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BERYL NYAMGEROH
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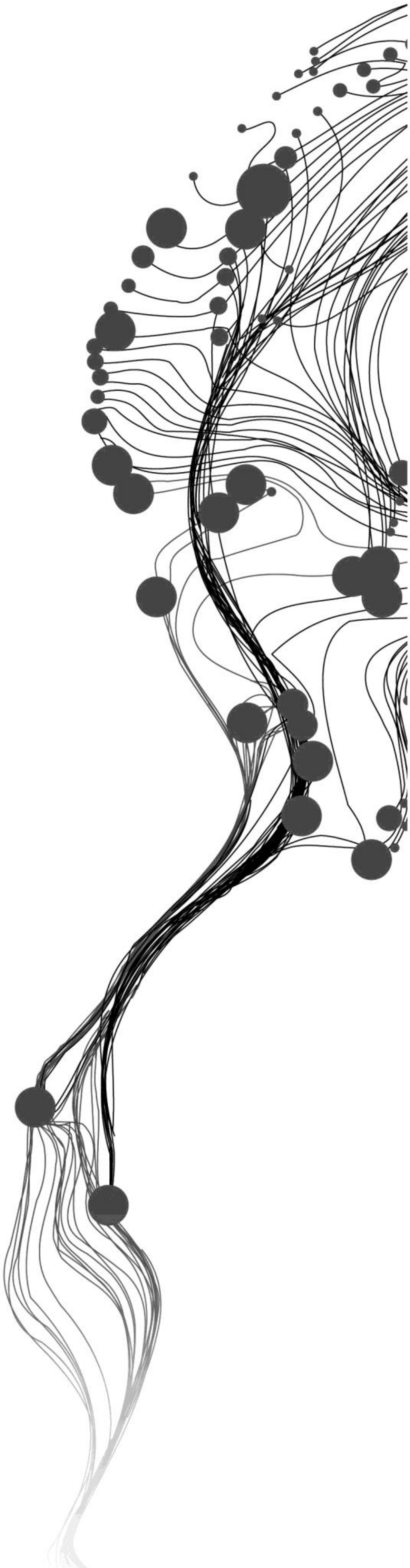

OBJECT ORIENTED DETECTION OF CANOPY GAPS FROM VERY HIGH RESOLUTION AERIAL IMAGES

BERYL NYAMGEROH
Enschede, The Netherlands, March, 2015

Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation.
Specialization: Natural Resource Management

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ABSTRACT

Inventory has long focused on timber production but less on other non-timber forest values such as biodiversity. It provides goods and services which are a lifeline for existence. Biodiversity has been declining over the years with growing economic development. This has made it even more important now that this resource is monitored for conservation purposes. The European Union has moved towards this end through the Natura 2000 legislation ratified in the year 1993. This policy has seen the establishment of protected sites in forest that are of ecological importance for all European member countries. For better management and conservation for sustainable development, these sites require monitoring. Measurement of the biodiversity in forest is therefore necessary. Indicators of biodiversity have been used to quantify this resource and canopy gaps in most studies have proved to be the best indicator.

To date, studies on canopy gap delineation are few and methods to delineate canopy gaps even fewer. Traditional methods of classification using spectral reflectance of pixels have proven to generally not perform well due to saturation in areas with high levels of biomass and noise in the classification which reduces the accuracy. Object oriented methods that work best with high resolution images are not limited by these issues and have therefore been chosen for use in this study. The study explores two object oriented methods; Object Based Image Analysis (OBIA) and a novel method Image Texture Based Analysis (ITBA) as the main object oriented methods. OBIA has been known to give high classification accuracies in forestry studies but is not lacking in limitations. It has also not been extensively applied to canopy gaps delineation. The new method seeks to reduce these limitations. The evaluation of their relative performance was carried out finally and the implication of the performance on biodiversity was briefly discussed.

A visual evaluation of performance of the methods was looked at in terms of the different parameter settings chosen. Statistical comparison of the methods was performed using Pearson's correlations and Root Mean Square Error. Over and under estimation of gap fractions was observed from a 1:1 relationship scatter plot. The results show that correlations of the estimates from the image with field data are moderate ranging from 0.30 to 0.43 and are not very different between the methods. However the error analysis shows that the novel method gives the lowest error (14%) with field data at a parameter setting of 21.

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1. INTRODUCTION

1.1. Background, Literature review and Justification.

1.1.1. Inventory and biodiversity

Information based on the quantity and quality of forest resource is achieved through carrying out a forest inventory (Husch et al., 2002). This procedure was first carried out in the mid-19th Century for the purpose of assessing the timber supply available to sawmilling companies (Peters, 1996). These companies came to the realization that inventory data was important for forest management and planning purposes (Gillis & Leckie, 1993). Although most inventories focus on timber estimation, there is a rising need for information on non-timber values such as the biodiversity that exists in forests, so that management from this kind of information aims at maintaining and enhancing forest health (Husch et al., 2002; Kohm & Franklin, 1997).

We see this increasing need for sustainable development policies in Europe where in the year 1992, European Union governments took a legislative initiative towards protection of the most seriously threatened habitats and species in Europe. All Member States contribute to the network of sites. The Birds Directive calls for the creation of Special Protection Areas (SPAs) for birds. The Habitats Directive likewise calls for Special Areas of Conservation (SACs) to be selected for other species, and habitats. Collectively, SPAs and SACs constitute the network of protected sites known as Natura 2000 (Gruber et al., 2012). Studies by Grodzinska-Jurczak & Cent (2011); Keulartz (2009) indicate that there is still a problem with implementation which are related to among other issues, lack of scientific data and tools.

Biodiversity has been simply defined by Kangas & Kuusipalo (1993) as the "variety of life" of both plants and animals. It provides a basis of various goods from the forest that include, but are not limited to, fuelwood, medicinal herbs, fruits, game and fodder and with services such as soil conservation, nutrient recycling, genetic and species diversity. Gao, Hedblom, Emilsson, & Nielsen (2014) observed that one of the ways of integrating biodiversity conservation in forest management planning, was by monitoring the spatial and temporal changes of the extent of the forest. Quantification of this information for better management and decision making is important (Husch et al., 2002). Measurable indicators of biodiversity are therefore used for quantification as direct measurement is difficult to achieve (Boutin et al., 2009).

1.1.2. Indicators of biodiversity

A direct indicator of potential biodiversity is structural diversity which is known to offer better habitat for both plants and animals (Powelson, 2001; Gao et al., 2014). This is contributed by temporal changes in understory vegetation, regeneration patterns and microclimatic variations (Spies & Franklin, 1989; Song et al., 1997). Among the three significant components of forest structural diversity as stated by Pommerening (2002) in (Figure.1-1), species diversity studies carry the majority of remote sensing applications (Foody & Cutler, 2006; Gillespie & Foody, 2008). Spatial distribution and variations in tree sizes are relatively newer issues in forest inventory (Ozdemir & Karnieli 2011). The two issues are important components of forest structure and can be characterized by several variables, including canopy cover, tree density, basal area' stem volume, biomass, leaf area index, tree species mixture and spatial arrangement of vegetation (Ozdemir & Karnieli, 2011).

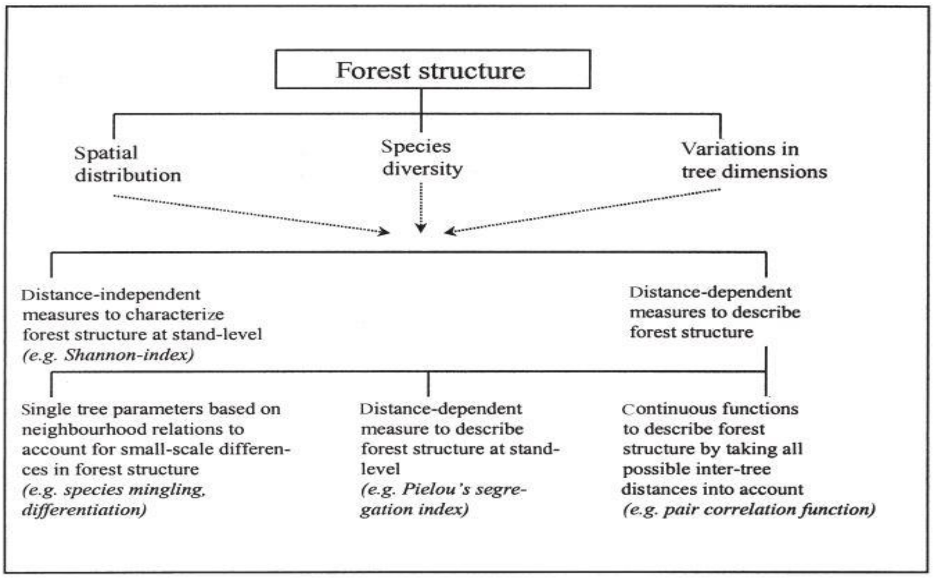


Figure 1-1: Overview of the three major characteristics of forest structure and the groups of variables by which it is assessed (adapted from a modification by Albert, 1999).

Forest structural parameters have conventionally been assessed by manual means (Herold & Ulmer, 2001) which proved time and again to be tedious, expensive and time consuming. Aerial photo interpretation then supplemented field measurements in the mid-1900s as the first method of remote sensing (Campbell & Wynne, 2011). It provides a faster, cheaper and less tedious method for determining forest structural parameters Yao et al., (2011) and is still widely used today along with other newer techniques of imagery such as LiDAR. Aerial imagery has important advantages over other forms of remote sensing, specifically the higher spatial resolution that it offers. Airborne techniques have been observed to generally have a higher resolution than space borne ones (1-10 m and 0.01-5 km respectively) (Bongers, 2001).

1.1.3. Remote sensing for forestry

Recently, digital aerial photography offers additional advantages over analogue aerial photographs and other remote sensing methods. Digital aerial imagery compared to analogue aerial photos can be captured with a resolution of 10cm per pixel or less (White, 2012). High resolution imagery has been beneficial in forest resource inventory and monitoring (Muinonen et al., 2001) for instance the case of Canada where forest inventories have been produced primarily from the interpretation of aerial photographs (Gillis & Leckie, 1993).

Remote sensing has been used for modeling and mapping forest structural parameters such as basal area (BA), stem volume, mean tree height, biomass, leaf area index (LAI) and mean diameter at breast height (DBH) (Ozdemir & Karnieli, 2011; Gillespie & Foody, 2008; Kayitakire, Hamel, & Defourny, 2002; Cosmopoulos & King, 2004). Cho, Skidmore, & Sobhan (2009) used hyperspectral images to estimate structural attributes in closed canopy beech forest (*Fagus sylvatica)* while the study by Anderson et al (2008) integrated hyperspectral data and LiDAR to improve performance in estimation of forest measurements of basal area(BA), above-ground biomass (AGB) and quadratic mean stem diameter (QMSD). This shows the potential of remote sensing for forest mensuration. While other forest structures have been studied extensively using remote sensing, canopy gaps have been studied less relative to other forest structural parameters.

1.1.4. Canopy gaps

As noted above, canopy cover is one of the important forest variables that affect species diversity and distribution (Gao et al., 2014). This study focuses on canopy gaps in the forest as an essential parameter which supports many plant and animal species as compared to forests without canopy gaps (Moore & Vankat, 1986). A lot of research has focused on canopy structure in terms of crown percentage area, crown diameter, canopy density and crown volume among other crown parameters for biomass estimation but few on canopy gaps for biodiversity.

First and foremost, understanding stand dynamics, including quantification of canopy gap patterns is important. It is an area that has been studied intensively by ecologists (Lawton, Putz & Lawton, 1988). Ozdemir et al. (2012) stated that a structurally diverse stand provides living space for a number of organisms. These naturally occurring gaps contribute to the rich diversity in the forest. According to Lorimer (1989), canopy gaps are defined as openings in the tree canopy of a forest. The sizes can range from <25m^2 to about 0.1 ha on a small scale with disturbances characterized by death of one or a group of trees; while large scale canopy gaps can range from 1 to 3000ha caused by periodic disturbances (Runkle, 1989). These disturbances can be caused by a number of factors including natural disasters, tree fall, diseases, logging among others (Runkle, 1989).

There are some studies that have been carried out in forests regarding canopy gaps by; Zeibig et al. (2005) who carried out a study based on an inventory of the horizontal canopy structure. They investigated disturbance patterns of a (*Fagus sylvatica)* virgin forest residue in Slovenia. In addition to canopy gaps structure, Danková & Saniga (2013) also studied tree regeneration patterns in these gaps. They were able to answer the questions concerning the spatial scale of disturbance events, how gap sizes affected the density of tree seedlings and saplings and what differences there were in species composition of the same between the closed canopy and expanded gap in a mixed old growth forest in Slovakia. Ihók et al. (2007) conducted a study on gap regeneration patterns where the goal was to examine the effect of gaps on regeneration processes. A more related study to this research was by (Blackburn & Milton, 1997) whose aim was to characterize spatial properties of gaps using an airborne spectrographic imager. The results were used to infer ecological status of the forest. These studies not only show the importance of canopy gaps, but also tell the avenues have already been taken to quantify them.

1.1.5. Detection of canopy gaps

The mapping and detection of forest gaps has been found to be important as far as forest management and biodiversity conservation is concerned (Scarth et al., 2002). Forest gaps have been mapped and detected by manual means where the survey involves measuring the length and the width of the gaps then calculating the area with the assumption that the gap is either a circle or an ellipse (Stewart, Rose, & Veblen, 1991). This of course is not a true representation of the gap as we know that natural features are not regular in shape. They have also been mapped on aerial photos or by ground measuring tools like a hemispherical camera (Schwarz et al., 2003). Bucha & Stibig, (2008) suggested that canopy openings in forests can be mapped using remotely sensed image methods like visual interpretation and unsupervised classification. Supervised classification was also used earlier in land cover mapping and involved pixel based analysis which was later found to have limitations (Raines, 2008; Cracknell, 1998). The key issue was reduced accuracy due to the "salt and pepper" effect in classification which hampers proper planning and decision making (Raines, 2008). These issues are highlighted in the next paragraph.

To begin with, pixel based analysis uses spectral information known as digital numbers to generate clusters of similar spectral reflectance, Campbell & Wynne (2011) and although the technique is well developed, the method disregards the spatial dimension of objects (Yan, Mas, Maathuis, Xiangmin, & Van Dijk, 2006). Secondly, it uses spectral band ratios such as Normalized Difference Vegetation Index (NDVI) to map vegetation which can also help to separate gaps from areas with trees. The problem comes in when the region has high biomass like in multi-storied forest canopies where the method saturates (Huete, Liu, & Leeuwen, 1997). Synthetic Aperture Radar (SAR) is a technique that is also very reliable in mapping of biomass and is also important to mapping gaps but as in the aforementioned technique, it also saturates in regions of dense forest canopy (Kasischke, Melack, & Dobson, 1997; Ouchi, 2013). LiDAR is the most recent technology in remote sensing and the most dependable for mapping forest structure relative to field data, it is however a very expensive technology in terms of the equipment, the expertise and the availability of data (Dubayah & Drake, 2000; Lim et al., 2003). Ultimately, object oriented classification has no such constraints and has been known to improve classification accuracy (Raines, 2008 and Blaschke, 2010).

1.1.6. Object oriented methods

Documented work in segmentation techniques began in 1976 as an alternative to pixel classification (Kok et al., 1999; Benz et al., 2004). Segmentation not only uses spectral qualities of pixels but also other qualities like the tone, texture, association etc. Even though image segmentation began being used in the 70s, it was not until later with more availability of high resolution imagery and improved software and hardware capabilities that object based approach took a forefront (Kok et al., 1999). As object based approach gained more use with high resolution imagery, pixel based analysis declined in use because of the problems it encountered with high resolution images, notably the "salt and pepper effect" (Mansor et al., 2003). Object oriented approach was found to eliminate the problem.

1.1.6.1. Object based image analysis (OBIA)

This is a technique used to analyze digital imagery that involves segmenting an image into units called image objects. It is done by considering the homogeneity of objects in terms of their spectral properties, size, shape, texture and a neighborhood surrounding the pixels (Hay et al., 2005; Benz et al., 2004). The objects formed are primarily based on scale parameter which is the value that determines maximum possible change of heterogeneity and thus how large the objects can grow (Mansor et al., 2003). Software known as eCognition was developed in the early 2000s which is currently being used for object based image analysis. OBIA segmentation can create image objects that closely resemble the size and shape of real features as in the image. OBIA, like any other automated techniques, has its limitations, the main one being the inability to separate objects spectrally and the shadow effects (Koukoulas & Blackburn, 2004).

