0.15	0.19	0.42	0
RDVI	0.15	3.91	0.12	0.14	0.13	1.09	0.11	2.8	0.03	0.2	0.14	0
WDVI	0.53	2.91	0.59	0.1	0.59	0.75	0.37	2.35	0.18	0.18	0.57	0
SAVI	0.37	3.35	0.43	0.11	0.43	0.88	0.26	2.55	0.14	0.19	0.41	0
SAVI 1	0.49	3.02	0.55	0.1	0.56	0.78	0.33	2.43	0.2	0.18	0.53	0
SAVI 2	0.39	3.3	0.45	0.11	0.45	0.87	0.28	2.52	0.15	0.19	0.43	0
GEMI	0.35	3.41	0.37	0.12	0.39	0.91	0.25	2.56	0.13	0.19	0.37	0
NLI	0.01	4.23	0	0.15	0.01	1.17	0	2.96	0	0.2	0.01	0
Best VI	0.53	2.91	0.59	0.1	0.59	0.75	0.37	2.35	0.2	0.18	0.57	0
Avg VI	0.34	3.41	0.39	0.12	0.39	0.91	0.24	2.58	0.13	0.19	0.37	0
SMA-S	**0.74**	2.14	**0.8**	0.06	**0.79**	0.55	**0.5**	2.19	**0.22**	0.18	**0.78**	0

Though SMA is not a vegetation index, it has shown to be successful at providing between correlations to forest structure parameters than any of the vegetation indices. This, and other methods in hyperspectral remote sensing, may be resourceful for guiding resource management in reference to treatments or silviculture. This type of analysis may also be beneficial at looking at regrowth surveys or other types of disturbance mapping within forestry settings.

FUTURE DIRECTIONS OF REMOTE SENSING

Over time, remote sensing has developed better accuracy both spatially and spectrally due to more advanced sensors and platforms, including video cameras, photographic and digital cameras, and airborne sensors (Wulder et al. 2003). This has allowed for the capture of both multispectral and panchromatic images, and has even evolved to allow for the capture of very high resolution images using hyperspectral sensors, as described above. These sensors have allowed features of forest cover, composition, and structure to be captured at high accuracies. (Wulder et al. 2003) Several other advancements have come from remote sensing including RADAR applications that penetrate the forest canopy to reveal characteristics below, and LIDAR which has been shown to acquire very good correlations with forest properties such as biomass, height, and other vertical structure parameters (Wulder et al. 2003).

RADAR satellite monitoring often using a technique known as Synthetic Aperture Radar (SAR); another method in digital image observations. As an overview, RADAR (RAdio Detection And Ranging) is essentially a distance measuring device (Mansourpour et al. 2006). RADAR sends out pulses microwave electromagnetic radiation. It then measures the strength and time between the transmitted and reflected pulses. To determine features of the earth's surface, such as roughness, moisture content, and overall geometry, different pules intervals, wavelengths, and polarizations can used. Additionally, a Synthetic Aperture Radar (SAR) system uses microwaves to illuminate a scene using the amplitude and phase of back-scattered radiation, using the received signals to convert it into a digital image (Mansourpour et al. 2006). All RADAR imageries contain "speckle noise" which is essentially variation in the backscattered radiation from heterogeneous areas (cells). This speckle noise gives the grainy appearance to RADAR images. It can have a negative effect on these images by reducing the image contrast, which alters texture-based analysis. Thus, a speckle noise reduction or removal process is often used . This, however, also changes the image so filters (i.e. mean, standard deviation, etc.) are applied to keep these effects to a minimum

(Mansourpour et al. 2006). Objects can then be mapped and delineated on the surface of the earth. This can have several applications in mapping both the canopy and understory of a forest, which can be helpful in resource management, timber cruising, habitat mapping, etc. There are also new applications of ground penetrating radar for geologic and mining applications (NRCan 2015).

LIDAR, which stands for LIght Detection And Ranging, is a very similar method to RADAR, however it uses light as its pulse to measure distances to the Earth. These light pulses have been able to generate precise, three-dimensional, point-based information about the topography of the earth's surface and its characteristics (NOAA 2017). It is able to acquire information about an object based on the scattering, absorption, reflection, and fluorescence of the beams (Carlos et al. 2013). As RADAR and LiDAR are very similar, there are some advantages to LiDAR. Unlike RADAR, LiDAR pulses are not as affected by weather conditions like rain or clouds because it is airborne. The use of LiDAR, however, is still quite expensive, and as technology advances it will be more available for a wide variety of applications (Anon 2018a).

As remote sensing practices becomes more common, the availability of multiresolution images and multisource data will expand. This will allow researchers in several fields, such as forestry, to acquire data and create maps more accurately and efficiently. Remote sensing capabilities continue to improve, which will allow forest attribute mapping to increase its correlation to ground truth data, which will allow for less time and money to be spent collect data on the ground. This will ultimately contribute to better assessment of the forest to allow for the sustainability and management of these areas to prosper (Wulder et al. 2003).

CONCLUSION

In the past, forest inventories and data collection have primarily revolved are timber management to capture the extent to which a species grows – its area and its potential harvestable volume. However, as times evolved, new values have arisen and the management of forest properties have adjusted and broadened accordingly. This has expanded to include non-harvest related characteristics such as forest structure (vertical and horizontal), wildlife biodiversity, and wildlife habitat. With remote sensing, these attributes can be grouped into units that may relate to stand species composition, height, age, basal area, density, and several others. These features can be mapped and interpreted for further analysis for several applications. Remote sensing sources such as airborne and satellite imagery, RADAR, LiDAR, and associated methods such as spectral indices have been valuable in collecting, mapping, and updating forest properties such as structure, biodiversity, disturbance, and habitat. As remote sensing has been increasing in importance, its utility and accuracy will continue to update and expand to improve resource management activities worldwide (Wulder et al. 2003).

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