OBIA has been used to successfully delineate forest stands. A study by (Chant & Kelly, 2009) used the method to quantify changes on a canopy structure by identifying dead oak trees in a forest and as well the extent of the dead tree on the ground. The method had the ability to detect within object variability and therefore enable monitoring. Hese & Schmullius (2005) also used OBIA to detect changes in a forest due to deforestation and the classification with this method were found to increase accuracy of the change classes. Wang (2012) was able to successfully extract canopy gaps from high resolution aerial images for a tropical forest.

1.1.6.2. Texture based image analysis (ITBA)

This is also an object oriented approach. Fourteen texture features were defined by (Haralick, 1979). These texture features have been used in a number of studies as shown in (Table 1-1). According to Wulder et al. (1998), texture describes the relationship between elements on surface of the earth. It refers to the smoothness or roughness of a surface and in particular the frequency of change in tone of pixels in images (Haralick, 1979). ITBA uses a predefined number of pixels known as the window size, which defines the area that is used for statistical calculations (Coburn & Roberts, 2004). Like scale parameter in OBIA, the size of the moving window determines the size of texture objects created. Studies by Cohen & Spies (1992) show that texture features extracted from higher spatial resolution images have advantages for forestry applications. High variability in texture indicates high variability in structure of vegetation signifying variable habitat types (Hepinstall & Sader, 1997). Indeed, Wulder et al., (1998) noted that textural features had more information content than spectral features especially in forest stands where the spectral information was heterogeneous. In Canada, research carried out by Ozdemir & Karnieli, (2011) showed that forest structural parameters were significantly correlated with image texture features. Commonly used texture features such as contrast, entropy, homogeneity (Table 1-1) in remote sensing, have shown to be useful for modelling forest structure attributes (Cosmopoulos & King, 2004).
Texture features have already been used to estimate stand structure variables (Table 1-1) but few studies have used texture analysis to study gaps. Betts, Brown, & Stewart (2005) described the use of texture analysis based on high resolution DEM to detect and characterize canopy gaps.

Table 1-1: Studies on forest variables using texture features

FOREST VARIABLES	REFERNCES
Species	(Solberg, 1999)
Height, age class, density, basal area, DBH and crown diameter	(Kayitakire et al., 2002)
Density, Basal area, Stem volume and structural diversity indices	(Ozdemir & Karnieli, 2011)
Biomass	(Eckert, 2012)
Crown sizes and positions, canopy closure, understory and ground vegetation, of standing and fallen dead wood.	(Pasher & King, 2010)
DBH and height.	(Tuominen & Pekkarinen, 2005)

The two object oriented methods (Object based and texture based) emphasize on two different criteria for the formation of meaningful objects. That is the color criterion for OBIA Gao & Mas (2008) and texture criterion for ITBA. It is therefore quite interesting to look at how the different basis for formation of meaningful objects compare to each other in terms of mapping of canopy gaps. We therefore look at two object oriented methods which emphasize on two basic elements of digital numbers in pixels from digital images that aid in identifying objects; tone and texture for OBIA and ITBA respectively.

1.2. Problem Statement

Bulgaria joined the European Union in 2007 and since then, selected sites in the country have been added to the birds and habitat directive under Natura 2000. However, since the inclusion of some Bulgarian forest areas under Natura 2000, there is still no management plan (Nikolov, Kornilev, Popgeorgiev, Stoychev, & Georgiev, 2014). Only research has been done but no full inventory; hence the need for this study which might contribute to the building of a management plan.

Since 1990, the disturbance of the forest in the Bulgaria (Table.1-1) has been studied and monitored statistically, but not spatially.

Table 1-2: Average annual area of forest in Bulgaria affected by disturbance (1000 hectares).

Data source: FAO, Global Forest Resources Assessment 2010.

FRA 2010 category	Affected forest area (1000 hectares)		
	1990	2000	2005
Disturbance by insects	104	186	82
Disturbance by diseases	52	36	32
Disturbance by other biotic agents	0.4	0.3	1
Disturbance caused by abiotic factors	9	23	6.7
Total area affected by disturbances	**165**	**245**	**122**

Forest resource inventory and monitoring are among the major goals of remote sensing applications in forestry (Muinonen et al., 2001). The goals for forest inventory in protected natural forest differ from those in plantation and production forest and hence the need for supplementary information and measurements that include;

- Ground vegetation
- Regeneration
- Fallen or standing dead wood and/or decomposing wood
- The diameter and height so as to obtain picture of the structure of the forest

Most of these information is found inside gaps and support many plant and animal species as compared to forests without gaps (Moore & Vankat, 1986). It has been shown that, too much forest fragmentation can also affect the organisms in the forest negatively (Lenor, 2014). Previous research has focused on the structural patterns and the biodiversity within canopy gaps but few have explored ways in which to accurately map the canopy gaps. This is necessary for purposes of constant monitoring of the forest (Perotto-Baldivieso et al., 2009). Conservationists have been known to require maps of gap size and location to assess spatial relationship between canopy gap and wildlife species (Fox et al., 2000) and that is why there is need for accurate mapping and detecting forest gaps for forest management and biodiversity conservation (Scarth et al., 2002).

Monitoring of canopy gaps, like any other resource monitoring, requires acquisition of accurate information to be able to detect accurate changes in the gap size. Delineation of gaps from images to closely match ground situation is therefore necessary. OBIA is a more relatively reliable method in land cover mapping that has been used extensively in forests but less so in explicitly mapping canopy gaps. This method has its limitations as mentioned in section 1.1 above. New methods that delineate canopy gaps have also not been extensively looked into. This research seeks to use advances in remote sensing technology that includes digital aerial photography and new methods of canopy gaps analysis using object oriented methods where a comparison is made between object based image analysis (OBIA) and image texture based analysis (ITBA) methods. The two methods are explored in terms of ability and to what extent they are able to estimate canopy gap fractions. This is with the expectation of offering opportunities for accurate delineation of gaps and the need for further investigation.

1.2.1. Main Objective

The aim of this research is to explore two methods, Object Based Image Analysis (OBIA) and Image Texture Based Analysis (ITBA), for delineating canopy gaps from a very high resolution aerial imagery.

1.2.2. Research Objectives and Questions

1. To detect and quantify canopy gaps from OBIA and ITBC.
    - What are the suitable parameters to use for extracting canopy gaps from the methods?
2. To assess the results of quantification of canopy gaps.
    - Do the canopy gaps obtained with both methods correspond to the sampled gaps in the field?
    - How different is the quantification of the individual gaps between the two methods?
    - How accurately can canopy gaps be estimated from the two methods?
3. To investigate the influence of forest type on assessments of the two methods.
    - To what extent does forest type influence accuracy of the two methods?

1.2.3. Hypothesis

1. H_1: There is significant relationship between canopy gaps from field collected data and image estimated canopy gaps.
2. H_1: OBIA and ITBC methods are not significantly different in quantification of canopy gaps.
3. H_1: Change in parameter settings within ITBA and OBIA method leads to a significant change in results.
4. H_1: Detection of canopy gaps in needle leaved forest is more accurate than in broadleaved forest.

2. MATERIALS AND METHODS

2.1. Study area

The study were located in two regions, the Balkan Mountain ranges and Rhodope Mountain ranges in Bulgaria, at co-ordinates (42°43'00"N 24°55'04"E) and (41°36'04" N 24°34'27"E) respectively (Figure. 2-1). The Balkan mountain range in the west of Bulgaria has a length of 530 Km and a width of 15–50 Km. It borders Serbia to the West.

The altitude is between 550m to 2376m. The wooded area covers 44,000.8 ha and treeless area 27,668.7 ha. The Balkan mixed forest belongs to the temperate broadleaf and mixed forest biome. The topography of the study area is characterized by high valleys and sheltered slope with European beech (*Fagus sylvatica*) as the dominant species.

The Rhodopes covers an area of 11, 596 Km^2. It is spread over 14, 735 km^2, of which 12,233 km^2 are on Bulgarian territory the rest falls in Greece to the south. The Mountains are about 240 Km long and about 100 to 120 Km wide with an average altitude of 785 m. The Rhodopes are a comprised of deep valleys and ridges.
The temperature varies from 5 to 9 °C and can go as as low as −15 °C. Due to this the Rhodopes are the southernmost place in the Balkans where tree species that dominate are Norway spruce (*Picea abies*) and the silver birch (*Betula pendula*) can be found. Some fir trees (*Abies alba*) are also found here.

The forests in both the mountain ranges fall under the Habitats Directive and Birds Directive which forms the cornerstone of Europe union's nature conservation policy. It is built around two pillars: the Natura 2000 network of protected sites and the strict system of species protection. These directives protects over 1,000 animals and plant species and over 200 so called "habitat types" which are of European importance (Gruber et al., 2012).

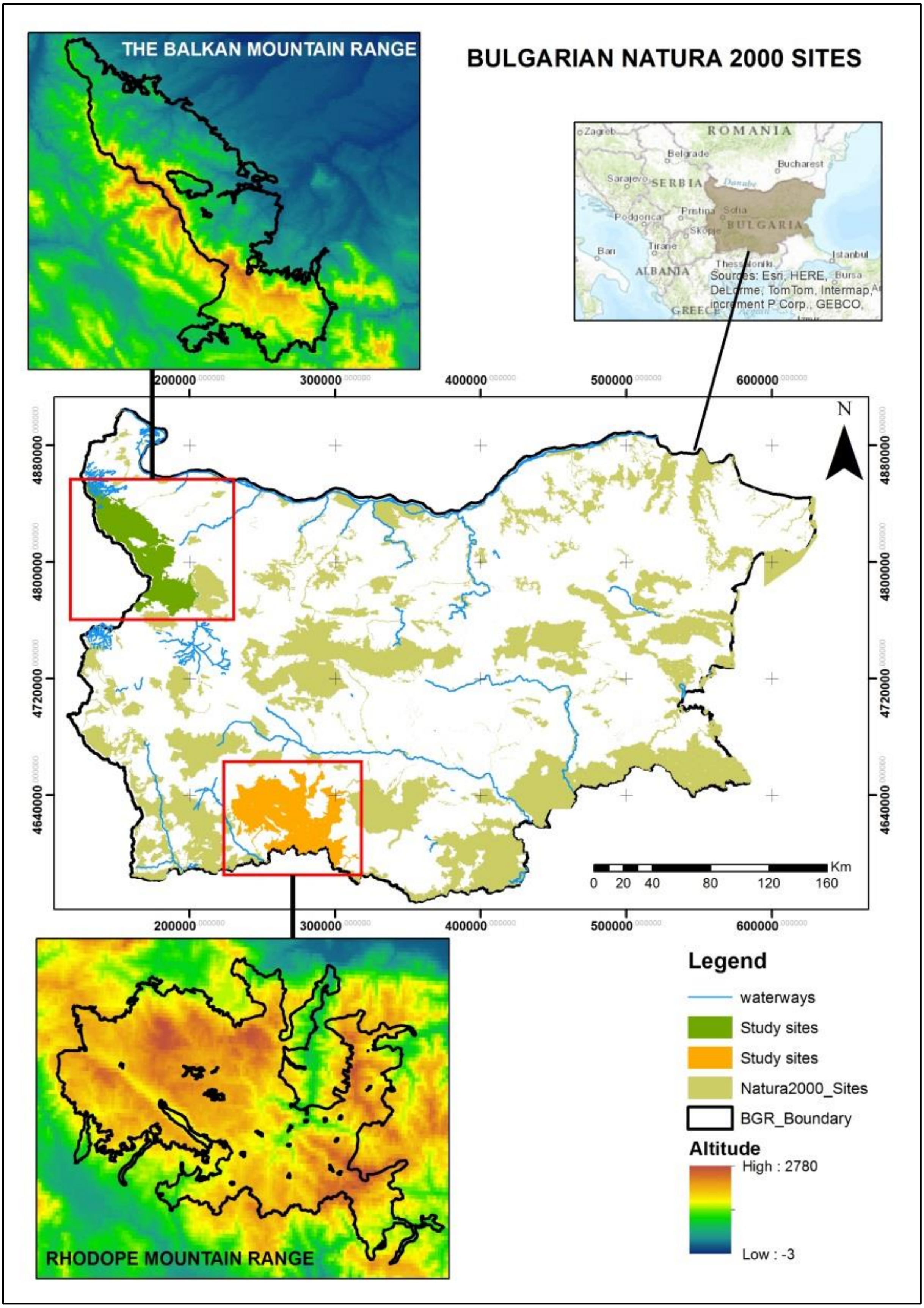


Figure 2-1: Location of study area showing the Natura 2000 sites.

2.2. Data

The study was based on data provided by the Forestry Research Institute in Sofia. Very high resolution true colour pre-processed aerial image of a spatial resolution of 13cms was captured in the year 2011.

The image was made available in 100 clipped sections of 300m×300m for each of the ground based sampled plot where inventory data was available. Some of the images for each plot area were eliminated by the processing tools, some were missing and some could not be used due to image corruption. Eventually only 93 images were used for the study.

The field work took place in different years, 2013 for West Balkan Mountains and 2014 for Rhodope Mountains. The fieldwork was for a project that was aimed at sampling old growth forests and proposing areas with less forestry activity in Bulgaria. As relates to this study, the objective was to identify and estimate canopy gaps. The datum of the areas of study is WGS_1984_UTM_Zone_35N.

2.3. Methods

2.3.1. Field data collection

Plot selection was purposive and mostly depended on the accessibility of the terrain. 100 square plots each of the size (150×150m) were established over two types of forests. In each plot 25 circular sub-plots were made each with a radius of 5.6m. The sub-plots were separated from one another by a distance of 30meters from the centers. This is illustrated in (Figure 2-2).

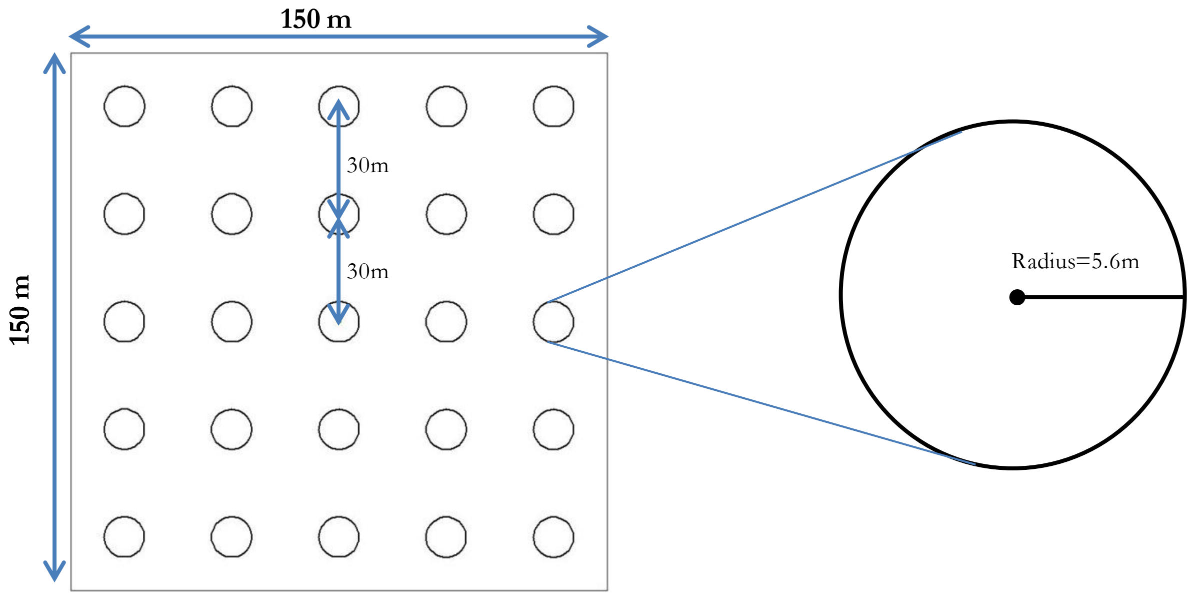


Figure 2-2: Formation of the sampling plot.

This was to remove any bias of choosing sub-plots that had our desired quality. 48 square plots were established in the West Balkan mountain ranges and predominantly consisted of broadleaved trees. 52 square plots were also sampled in the Rhodope Mountains and more than half of the plots sampled were in a needle leaved type of forest. In total, 66 sample plots were sampled in a broadleaved type of forest while a total of 34 plots were sampled in a needle leaved type of forest. In total there were 2500 sub-plots for the study.

A canopy gap was defined as an opening within trees that were more than half the height of the tallest tree on the boundary of the gap and had an area not less than $50m^2$. Each gap was considered closed if the tall trees adjacent to the boundary had their tips at a distance of less than 7m between them.

The gaps within the plot were estimated visually and then the fraction of the gap intersecting into the circular sub-plots estimated in percentage. Only the center sub-plot (sub-plot 13) had the coordinates recorded. The average gap fractions were calculated over all 25 sub-plots to create an average gap fraction for the entire plot.

The sampling method was line intersect sampling method where circular sub-plots were made along the invisible transect line established along a compass direction (Figure 2-3). Gaps were likely to be sampled if part or whole of it intersected with the $100m^2$ sub-plot made along the transect line. The fraction of the gap in the sub-plot was recorded after estimating the area of the larger gap.

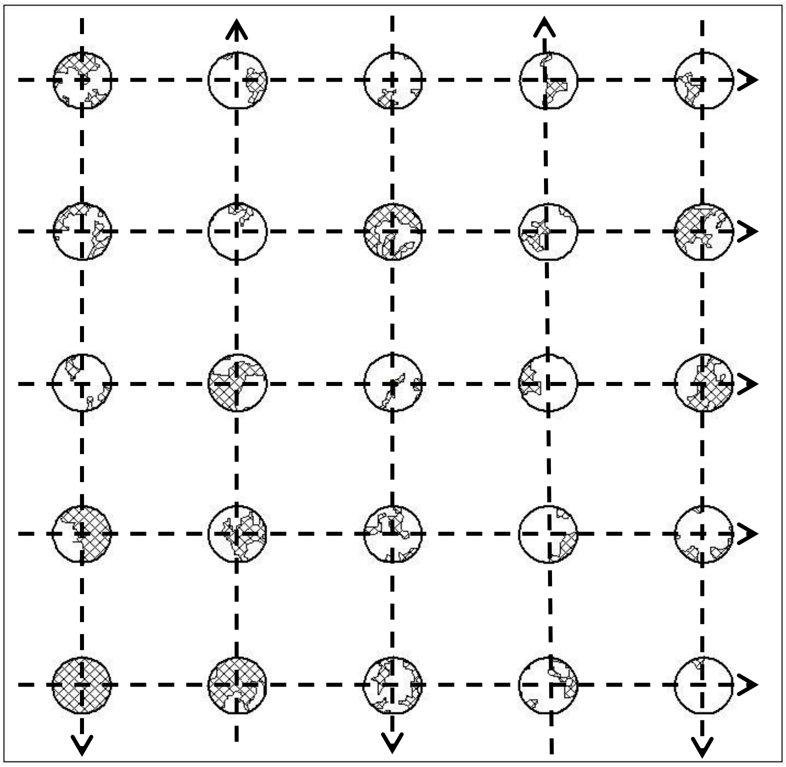


Figure 2-3: Checked areas represent gap fractions intersecting the sub plots.

2.3.2. Canopy gap detection

The process of canopy gaps detection is generally described in (Figure 2-4).

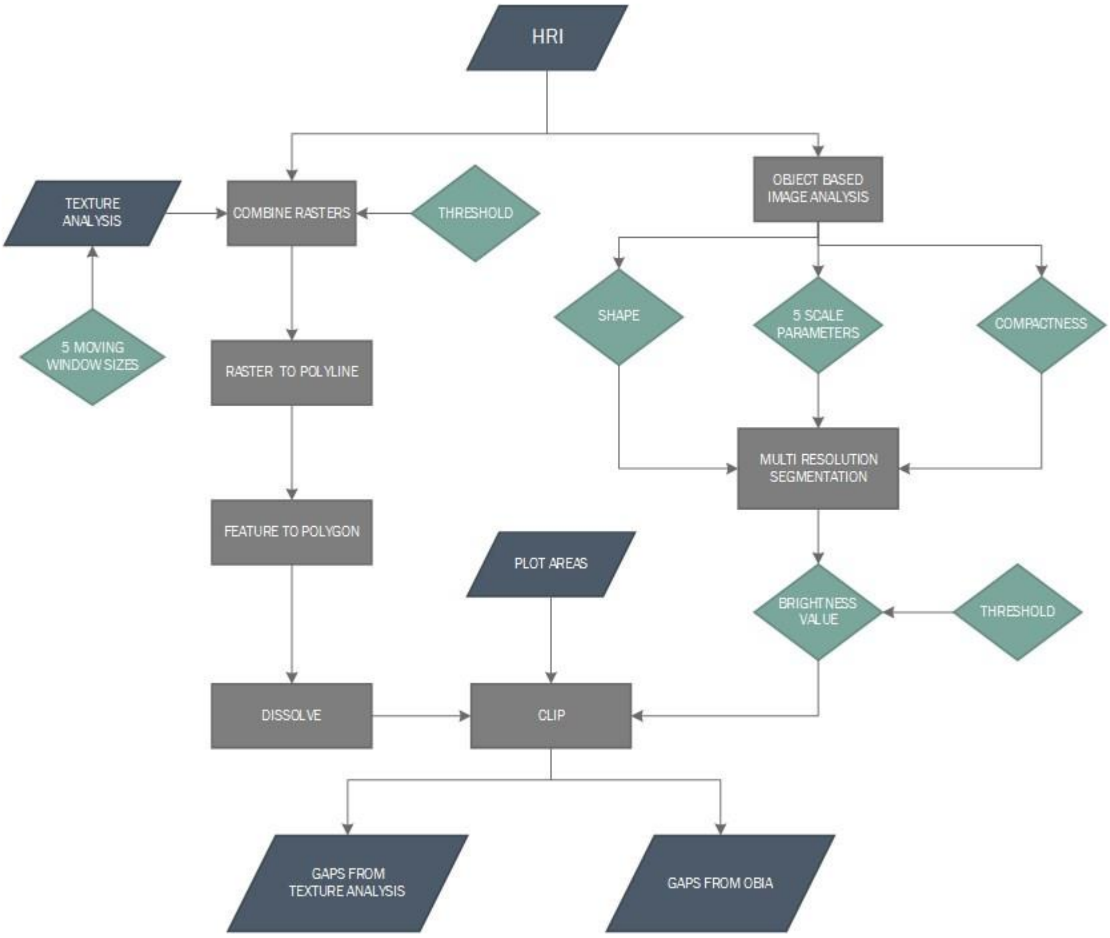


Figure 2-4: Overview of step by step process of methods.

One of the advantages of using very high resolution imagery was that for each pixel, the likelihood of only one object being represented is high, improving the potential to separate gaps from non-gaps (Nackaerts et al., 2001). Another advantage is that many combinations of techniques could be applied to any or all of the three RGB bands (Fernandes et al., 2004).

There is no known literature with a standard parameter setting for object based approaches for segmenting features in forest stands therefore; several tests are run until appropriate parameters are found. The final selection of the chosen parameters included small parameter setting which was chosen to represent intra-object variation (within-crowns and shadows) while larger ones were to represent inter-object variation (crowns or canopy objects versus between –crown shadows). Parameter settings below 5 for OBIA and 5×5 for ITBA were tested but not used because the over estimation was too much and this was vice versa for parameter settings larger than 21 for OBIA and 21×21 for ITBA where under estimation was too much. The other criteria used in the study are set standard for all images for the purposes of repeatability.

2.3.2.1. Texture Based Image Analysis

Texture based image analysis was done using ArcGIS software from ESRI. It involves characterizing regions of an image using the smoothness or the roughness. This refers to variation in reflectance values. In this method we use standard deviations to find the texture boundaries which would be indicative of the change in the structure of the canopy. This helps in detecting the gaps.

The selection of the chosen parameters setting ranged from small to large. Before this selection ten sample images were chosen randomly from the total number of images and the different criteria tested until a suitable criterion was reached. Suitability was judged by the criteria allowing detection of gaps to be as close to reality as possible.

The first step is to create texture features which eventually will be used to detect gaps using the appropriate parameters. To create the texture features, a decision was made to use a moving window approach where a standard deviation statistic type was derived as an indicator of variability in such a moving window. For this approach moving window sizes had to be chosen (5×5, 7×7, 11×11, 15×15 and 21×21). The result was a texture feature image. A transition point from high standard deviations to low standard deviations of pixel values indicated a change in land cover as shown in (Figure 2-5).

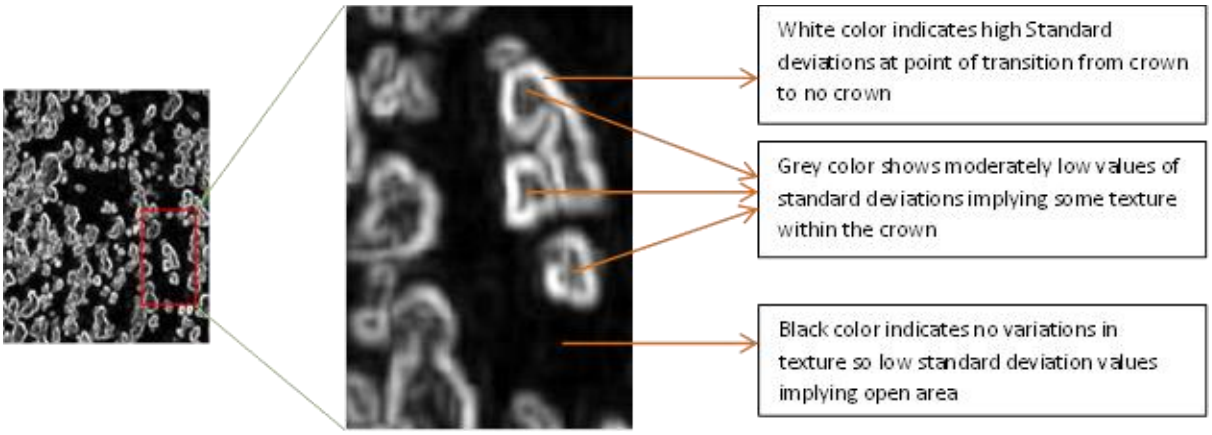


Figure 2-5: Grey scale filtered image showing the meaning of the grey scale colour range to signify texture differences.

This texture feature image gives us standard deviation values for each pixel which was used in setting the threshold for gaps. Areas with homogenously low texture values (smooth areas) and were surrounded by extremely high values of standard deviation were defined as gaps (Figure 2-5). This part of the process led to detection of smooth canopy surfaces as gaps. A decision was therefore made to add an extra criterion of including greenness values to the selection of threshold. This was done by use of the combine tool to integrate values from the filtered image and the green pixel values of the RGB image. The result was a raster image with unique output values of a combination of the values from the two input raster images (Figure 2-6).

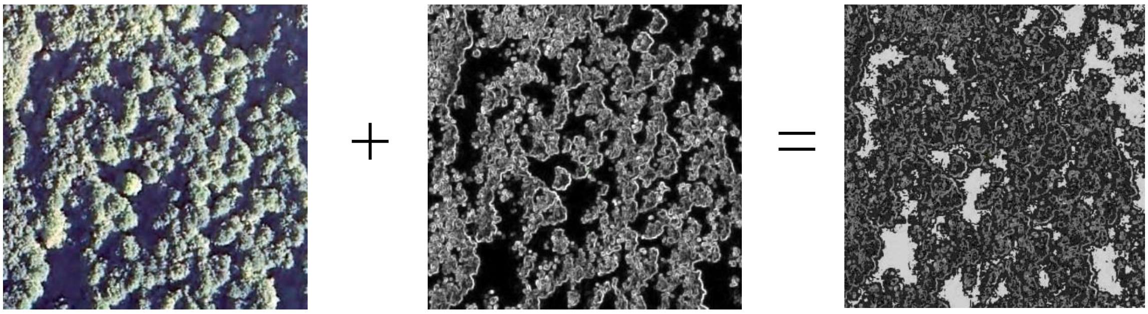


Figure 2-6: Combination of aerial image and filtered image to produce a raster map with values that include standard deviation values and RGB values.

The output values were used to set the threshold for gaps. For uniformity the chosen threshold was applied to all the images. The thresholds differed for the different moving windows as shown in (Table 2-1).

Table 2-1: Increasing moving windows with increasing thresholds.

MOVING WINDOWS	THRESHOLD
5×5	<=4
7×7	<=5
11×11	<=5
15×15	<=7
21×21	<=7

With the selected criteria, the images were converted from raster to polylines and then converted to polygons which were then dissolved and clipped to the plot area. The total areas of the gaps were calculated and finally a record of gap fractions for each plot was derived for each moving window. The files were then joined with the database from the field, matching stand to stand so that finally a database of field based estimates was matched with image based gap estimates per moving window (Appendix 3 and 4).

2.3.2.2. Object Based Image Analysis

Object based image analysis uses eCognition software from Definiens Developer®. The instructions given to the software by the user to carry out functions based on chosen parameters is called a ruleset (Figure 2-7). The first basic rule in the method involves cutting the image into image objects in a process known as segmentation and this is the building block for further analysis and refinement of the ruleset. Segmentation considers the homogeneity of objects in terms of their spectral properties, size, shape, texture and a neighborhood surrounding the pixels (Benz et al., 2004; Hay et al., 2005).

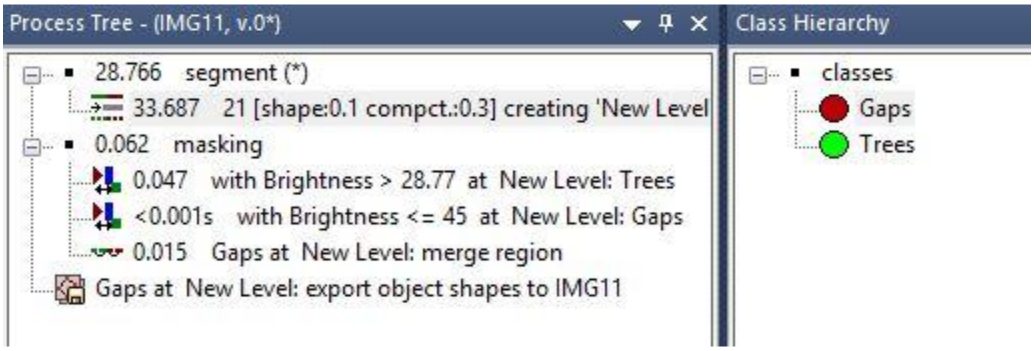


Figure 2-7: eCognition interface for setting rulesets for segmentation process

Multi-resolution segmentation was chosen in this study as it has been successfully used in other mountainous regions (Drăguţ & Blaschke, 2008). It implies that objects can be created at any chosen resolution and therefore allows separation of many levels of object categories (Rahman & Saha, 2008). This type of segmentation lumps together objects based on relative homogeneity which is a combination of spectral and shape criteria to create a larger object. It can be modified by a scale parameter which is the value that determines maximum possible change of heterogeneity. It therefore influences how large the objects can grow by how many pixels can be grouped into an object (Figure 2-8) (Üreyen, Hü, & Schmullius, 2014).

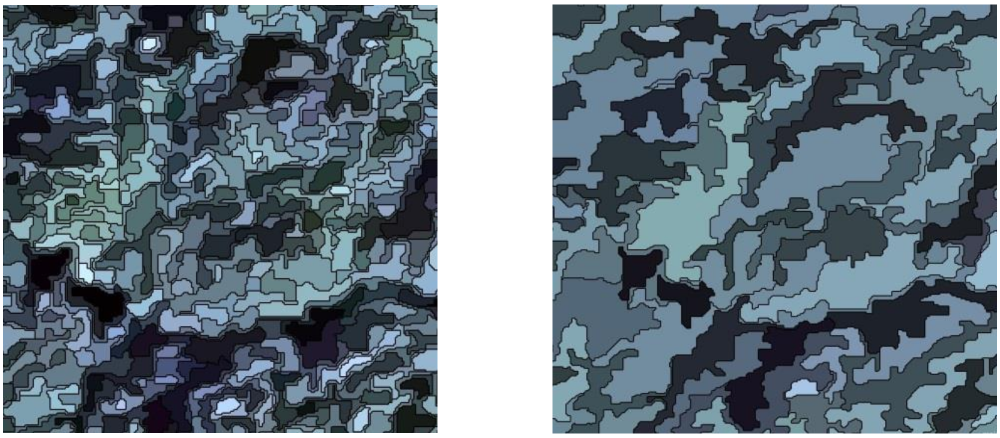


Figure 2-8: More objects in small scale parameter and fewer objects in large scale parameter.

It was therefore decided to use five scale parameters; 5, 7, 11, 15 and 21 which were chosen to vary possibilities of results. The values corresponded to the pixel sizes that were selected for texture method for ease of comparison. The problem of under segmentation is reduced because the algorithm gives the option of merging small segments (Saliola, 2014).

The other homogeneity criterion used in segmenting was shape and compactness. Both Shape and compactness values can go up to 0.9(Gao & Mas, 2008; Kim, 2009).

- Shape indicates how much of the spectral values affect heterogeneity of the objects. It is the relative weighting that determines the degree in which shape influences the segmentation compared to color. In this study, a value of 0.1 was chosen meaning that color was given more weight of 0.8. We want color to have more weight because the spectral values are important for separating shadows from trees.

- In the same way the value chosen for compactness is a relative weighting against smoothness. A value of 0.3 was chosen meaning smoothness had a value of 0.6 therefore giving slightly more weight to smoothness. We want smoothness to have more weight because gaps are natural features and therefore less compact but can also be quite irregular.

A weight of 2 for the green layer was chosen in preference to the red or blue layer. This was due to the importance of separating the green color of trees from gaps. These were the optimum fixed values to be used for segmentation obtained after trial and error method (Figure 2-9). Meaning that the process is repeated severally using different values until one is satisfied with the segmentation that appears closest to the real features. Since the image was homogenous (forest area), the values for shape and compactness were applied to all the images.

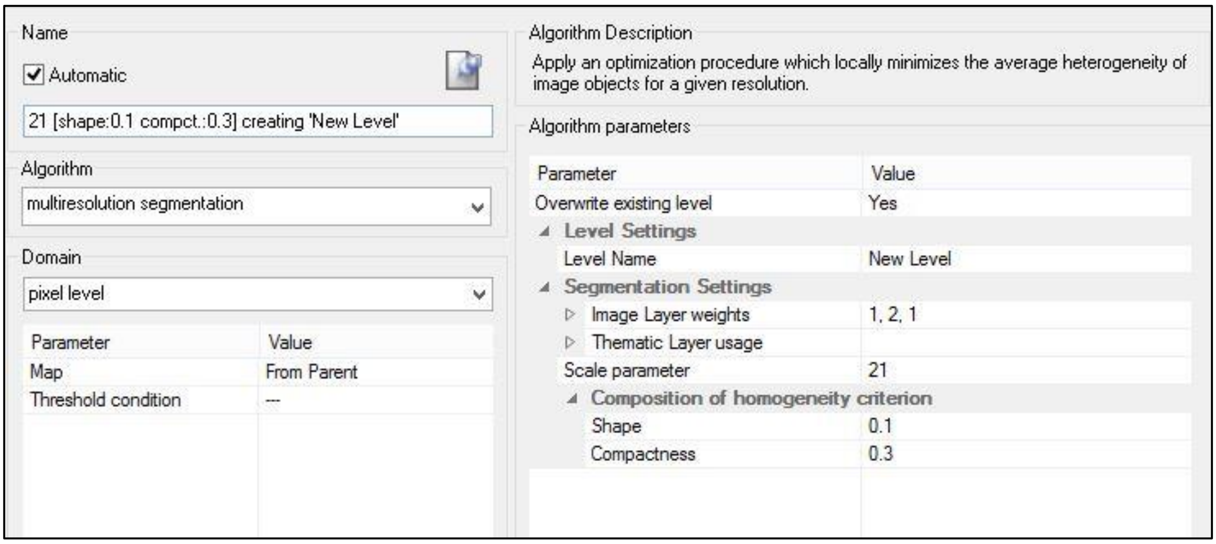


Figure 2-9: eCognition interface for setting of layer weights, scale parameter, shape and compactness criteria.

The segments created are a mixture of trees and gaps. To separate the two features, first a classification of the objects into trees and gaps was done then a separation of trees from the gaps was made which was the class of interest. A brightness threshold was chosen for classifying, where the brightness values of the objects were used to separate the two classes. Trees had higher reflectance values than gaps. Assign class algorithm was used to define the rules of classification. It included assigning a maximum brightness value in which almost all gaps were selected and the values above this maximum value represented the trees. These brightness values differed for each image and therefore the threshold for gaps differed per image. This was also a trial and error process until the values chosen, selected most of the gaps in the image (Campbell & Wynne, 2011).

After creating the two classes, the tree class was masked out so that only gaps remained. Since many objects were created within one class, a merge region algorithm was used to merge the split gap objects into one. Finally the extracted gaps were exported into ArcGIS for further analysis of area and gap fraction calculation. A join operation is performed with the field database which was also containing gap fraction estimates from the texture based analysis method to form one database used for statistical analysis.

2.3.3. Statistical analysis

The statistical analyses were done using R and excel software. The overall performance of the methods was evaluated based on two parameters; Pearson's Correlation (r) and Root Mean Square Error (RMSE)

a) Pearson's Correlation (r) to analyze the linear relationship between the images based gap fractions and the field based gap fractions.

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum(x_i - \bar{x})^2}\sqrt{\sum(y_i - \bar{y})^2}} \tag{1}$$

Where,
r = Correlation coefficient
x = Observed gap fractions
$\bar{x}$ = Mean quantified gap fractions
y = Estimate of gap fractions
$\bar{y}$ = Mean estimated gap fractions

b) Root Mean Square Error (RMSE).
RMSE was used to measure how much error there was between the field based gap fractions and the image estimated gap fractions by OBIA and ITBA methods. This calculation was done based on the following equation;

$$RMSE = \sqrt{\frac{\sum(x_i - y_i)^2}{n}} \tag{2}$$

Where,
RMSE = Root mean square error
x = Observed gap fractions
y = Estimate of gap fractions
n = Number of observed values

3. RESULTS

3.1. Detected canopy gaps from very high resolutiom imagery

3.1.1. Image Texture Based Analysis (ITBA) and Object Based Image Analysis (OBIA).

The bright colored areas show areas with high standard deviation values meaning a high variability in the tone values while the darker areas are low standard deviation areas with smoother texture and therefore low variability in tone values. Smaller parameter setting produce much more objects than larger parameter setting as shown in (Figure 3-1). More objects are formed in OBIA than in ITBA method.

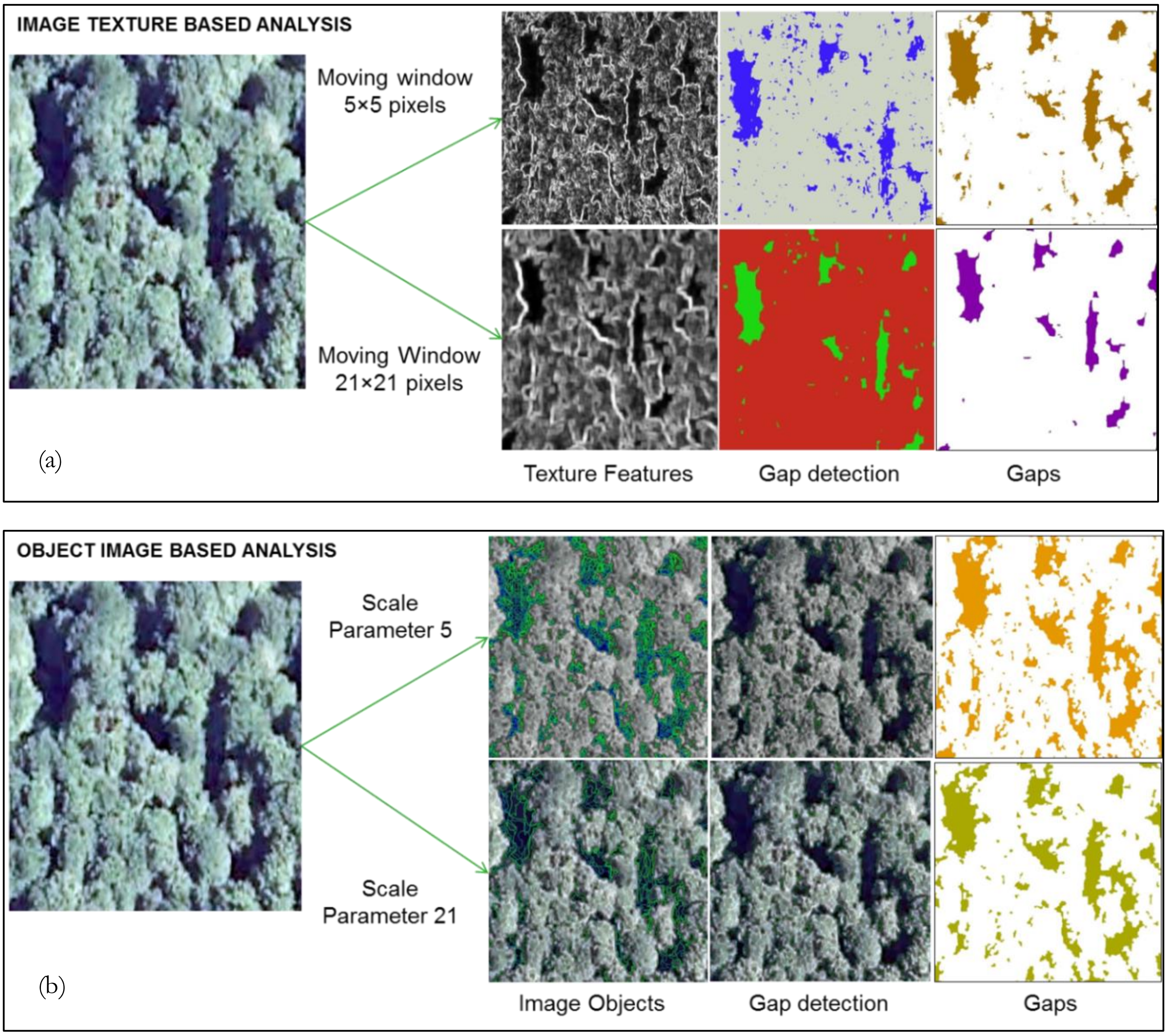


Figure 3-1: Extraction process of texture features and image objects using ITBA Method (a) and OBIA method (b).

3.2. Statistical Analysis

3.2.1. Image Texture Based Analysis and Object Based Image Analysis

Gap fraction distribution in the field data indicates that most of the gaps lie on the lower end. Larger gaps are undetected or are very few in both methods. OBIA method shows a slight normal distribution as illustrated in (Figure 3-3). ITBA method shows distribution closer to the field estimates. Observations from the field were expected because the data collection was not targeted towards canopy gaps so most of the plots did not record presence of gaps. This is why we see that from the field collected data, most of the gaps lie on the extreme lower end of the histogram (Figure 3-2).

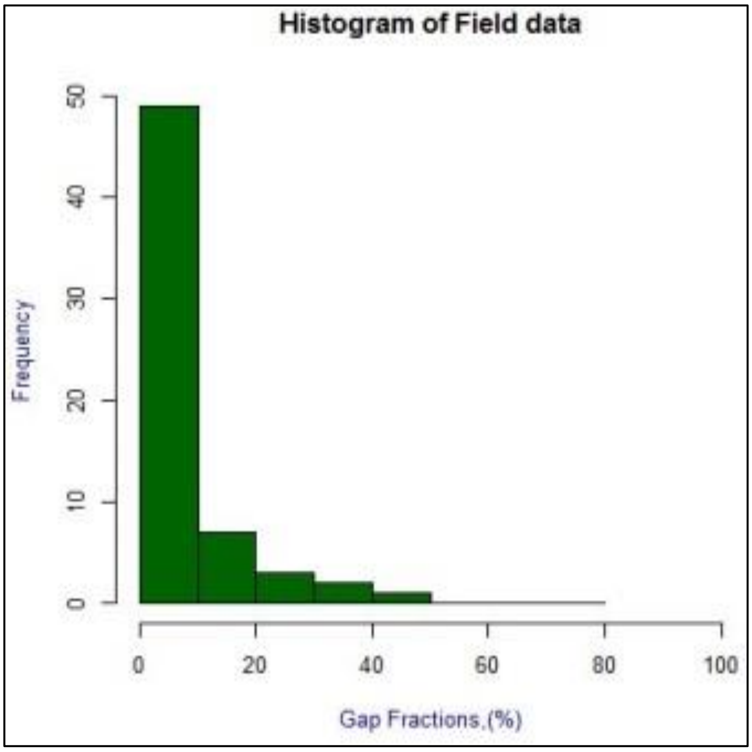


Figure 3-2: Distribution of field observed gap fractions.

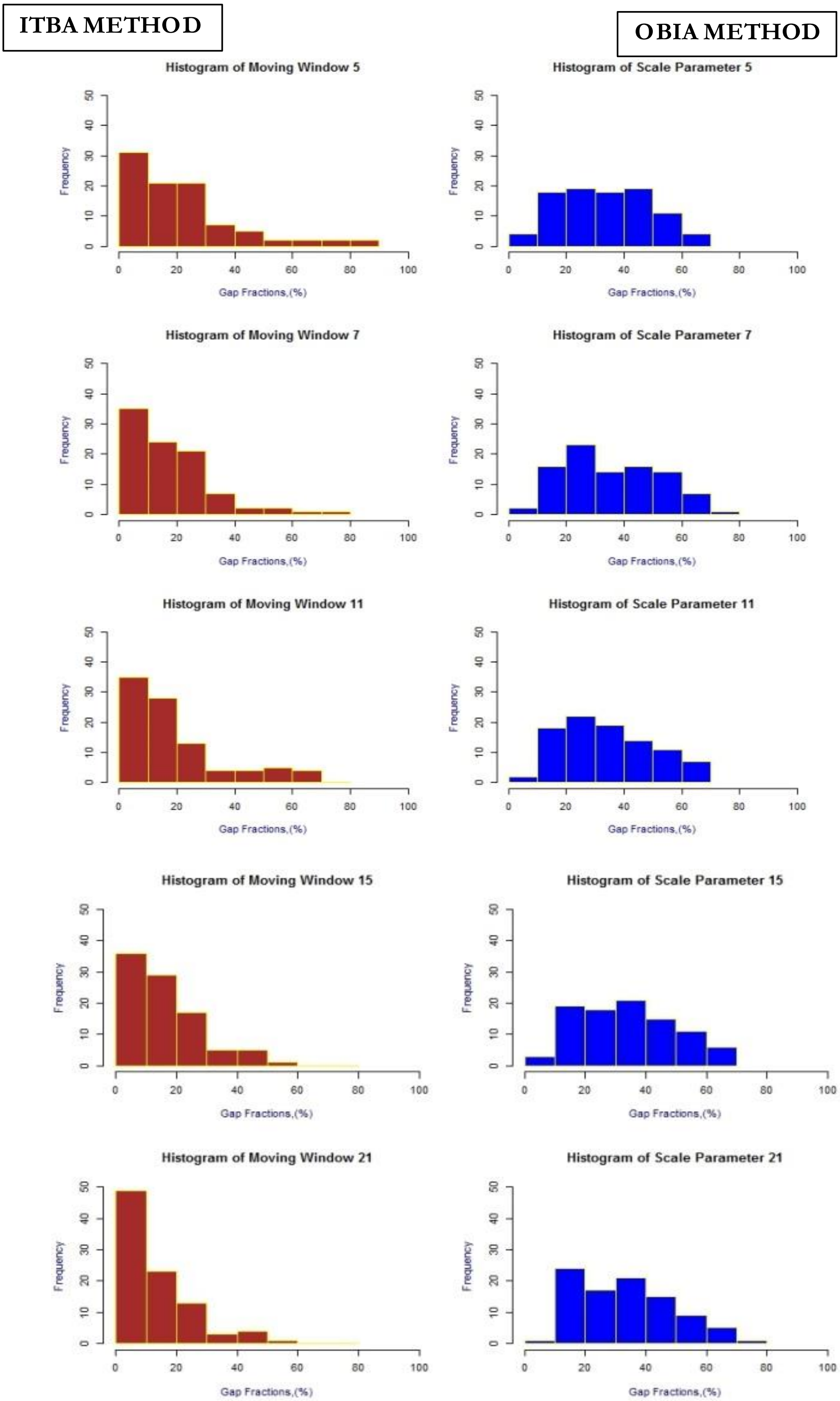


Figure 3-3: Distribution of estimated gap fractions in different parameter settings in ITBA and OBIA method.

3.2.2. Correlation analysis

3.2.2.1. Field based estimation Vs Image based estimations

The relationship between the field gap fractions and the image estimated gap fractions generally gave moderate positive correlations (Figure 3-4) and (Appendix 4). There was generally no trend with the changes in parameter settings. However, both OBIA and ITBA method proved to be statistically significant (Pearson's correlation test, N=93, $P < 0.05$) for ITBA and (Pearson's correlation test, N=93, $P < 0.001$) for OBIA method. We therefore reject null hypothesis 1.

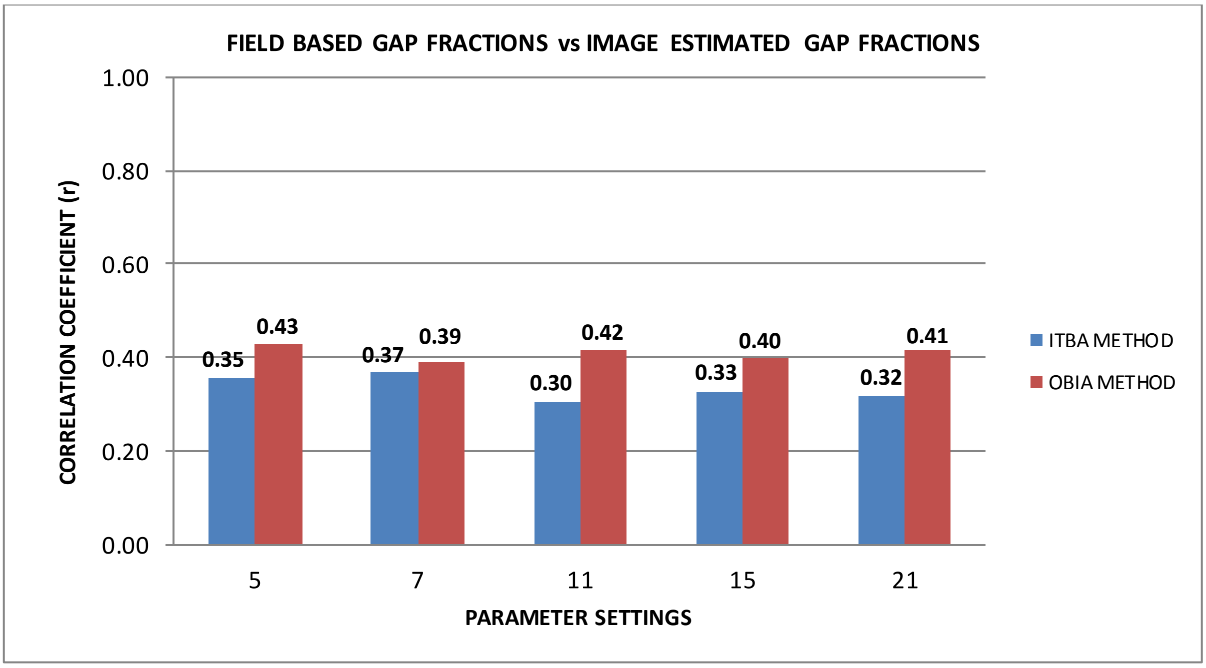


Figure 3-4: Correlations between the field based estimation of gap fractions with OBIA and ITBA based estimates of gap fractions in all forest types.

3.2.2.2. Broadleaved Field based estimations Vs Image based estimations

The relationship of values from the field with values from both methods generally gave very weak correlations close to zero (Figure 3-5) indicating no relationship exists. The negative correlation with the ITBA method means that with every increase in value there is a decrease in estimation of the value from the ITBA method. Both The methods were slightly statistically insignificant (Pearson's correlation test, N=62, $P > 0.05$).

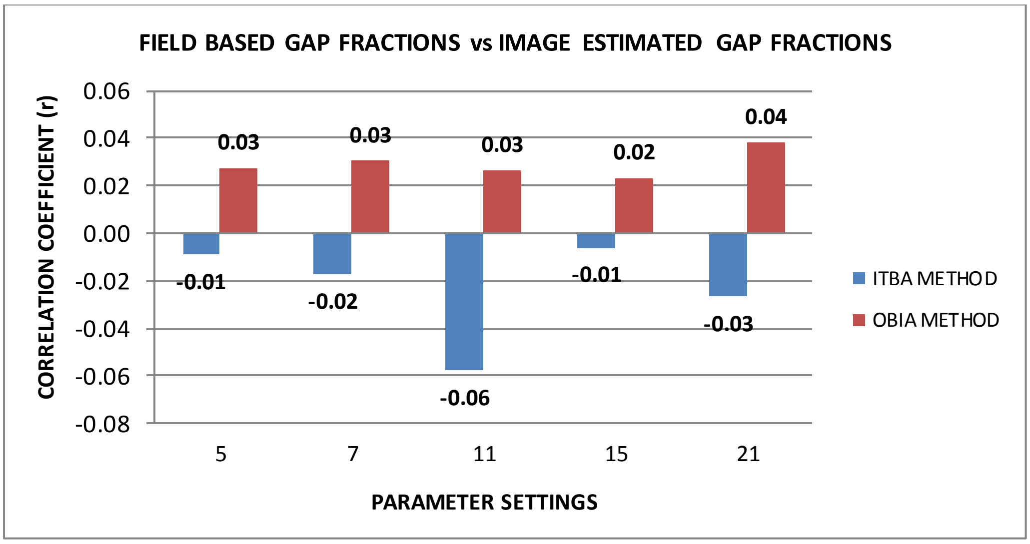


Figure 3-5: Correlations between the field based estimation of gap fractions in the broadleaved forest type with OBIA and ITBA based estimates of gap fractions.

3.2.2.3. Needle leaved Field based estimation Vs Image based estimations

The relationship between field measurements and image estimated gap fractions from the image gave overall moderate correlations (Figure 3-6). OBIA method gave a stronger relationship with field data than ITBA method. There is no trend with change in parameter settings in both methods. The methods were statistically significant (Pearson's correlation test, N=31, $P < 0.05$) for OBIA method and (Pearson's correlation test, N=31, $P < 0.05$ and $P<0.1$) for ITBA method. The null hypothesis is rejected.

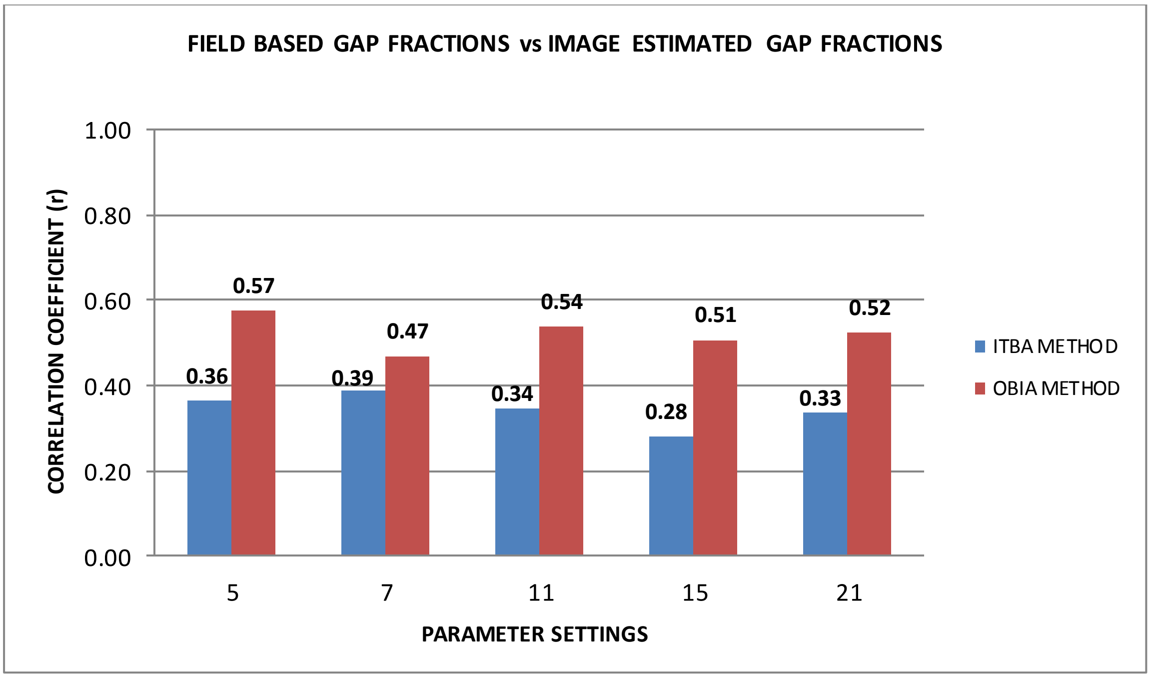


Figure 3-6: Correlations between the field based estimation of gap fractions in the needle leaved forest type with OBIA and ITBA based estimates of gap fractions.

3.2.2.4. Correlations between methods

There was an overall high correlation between the ITBA and OBIA methods in estimating gap fractions (Figure 3-7). There is an increasing trend where agreement increases with parameter setting increase then a decrease at the largest parameter setting.

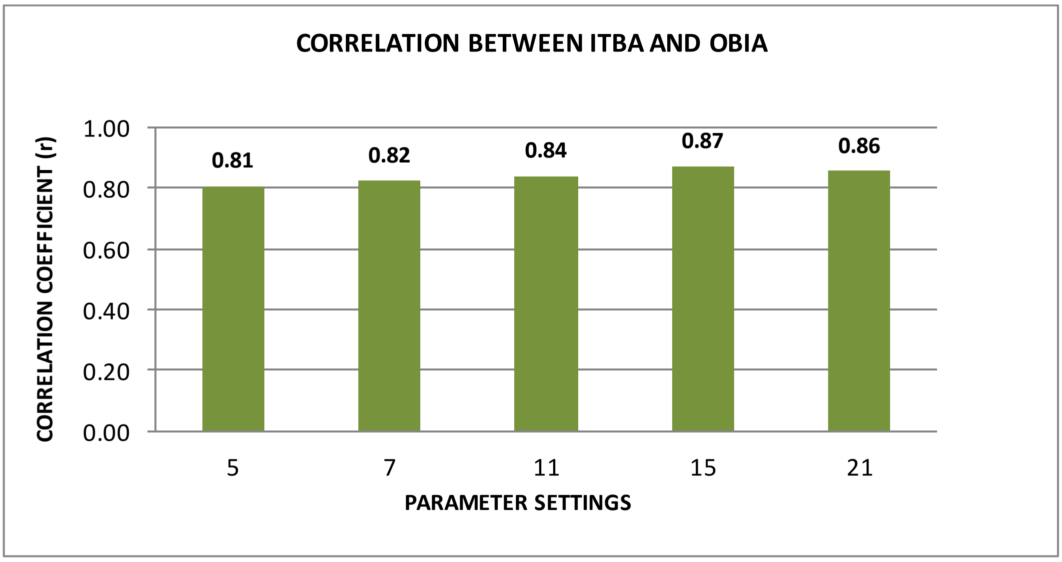


Figure 3-7: Strength of relationship between ITBA and OBIA methods in estimation of gap fractions.

There was an overall high agreement (Figure 3-8) between the methods in detecting gap fractions from a broadleaved forest and needle leaved forest. Generally, methods had a better agreement in the broadleaved forest type than in the needle leaved type of forest. The methods agreed best at larger parameter setting but generally we see a trend with broadleaved methods than with methods in needle leaved forest.

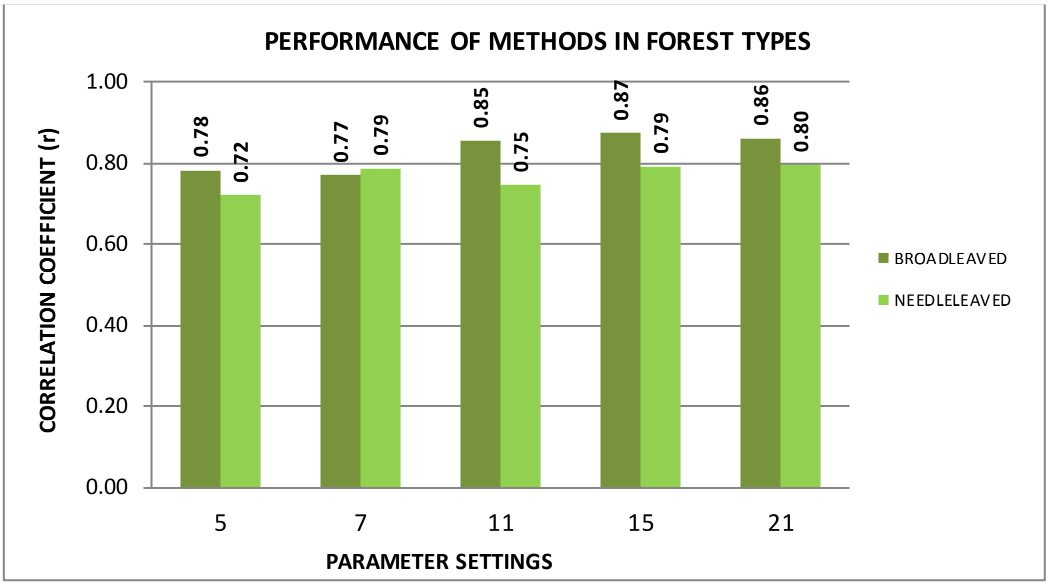


Figure 3-8: Strength of relationship between ITBA and OBIA methods in estimation of gap fractions the Broadleaved and Needle leaved forest types.

3.2.3. Root Mean Squared Error

3.2.3.1. RMSE between methods

Overall, the result shows that ITBA method gives lower RMSE values than OBIA method in estimations with field observed gap fractions (Figure 3-9). For ITBA method, the moving window 21 gives the lowest RMSE (14.438%) while scale parameter 7 gives the highest relative RMSE of 30.51%. In both methods, Moving window 21 gives the lowest RMSE in the group.

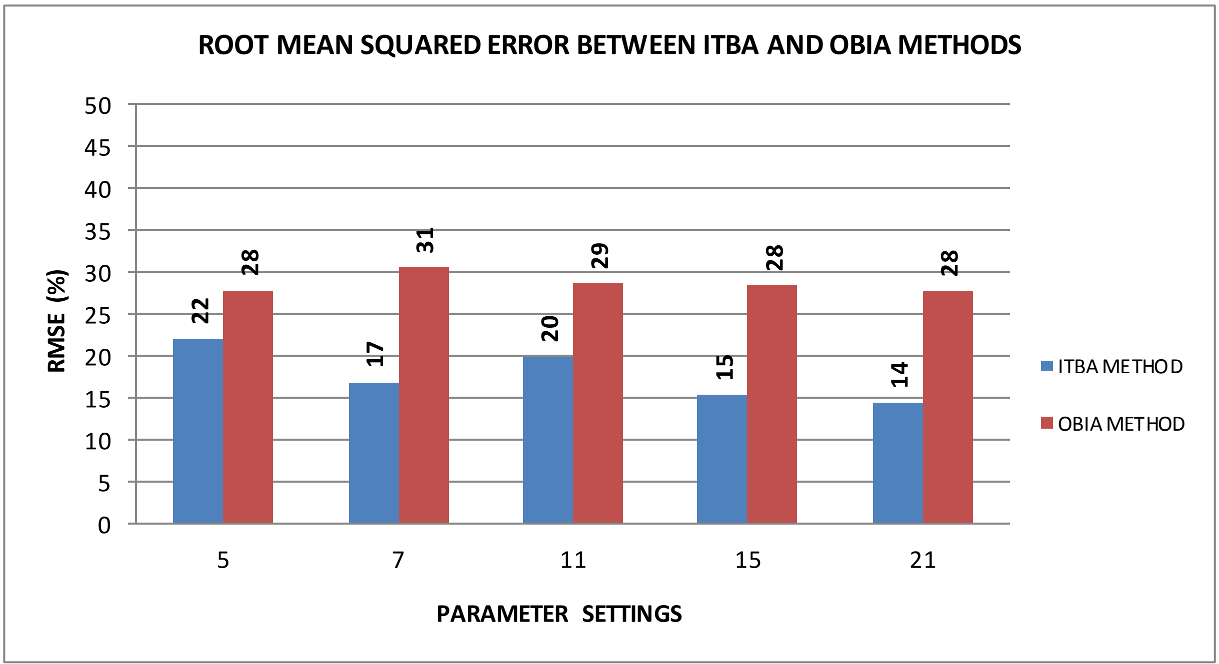


Figure 3-9: Root Mean Square error of ITBA and OBIA estimations of forest gaps with reference to estimations with field estimated gap fractions.

3.2.3.2. RMSE between methods forest types

RMSEs were generally high in both forest types. They were much higher in needle leaved forest type than broadleaved forest type. OBIA method gives higher errors in both forest types. The result shows a reducing trend in errors with increasing parameter settings especially in ITBA method (Figure 3-10 and Figure 3-11).

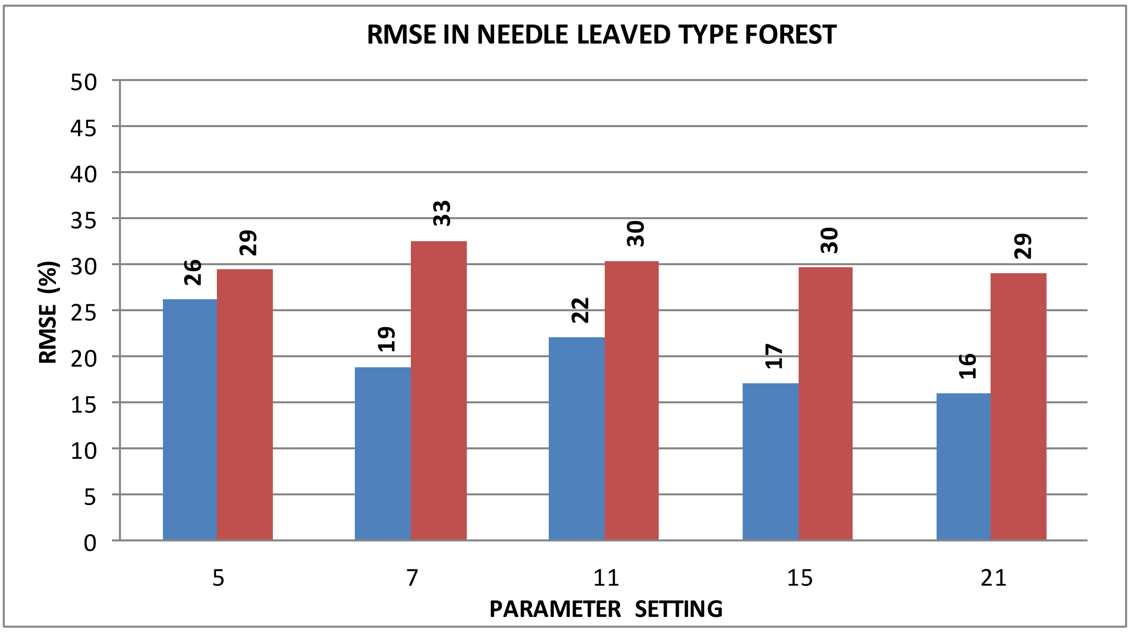


Figure 3-10: RMSE between image based gap fractions and field based gap fractions in a needle leaved type of forest.

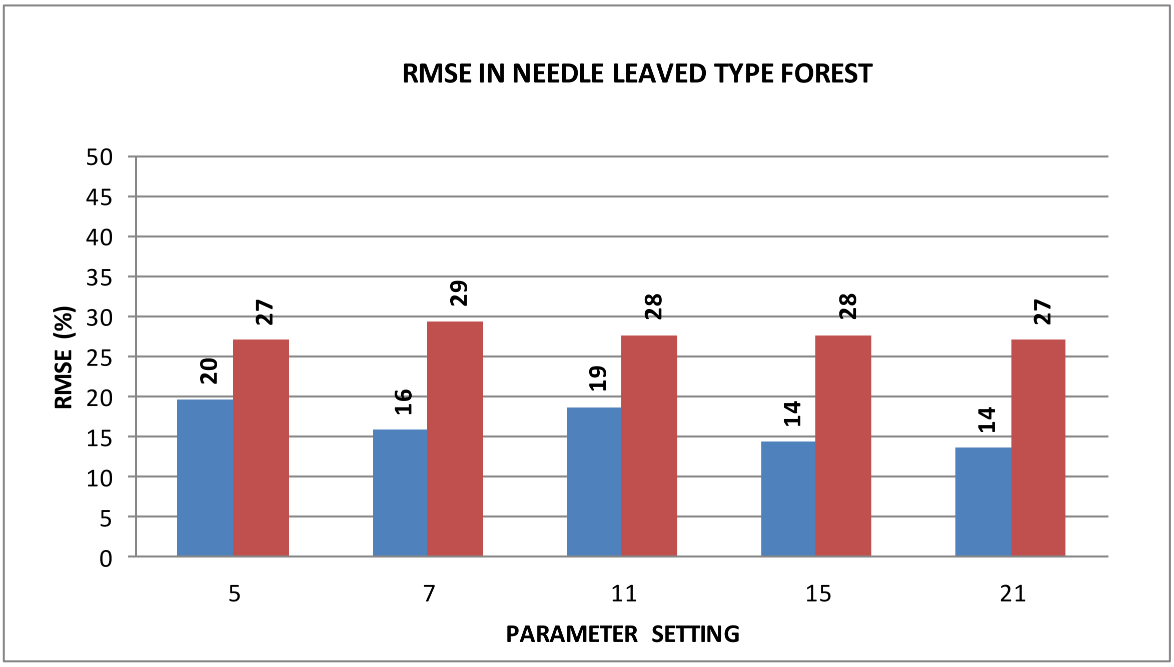


Figure 3-11: RMSE between image based gap fractions and field based gap fractions in a broadleaved type of forest.

3.2.3.3. Over/under estimation of gap fractions for different methods

There was an overall over estimation of gaps (Figure 3-11) with both the methods especially at the lower values of gap fractions. There was more underestimation of the medium sized gap fractions in all methods and more so with ITBA method but OBIA had better estimations of the medium sized gap fractions. However, ITBA method had much lower rates of overestimation as compared with the OBIA method and the points are scattered approximately on both sides of the 1:1 line and with decreasing errors. The scatter plots indicate the r value and the RMSE. The dots correspond to the estimated values.

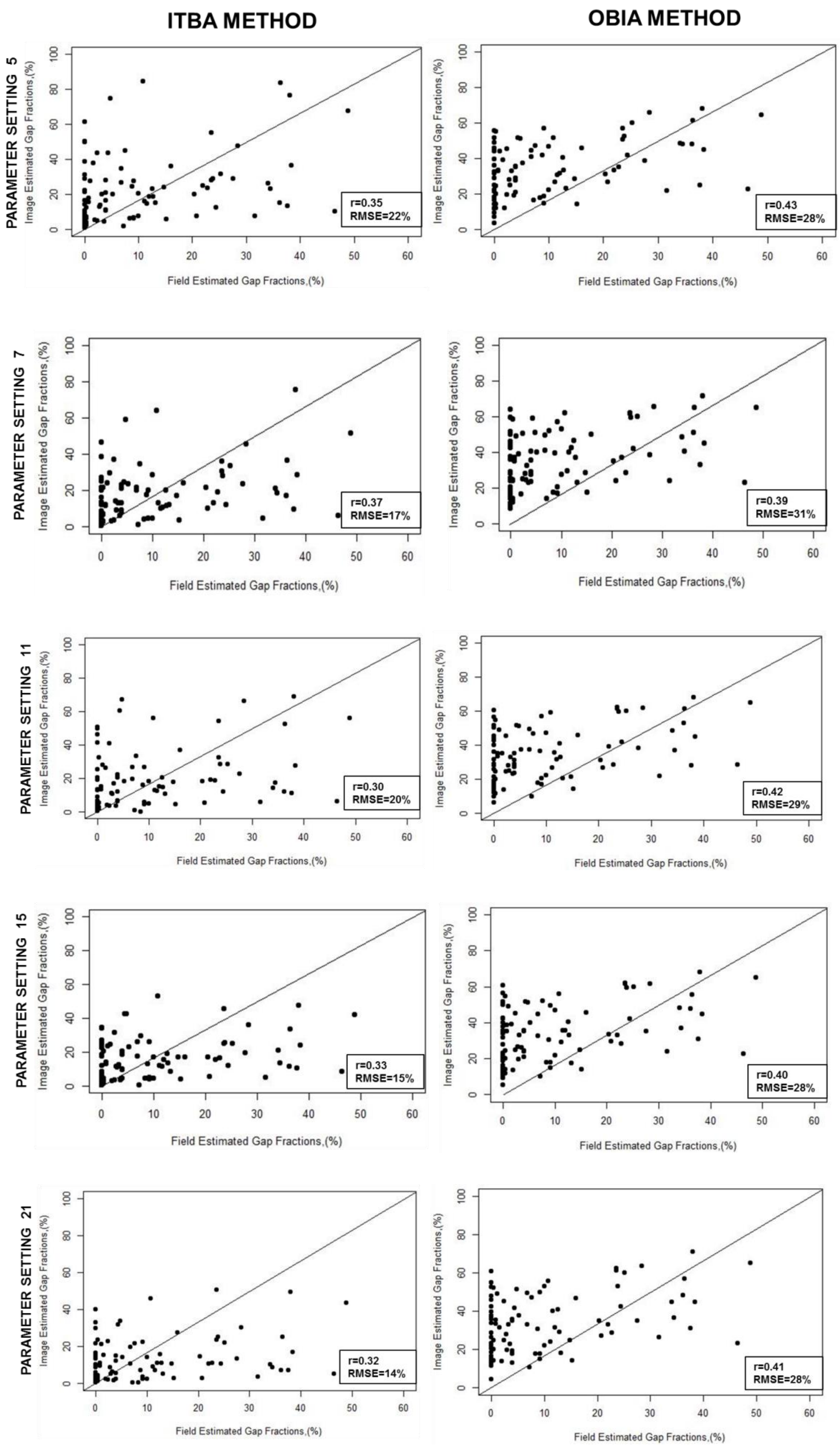


Figure 3-12: A 1:1 scatter plot of image estimates with field estimates that show over and under estimations.

4. DISCUSSION

4.1. Suitability of parameter settings for extraction of canopy gaps from OBIA and ITBA methods.

The results in (Figure 3-1) show that the parameters used in ITBA method and OBIA method were suitable in detecting canopy gaps from high resolution imagery. Results of gap fraction detection by ITBA were influenced by window size chosen. From the five window sizes chosen, moving window 5×5 led to detection of the smaller gaps but also to the under representation of larger gaps. A high moving window of 21×21 led the under-detection of small gaps and over generalization of the larger gaps as indicated in (Figure 3-1). These results match with the results of the research carried out by (Betts et al., 2005). It was observed that different parameter settings chosen for the study gave different results because of the effects of the number of objects that could be formed per parameter setting (Gao & Mas, 2008). It was noticed that the smaller parameter setting had a rough texture as compared with the larger parameter setting that looked smoother. This was probably due to the fact that the smaller parameter setting gave more detail of the canopy cover than the larger parameter setting. There is similarity of results with the ones in the study by Moskal & Franklin (2002), who used six window sizes from 3×3 to 21×21 and observed that the smallest window size had a rougher texture as opposed to the larger window size. Kelsey & Neff (2014) attributed the high roughness to differences within individual crowns and shadow areas while the lower roughness to variations between crown cover and shadows from crowns. This also suggests that with small parameter settings, the smaller gaps could be detected accurately but less so with the large parameter settings where larger gaps where detected more accurately.

It would be logical then, that there is an optimum parameter measure, probably an intermediate point where both the small gaps and the larger gaps are represented almost equally. This is demonstrated by studies of Betts et al., (2005) who chose three moving windows to detect and characterize canopy gaps from a high resolution digital elevation model. The intermediate window size of 17×17 was chosen as from window sizes of 9×9 and 25×25. However, this is not the case with this study where in figure (Figure 3-4) the correlations of estimates from methods with field data range between r values of 0.30 to 0.35 for ITBA and 0.39 to 0.43 for OBIA. This indicates no trend with change of parameter settings (Appendix 4). This suggests that there was no sensitivity of the results to change in parameter settings. Coburn & Roberts (2004) also observed that accuracies of forest stand classification using texture features increased with increasing window sizes between 5×5 to 15×15pixels. This is an indication that parameter settings are unpredictable and other additional factors play a role in their performance. This thwarted our theory that a change in parameter settings leads to a significant change in results.

For the purposes of repeatability, criterion of shape and compactness for OBIA method were set at standard values for all images. Only the thresholding step for both images is not standard due to differences in illumination and insufficient contrast of features per image. This was a necessary but time consuming activity especially with the large amounts of images. In addition, manual thresholding lacks transferability due to the subjectivity of the decision. Jonckheere et al. (2005), agreed with this and called for the use of automatic thresholding methods which was successfully applied to his study. His main aim was to find an alternative to manual thresholding in estimation of gap fractions and leaf area index by means of digital hemispherical photography. This would help to save time in the trial and error testing method and reduce subjectivity as well. Lievers & Pilkey (2004) also suggested a local thresholding technique that takes into account regional variations in sunlight illumination where this would be appropriate for this study considering that area is large area and has steep slopes.

4.2. Agreement of OBIA and ITBA based gap fractions with field based gap fractions.

The strong positive skewness of the gap fraction distribution (Figure. 3-2) from the field sampled data is common in most studies carried out in both needle leaved forests and deciduous forests (Miura, Manabe, Nishimura, & Yamamoto, 2001; Liu & Hytteborn, 1991; Hunter & Parker, 1993; Stewart et al., 1991). In field sampling, there was a lower threshold before a gap would be considered a gap while in the two methods; all open spaces were considered gaps. This is why higher frequencies are observed in gap fractions between 10% and 40% (Figure. 3-3). However, when we look at the histogram from ITBA method, the distribution of gap fractions resembles the field data in terms of frequency of distribution. This could be because the ITBA method is able to detect smaller gap fractions between 0% and 10% as compared to OBIA method which as seen in the distribution detects very little small gaps in that range.

Correlation was carried out to test for the most accurate parameter setting that gave strong correlations with field observed gap fractions. The result showed that there was a moderate relationship with field data in both methods and the r values all varied within a small range. This could be because the field data was not accurately estimated and therefore high correlations were not expected. It is assumed then that since there is no trend, we did not achieve an optimum parameter setting. Other performance evaluation signifiers like RMSE and over and under estimations would be used for evaluation. Karl, Duniway, & Schrader (2012) suggested that estimates of canopy gaps from the field were in some cases less precise than estimates from high resolution imagery. This would mean that maybe the estimates from the methods were more accurate that the field estimation. However, there is no way of knowing this in the study. Despite this, the results suggest that indeed there was a significant relationship between field based gap estimations and image derived gap estimations proving that at least some relationship existed between the field and image estimates.

4.3. Quantification of gaps between OBIA and ITBA methods.

The methods are not significantly different in detection and quantification of canopy gaps as we can observe by the high correlations in (Figure 3-7 and Figure 3-8). Generally there is a high agreement between methods in estimation of gap fractions from the image for all parameter settings, this could mean that the methods estimate gaps in a similar manner and this we can assume is because both methods are object oriented methods that divide an image into homogenous regions using features of association, spectral properties, size, shape, texture but with emphasis on different elements of colour for OBIA and texture for ITBA (Gao & Mas, 2008). At higher parameter settings, the methods agreed in detection of canopy gaps more than at lower parameter settings. The highest agreement is at parameter settings 15 (Figure 3-7). The methods agree less at the lowest parameter setting 5. This is due to the detection of smaller gaps differently in both methods (Figure 3-11) at the lower parameter measure where small gaps are detected more readily with ITBA method and not in OBIA method. The theory that the methods are not significantly different in estimating canopy gaps is proven to be true.

4.4. Comparison of gap estimation between OBIA and ITBA methods.

In (Figure 3-4 and Figure 3-9) there is high correlation at the smallest parameter measure and the lowest RMSE for the largest parameter measure. It would be expected that the method with the higher correlation would have the lowest RMSE. This is not evident in our results. The high correlations at OBIA method could have been created by the larger number of objects at the smaller scale parameter setting than the larger ones which had been estimated in the image and not the field. Low RMSE at ITBA method could have been due to the fact that the estimations in this method did not form many small objects and therefore the bias was less thus estimates were closer to the field based data. This phenomenal finding was also found by (Eckert, 2012) in his research on improved forest biomass and carbon estimations from texture measures in degraded and non-degraded forest areas. He also found that in the degraded forest, the strongest relationship existed with the smallest scale parameter while larger window sizes had the best fitting. This result is also supported and explained by the findings of Karl et al., (2012) where they found that association between the field and image based estimates increased with increase in canopy gap sizes as they were more easily distinguished from a high resolution imagery. Zhang et al. (2004) found that when using fine spatial resolution, texture measure became more highly sensitive to small variations in pixel values within the small moving window while larger widow sizes were seen to provide stable and more accurate estimations and even reduce random error.

4.4.1. Over and under estimation of gaps fractions

The study shows that there was a general overestimation of canopy gaps (Figure 3-11). This could possibly be because of shadowing so that shadows were detected as gaps (Figure 4-1). OBIA emphasizes on colour for formation of objects while ITBA emphasizes on texture for object formation. It would be assumed that colour has more sensitivity to shadows than texture and this could be why shadows are recognized as gaps in more in OBIA than ITBA methods. Texture was reduced in areas with a lot of shadow and so low standard deviation values while areas with low spectral reflectance values were detected as gaps by OBIA method. This is similar to findings by Betts et al., (2005) whose study on detection of gaps using texture of high resolution DEM, revealed that detection of gaps from aerial image are affected by sun angle and the angle at which the image is captured causing a problem of shadowing. Blackburn & Milton (1997) also found similar results when it was observed that there was reduced classification accuracy of gaps using moving window sizes was in a deciduous forest due to shadows within and around the canopy edges of trees. This could explain the higher overestimation of gaps in the OBIA method than in the ITBA method which is less affected by illumination differences (Thakare, Patil, & Sonawane, 2013). This over estimation is contrary to the studies by (Karl et al., 2012b) who concluded that there is a possible under estimation of gaps when using only high resolution imagery. This would be true in cases where shadows are classified as canopies while they are in fact a gap which is not the case in this study.

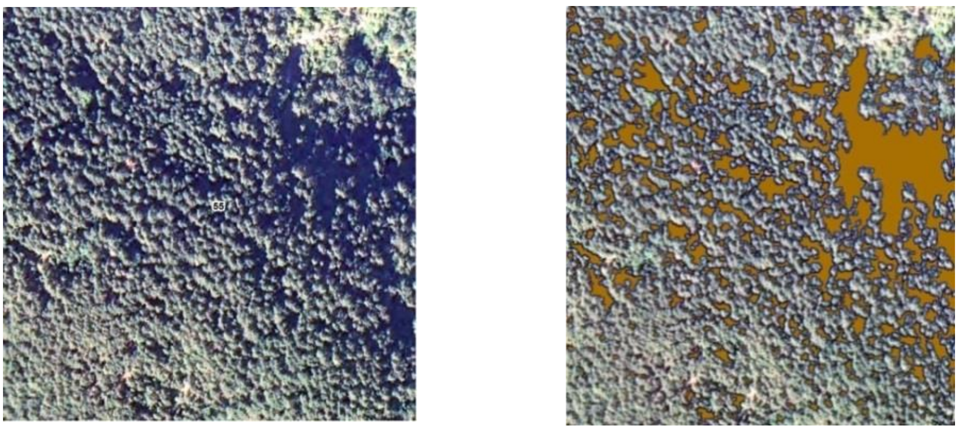


Figure 4-1: Shadows as observed from an aerial image and which are detected as gaps by methods.

There was a problem with highly illuminated objects which made canopies appear smooth and so reducing the texture efficiency (Figure 4-3) so that these areas were categorized under gaps in the texture analysis. (Figure: 4-3) shows (a) Before and (b) after applying the new criteria. The correlations improved slightly but the RMSE had a significant reduction meaning that the estimates moved closer to the field based measurements therefore improving the method.

(a) (b)

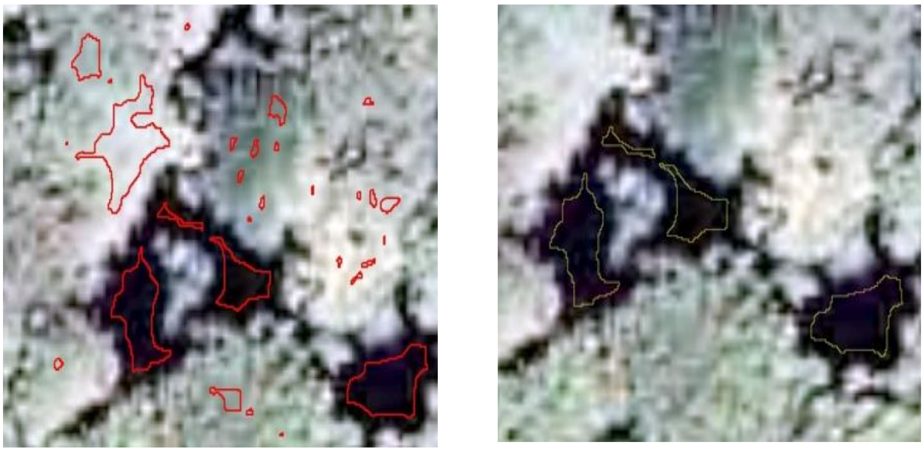


Figure 4-2: Image showing detection of canopies with smooth texture as gaps and detection after application of new threshold criteria.

4.5. Forest management and ecological implications.

The two methods detect gaps differently, with the larger gaps more accurately identified by OBIA method while the small gaps accurately detected by the ITBA method. This is the main benefit of application of these methods to forestry. The methods can be applied in different studies such as inventory of regeneration and invasive species. Whitmore (2014) observed that larger gaps were more likely to be prone to invasion by pioneer species while the smaller gaps allowed the regeneration of climax trees to take place. Conversely, Blackburn & Milton (1997) sited that the large gaps were able to harbor both the processes; invasion by pioneer species and regeneration of climax species because of the complex shape that allowed an array of light intensities.

Kennedy and Swaine (1992) further found that these processes were independent of gap size but performance of the species on the other hand was more related to gap size. This would call for management practices that seek to enlarge or introduce gaps to boost performance of the two kinds of species and indirectly may contribute in solving the problem of under representation of some species in the network of Natura 2000 sites. This was a problem that was identified by Keulartz (2009) in his study on the problems of the conservation policy of Natura 2000. He lastly recommends that a representation index that recognizes species that are underrepresented could be used to guide future conservation efforts.

4.6. Influence of forest type on OBIA and ITBA methods.

There were very weak correlations of estimated gap fractions by the methods in a broadleaved forest and were insignificant at an alpha value of 0.05. The assumption is that both methods somehow fail to estimate gaps fractions from the image in a broadleaved type of forest. Many studies have reported difficulty in segmentation in a deciduous forest (Erikson & Olofsson, 2005). This could be an issue with the structure of this type of forest where it is very complex in that the crowns are very irregular in shape.

The robust region growing algorithm used for segmentation favors the structure of a needle leaved forest which has a conical shape where the algorithm uses the tip as a seed point that grows to encompass the whole crown. This is difficult for the type of crown in a broadleaved forest so the algorithm does not work as well as it does in needle leaved forest where we see high correlations in (Figure 3-6). Wang, Gong, & Biging (2004) reached to this similar conclusion in his study of individual tree-crown delineation and detection of treetops. The results (Figure 3-5 and 3-6) favor the assumption that detection of canopy gaps in needle leaved forests is more accurate than in broadleaved forest.

The results as illustrated in (Figure. 3-8) reveal that the methods agree more in the broadleaved forest than in the needle leaved forest. It also shows that as the parameter setting increases in the broadleaved forest, the agreement between methods increases. While in the needle leaved forest there is no trend in agreements between the methods. This suggests that both the methods are unable to estimate canopy gaps in an image for a broadleaved forest (Figure 3-5). It is suggested therefore that accurate detection of gaps using only object oriented methods is not suitable in broadleaved forests. Lower agreement of methods in needle leaved forest suggests that there is room for improvement with one or both of the methods in detecting canopy gaps in that forest type.

5. CONCLUSION AND RECOMMENDATIONS

The measurement of gaps from the field was more or less mere estimations. It is therefore difficult to test the effectiveness of a particular method as we do not know the precise measure of the gaps. Nevertheless, we were able to objectively look at each method and evaluate the implication of the results in terms of suitability of the methods for gap fraction estimation and ecologically in view of the main objectives of the study.

LiDAR data collected on a rough terrain would be a more reliable data source for testing against our methods. It is however, an accurate source of data but equally expensive to acquire. Use of such instruments as the fish eye or hemispherical cameras can be a better and cheaper option to collecting more accurate field data. High resolution digital elevation models on such a terrain would also be helpful in increasing accuracies.

What are the suitable parameters to use for extracting canopy gaps from both methods?

A moving window of 21 for ITBA method gives the closest estimates (RMSE = 14%). This method is new and has shown potential for improvement and so is suitable to monitor, plan, manage and assess biodiversity in a forest.

Do the canopy gaps obtained with both methods correspond to the sampled gaps in the field?

OBIA method gives a slightly stronger relationship with field data as compared to ITBA method. Nonetheless, a scale parameter of 5 and a moving window of 7 give the strongest relationship and therefore are the parameter settings that give a more accurate estimation of gap fractions.

However, ITBA method would be the 'go to' method in terms of precision as it appears to give closer estimates to the presumed truth. ITBA estimates of gap fractions are better to monitor smaller gaps while OBIA method is better to monitor larger gaps. The choice of method would help in quick identification and assessment of plots that need further investigations by ecologists when monitoring gaps.

How different is the quantification of the individual gaps between the two methods?

At parameter setting of 15, the methods highly agree (r=0.87) in estimating gap fractions from the field. The study concludes that this is the optimal parameter setting for detection of gaps by the two object oriented methods and can be interchanged for the other depending on preference.

The high spatial resolution aerial image helped in identification of even very small gaps formed by death of single trees in both the methods but especially for ITBA which identified them more precisely. However, both methods facilitated the identification of a large range of gap fractions important for monitoring purposes.

How accurately, can canopy gaps be estimated from the two methods?

Smaller gaps are more accurately estimated by ITBA and larger gaps more accurately estimated by OBIA. However, ITBA methods have moved towards counteracting the weaknesses of OBIA method. Investigations to improve this method would be the ultimate option to accurately delineate gaps from a high resolution aerial image. Furthermore, another option would be to combine the two methods where they could be used for separating different canopy size classes.

Automatic thresholding such as cluster-based thresholding methods and histogram shape based methods among others should be considered to eliminate the problem of subjectivity and save processing time.

To what extent does forest type influence accuracy of the two methods?

Algorithms, criteria and aassumptions that work in needle leaved type of forest may not be necessarily transferable to a broadleaved type of forest due to the different architecture of the crowns. This is especially for OBIA method which uses a region growing algorithm that favors the conical shaped crowns of needle leaved tress. Algorithms and other parameters that work best in a broadleaved forest need to be investigated.

At parameter setting 15 (r=0.87), the methods highly agree that detection of gaps in a broadleaved forest from object oriented methods is poor. Lower parameter setting 5 (r=0.78) have room for improvement in one or both methods.

ITBA is the best choice to use in delineating gaps from images that have features under low exposure. It does not perfectly eliminate the shadow problem but has relatively less sensitivity to it and needs further investigation. Studies in a flatter terrain with images taken at nadir should be researched on to see whether shadowing is the only cause of under/over-estimation of gaps or that there are other factors in play

Final reflection of the methods in the research

Detection of gaps opens more possibility to deriving other gap features other than gap sizes. Such features would include gap connectivity and gap shapes which are relevant to ecology. Further studies can look into which of these methods provide this extra information more accurately and contribute to the efforts in sustainable development. This is especially important for Natura 2000 sites. Further investigation into how well image estimated gaps correlate with biodiversity would be interesting in evaluating performance of the methods.

LIST OF REFERENCES

Anderson, J., Plourde, L., Martin, M., Braswell, B., Smith, M., Dubayah, R., … Blair, J. (2008). Integrating waveform lidar with hyperspectral imagery for inventory of a northern temperate forest. *Remote Sensing of Environment*, *112*(4), 1856–1870. doi:10.1016/j.rse.2007.09.009

Benz, U. C., Hofmann, P., Willhauck, G., Lingenfelder, I., & Heynen, M. (2004). Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. *ISPRS Journal of Photogrammetry and Remote Sensing*, *58*(3-4), 239–258. doi:10.1016/j.isprsjprs.2003.10.002

Betts, H., Brown, L., & Stewart, G. (2005). Forest canopy gap detection and characterisation by the use of high-resolution Digital Elevation Models. *New Zealand Journal of Ecology*, *29*(1), 95–103. Retrieved from http://nzes-nzje.grdev.co.nz/free_issues/NZJEcol29_1_95.pdf

Blackburn, G. A., & Milton, E. J. (1997). An ecological survey of deciduous woodlands using airborne remote sensing and geographical information systems (GIS). *International Journal of Remote Sensing*, *18*(9), 1919–1935. doi:10.1080/014311697217954

Blaschke, T. (2010). Object based image analysis for remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing*, *65*(1), 2–16. doi:10.1016/j.isprsjprs.2009.06.004

Bongers, F. (2001). Methods to assess tropical rain forest canopy structure: an overview. *Plant Ecology*, *153*(1-2), 263–277. doi:10.1023/A:1017555605618

Boutin, S., Haughland, D. L., Schieck, J., Herbers, J., & Bayne, E. (2009). A new approach to forest biodiversity monitoring in Canada. *Forest Ecology and Management*, *258*, S168–S175. doi:10.1016/j.foreco.2009.08.024

Bucha, T., & Stibig, H.-J. (2008). Analysis of MODIS imagery for detection of clear cuts in the boreal forest in north-west Russia. *Remote Sensing of Environment*, *112*(5), 2416–2429. doi:10.1016/j.rse.2007.11.008

Campbell, J. B., & Wynne, R. H. (2011). *Introduction to Remote Sensing* (5th ed.). New York: Guilford Publications.

Chant, T. De, & Kelly, M. (2009). Individual Object Change Detection for Monitoring the Impact of a Forest Pathogen on a Hardwood Forest establishment. *Photogrammetric Engineering & Remote Sensing*, *75*(8), 1005–1013.

Cho, M. A., Skidmore, A. K., & Sobhan, I. (2009). Mapping beech (Fagus sylvatica L.) forest structure with airborne hyperspectral imagery. *International Journal of Applied Earth Observation and Geoinformation*, *11*(3), 201–211. doi:10.1016/j.jag.2009.01.006

Coburn, C., & Roberts, C. B. (2004). A multiscale texture analysis procedure for improved forest stand classification. *International Journal of Remote Sensing*, *25*(20), 4287–4308. doi:10.1080/0143116042000192367

Cohen, W. B., & Spies, T. A. (1992). Estimating structural attributes of Douglas-fir/western hemlock forest stands from landsat and SPOT imagery. *Remote Sensing of Environment*, *41*(1), 1–17. doi:10.1016/0034-4257(92)90056-P

Cosmopoulos, P., & King, D. J. (2004). Temporal analysis of forest structural condition at an acid mine site using multispectral digital camera imagery. *International Journal of Remote Sensing*, *25*(12), 2259–2275. doi:10.1080/0143116032000160507

Cracknell, A. P. (1998). Review article Synergy in remote sensing-what's in a pixel? *International Journal of Remote Sensing*, *19*(11), 2025–2047. doi:10.1080/014311698214848

Drăguţ, L., & Blaschke, T. (2008). Terrain segmentation and classification using SRTM data. *Advances in Digital Terrain Analysis*, (Goudie 2002), 141–158. doi:10.1007/978-3-540-77800-4_8

Dubayah, R. O., & Drake, J. B. (2000). Lidar Remote Sensing for Forestry Applications. *Journal of Forestry*, *98*, 44–46. Retrieved from http://www.geog.umd.edu/vcl/pubs/jof.pdf

Eckert, S. (2012). Improved Forest Biomass and Carbon Estimations Using Texture Measures from WorldView-2 Satellite Data. *Remote Sensing*, *4*(12), 810–829. doi:10.3390/rs4040810

Fernandes, R. A., Miller, J. R., Chen, J. M., & Rubinstein, I. G. (2004). Evaluating image-based estimates of leaf area index in boreal conifer stands over a range of scales using high-resolution CASI imagery. *Remote Sensing of Environment*, *89*(2), 200–216. doi:10.1016/j.rse.2002.06.005

Foody, G. M., & Cutler, M. E. J. (2006). Mapping the species richness and composition of tropical forests from remotely sensed data with neural networks. *Ecological Modelling*, *195*(1-2), 37–42. doi:10.1016/j.ecolmodel.2005.11.007

Fox, T. J., Knutson, M. G., & Hines, R. K. (2000). Mapping forest canopy gaps using air-photo interpretation and ground surveys. *Wildlife Society Bulletin*, *28*(4), 882–889. Retrieved from http://www.jstor.org/stable/3783843

Gao, T., Hedblom, M., Emilsson, T., & Nielsen, A. B. (2014). The role of forest stand structure as biodiversity indicator. *Forest Ecology and Management*, *330*, 82–93. doi:10.1016/j.foreco.2014.07.007

Gao, Y., & Mas, J. (2008). A comparison of the performance of pixel-based and object-based classifications over images with various spatial resolutions. *Online Journal of Earth Sciences*. Retrieved from http://docsdrive.com/pdfs/medwelljournals/ojesci/2008/27-35.pdf

Gillespie, T., & Foody, G. (2008). Measuring and modelling biodiversity from space. *Progress in Physical …*. Retrieved from http://ppg.sagepub.com/content/32/2/203.short

Gillis, M. D., & Leckie, D. G. (1993). Forest inventory mapping procedures across Canada. *Information report/Forestry Canada, Petawawa …*, *114*. Retrieved from http://www.cfs.nrcan.gc.ca/publications/?id=4365

Grodzinska-Jurczak, M., & Cent, J. (2011). Expansion of nature conservation areas: Problems with natura 2000 implementation in Poland? *Environmental Management*, *47*, 11–27. doi:10.1007/s00267-010-9583-2

Gruber, B., Evans, D., Henle, K., Bauch, B., Schmeller, D. S., Dziock, F., … Dormann, C. F. (2012). "Mind the gap!" – How well does Natura 2000 cover species of European interest? *Nature Conservation*, *3*, 45–63. doi:10.3897/natureconservation.3.3732

Haralick, R. M. (1979). Statistical and structural approaches to texture. *Proceedings of the IEEE*, *67*(5), 786–804. doi:10.1109/PROC.1979.11328

Hay, G. J., Castilla, G., Wulder, M. A., & Ruiz, J. R. (2005). An automated object-based approach for the multiscale image segmentation of forest scenes. *International Journal of Applied Earth Observation and Geoinformation*, *7*(4), 339–359. doi:10.1016/j.jag.2005.06.005

Hepinstall, J. A., & Sader, S. A. (1997). Using Bayesian Statistics , Thematic Mapper Satellite Imagery , and Breeding Bird Survey Data to Model Bird Species Probability of Occurrence in Maine. *Photogrammetric Engineering & Remote Sensing*, *63*(10), 1231–1237.

Herold, A., & Ulmer, U. (2001). Stand stability in the Swiss National Forest Inventory: assessment technique, reproducibility and relevance. *Forest Ecology and Management*, *145*(1-2), 29–42. doi:10.1016/S0378-1127(00)00572-7

Hese, S., & Schmullius, C. (2005). Object Context Information for Advanced Forest Change Classification Strategies. *1st International Conference on Object-Based …*. Retrieved from http://www.isprs.org/proceedings/xxxvi/4-c42/Papers/OBIA2006_Hese_Schmullius.pdf

Huete, R., Liu, H. L. H., & Leeuwen, W. J. D. Van. (1997). The use of vegetation indices in forested regions: issues of linearity and saturation. *IGARSS'97. 1997 IEEE International Geoscience and Remote Sensing Symposium Proceedings. Remote Sensing - A Scientific Vision for Sustainable Development*, *4*(1), 1966–1968. doi:10.1109/IGARSS.1997.609169

Hunter, J. C., & Parker, V. T. (1993). The disturbance regime of an old-growth forest in coastal California. *Journal of Vegetation Science*, *4*(1), 19–24. doi:10.2307/3235729

Husch, B., Beers, T. W., Kershaw, J. A., & Jr. (2002). Forest Mensuration (4th ed., p. 456). John Wiley & Sons. Retrieved from http://books.google.com/books?hl=en&lr=&id=p0v3m8Pau-kC&pgis=1

Jonckheere, I., Nackaerts, K., Muys, B., & Coppin, P. (2005). Assessment of automatic gap fraction estimation of forests from digital hemispherical photography. *Agricultural and Forest Meteorology*, *132*(1-2), 96–114. doi:10.1016/j.agrformet.2005.06.003

Kangas, J., & Kuusipalo, J. (1993). Integrating biodiversity into forest management planning and decision-making. *Forest Ecology and Management*, *61*, 1–15. doi:10.1016/0378-1127(93)90186-Q

Karl, J. W., Duniway, M. C., & Schrader, T. S. (2012a). A Technique for Estimating Rangeland Canopy-Gap Size Distributions From High-Resolution Digital Imagery. *Rangeland Ecology & Management*, *65*(2), 196–207. doi:10.2111/REM-D-11-00006.1

Karl, J. W., Duniway, M. C., & Schrader, T. S. (2012b). A Technique for Estimating Rangeland Canopy-Gap Size Distributions From High-Resolution Digital Imagery. *Rangeland Ecology & Management*, *65*(2), 196–207. doi:10.2111/REM-D-11-00006.1

Kasischke, E. S., Melack, J. M., & Dobson, M. C. (1997). The use of imaging radars for ecological applications - A review. *Remote Sensing of Environment*, *59*(96), 141–156. doi:10.1016/S0034-4257(96)00148-4

Kayitakire, F., Hamel, C., & Defourny, P. (2002). Retrieving forest structure variables based on image texture analysis and IKONOS-2 imagery. *Remote Sensing of Environment*, *102*(3-4), 390–401. doi:10.1016/j.rse.2006.02.022

Kelsey, K. C., & Neff, J. C. (2014). Estimates of aboveground biomass from texture analysis of landsat imagery. *Remote Sensing*, *6*, 6407–6422. doi:10.3390/rs6076407

Keulartz, J. (2009). European nature conservation and restoration policy - Problems and perspectives. *Restoration Ecology*, *17*(4), 446–450. doi:10.1111/j.1526-100X.2009.00566.x

Kim, M. (2009). *Object-based spatial classification of forest vegetation with IKONOS imagery*. University of Georgia. Retrieved from https://getd.libs.uga.edu/pdfs/kim_minho_200905_phd.pdf

Kohm, K., & Franklin, J. (1997). Creating a forestry for the 21st century. Retrieved from http://agris.fao.org/agris-search/search.do?recordID=US201300305259

Kok, R. De, Schneider, T., & Ammer, U. (1999a). Object-based classifiaction and applications in the alpine forest environment. *International Archives of Photogrammetry and Remote Sensing*, *32*(1976), 3–4. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.27.9175&rep=rep1&type=pdf

Kok, R. De, Schneider, T., & Ammer, U. (1999b). Object-Based Classification and Applications in the Alpine Forest Environment. *International Archives of Photogrammetry and Remote Sensing, 32*(1976), 3–4. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.27.9175&rep=rep1&type=pdf

Koukoulas, S., & Blackburn, G. (2004). Quantifying the spatial properties of forest canopy gaps using LiDAR imagery and GIS. *International Journal of Remote Sensing*, *25*(15), 3049–3072. doi:10.1080/01431160310001657786

Lenor, F. (2014). Effects of Habitat Fragmentation on Biodiversity, *34*(2003), 487–515. Retrieved from http://www.jstor.org/stable/30033784

Lievers, W. B., & Pilkey, K. (2004). An evaluation of global thresholding techniques for the automatic image segmentation of automotive aluminum sheet alloys. *Materials Science and Engineering*, *381*, 134–142. doi:10.1016/j.msea.2004.04.002

Lim, K., Treitz, P., Wulder, M., St-Onge, B., & Flood, M. (2003). LiDAR remote sensing of forest structure. *Progress in Physical Geography*, *27*, 88–106. doi:10.1191/0309133303pp360ra

Liu, Q., & Hytteborn, H. (1991). Gap structure, disturbance and regeneration in a primeval Picea abies forest. *Journal of Vegetation Science*, *2*(3), 391–402. doi:10.2307/3235932

Lorimer, C. G. (1989). Relative effects of small and large disturbances temperate hardwood forest structure. *Ecological Society of America*, *70*(3), 565–567. Retrieved from http://www.jstor.org/stable/1940207

Mansor, S. B., Mispan, M. R., Ahmad, N., & Sulaiman, W. N. (2003). Feature extraction based on object oriented analysis. *Proceedings of ATC …*, 1–10. doi:10.1038/kisup.2013.30

Mihók, B. M., Galhidy, G., Kenderes, K. K., & Standovár, S. (2007). Gap Regeneration Patterns in a Semi-natural Beech Forest Stand in Hungary. *Acta Silv Lign Hung*, *3*, 31–45. Retrieved from http://www.nyme.hu/fileadmin/dokumentumok/fmk/acta_silvatica/cikkek/Vol03-2007/03_standovar_2007p.pdf

Miura, M., Manabe, T., Nishimura, N., & Yamamoto, S. (2001). Forest canopy and community dynamics in a temperate old-growth evergreen broad-leaved forest, south-western Japan: a 7-year study of a 4-ha plot. *Journal of Ecology*, *89*(5), 841–849. doi:10.1046/j.0022-0477.2001.00603.x

Moore, M. R., & Vankat, J. L. (1986). Responses of the herb layer to the gap dynamics of a mature beech-maple forest. *American Midland Naturalist (USA)*. Retrieved from http://agris.fao.org/agris-search/search.do?recordID=US8645159

Moskal, L. M., & Franklin, S. E. (2002). Multilayer Forest Stand Discrimination with Spatial Co-occurrence Texture Analysis of High Spatial Detail Airborne Imagery. *Geocarto International*, *17*(4), 55–68. doi:10.1080/10106040208542254

Muinonen, E., Maltamo, M., Hyppänen, H., & Vainikainen, V. (2001). Forest stand characteristics estimation using a most similar neighbor approach and image spatial structure information. *Remote Sensing of Environment*, *78*(3), 223–228. doi:10.1016/S0034-4257(01)00220-6

Nackaerts, K., Wagendorp, T., Coppin, P., Muys, B., & Gombeer, R. (2001). A correction of indirect LAI measurements for a non random distribution of needles on shoots. *Systems and Sensors for the New Millenium*, 413–424. Retrieved from https://lirias.kuleuven.be/handle/123456789/236866

Nikolov, S. C., Kornilev, Y., Popgeorgiev, G., Stoychev, S., & Georgiev, B. B. (2014). Challenges for Habitat and Species Conservation in the Natura 2000 Network , Bulgaria: an Overview from Two Special Protection Areas. *Acta Zoologica Bulgarica*, *5*, 3–8. Retrieved from http://www.researchgate.net/profile/Georgi_Popgeorgiev/publication/links/54a24fa40cf257a636037f23.pdf

Ouchi, K. (2013). Recent trend and advance of synthetic aperture radar with selected topics. *Remote Sensing*, *5*, 716–807. doi:10.3390/rs5020716

Ozdemir, I., & Karnieli, A. (2011). Predicting forest structural parameters using the image texture derived from WorldView-2 multispectral imagery in a dryland forest, Israel. *International Journal of Applied Earth Observation and Geoinformation*, *13*(5), 701–710. doi:10.1016/j.jag.2011.05.006

Pasher, J., & King, D. J. (2010). Multivariate forest structure modelling and mapping using high resolution airborne imagery and topographic information. *Remote Sensing of Environment*, *114*(8), 1718–1732. doi:10.1016/j.rse.2010.03.005

Perotto-Baldivieso, H. L., Meléndez-Ackerman, E., García, M. a., Leimgruber, P., Cooper, S. M., Martínez, A., … Pons, G. (2009). Spatial distribution, connectivity, and the influence of scale: Habitat availability for the endangered Mona Island rock iguana. *Biodiversity and Conservation*, *18*, 905–917. doi:10.1007/s10531-008-9520-3

Peters, C. M. (1996). The Ecology and Management of Non-Timber Forest Resources. *Papers*. Retrieved from http://ideas.repec.org/p/fth/wobate/322.html

Pommerening, A. (2002). Approaches to quantifying forest structures. *Forestry*, *75*(3), 305–324. doi:10.1093/forestry/75.3.305

Powelson, P. (2001). Spacing to Increase Diversity within Stands. *Stand Density Management DIagram*, 8.

Rahman, M. R., & Saha, S. (2008). Multi-resolution segmentation for object-based classification and accuracy assessment of land use/land cover classification using remotely sensed data. *Journal of the Indian Society of Remote …*. Retrieved from http://www.springerlink.com/index/R1T2540047725323.pdf

Raines, J. (2008). *A Comparison of Pixel-based and Object-oriented Image Classification Techniques for Forest Cover Type Determination in East Texas* (p. 92). ProQuest. Retrieved from http://books.google.com/books?id=Id27RcsTWw0C&pgis=1

Runkle, J. R. (1989). Synchrony of Regeneration, Gaps, and Latitudinal Differences in Tree Species Diversity. *Ecology*, *70*(3), 546. doi:10.2307/1940199

Saliola, A. (2014, June 1). Object-based Image Analysis for the Delineation of Canopy Gaps and Individual Tree Crowns using Multi-source Data: A Case Study in Haliburton Forest, Ontario. Ontario: University of Toronto. Retrieved from https://tspace.library.utoronto.ca/handle/1807/65603

Scarth, P., Phinn, S. R., & Mcalpine, C. (2002). Integrating high and moderate spatial resolution image data to estimate forest age structure. *Canadian Journal of Remote Sensing*, *27*(2), 129–142. Retrieved from http://cat.inist.fr/?aModele=afficheN&cpsidt=945962

Schwarz, M., Steinmeier, C., Holecz, F., Stebler, O., & Wagner, H. (2003). Detection of Windthrow in Mountainous Regions with Different Remote Sensing Data and Classification Methods. *Scandinavian Journal of Forest Research*, *18*(6), 525–536. doi:10.1080/02827580310018023

Solberg, A. H. S. (1999). Contextual data fusion applied to forest map revision. *IEEE Transactions on Geoscience and Remote Sensing*, *37*(3), 1234–1243. doi:10.1109/36.763280

Song, B., Chen, J., Desander, P. V., Reed, D. D., Bradshaw, G. A., & Franklin, J. F. (1997). Modeling canopy structure and heterogeneity across scales: From crowns to canopy. *Forest Ecology and Management*, *96*(3), 217–229. doi:10.1016/S0378-1127(97)00021-2

Spies, T., & Franklin, J. (1989). Gap characteristics and vegetation response in coniferous forests of the Pacific Northwest. *Ecology*. Retrieved from http://www.jstor.org/stable/1940198

Stewart, G. H., Rose, A. B., & Veblen, T. T. (1991). Forest development in canopy gaps in old-growth beech (Nothofagus) forests, New Zealand. *Journal of Vegetation Science*, *2*(5), 679–690. doi:10.2307/3236178

Thakare, V. S., Patil, N. N., & Sonawane, J. S. (2013). Survey On Image Texture Classification Techniques. *International Journal of Advancements in Technology*, *4*(1), 97–104. Retrieved from http://ijict.org/

Tuominen, S., & Pekkarinen, A. (2005). Performance of different spectral and textural aerial photograph features in multi-source forest inventory. *Remote Sensing of Environment*, *94*(2), 256–268. doi:10.1016/j.rse.2004.10.001

Üreyen, S., Hü, C., & Schmullius, C. (2014). Modeling Growing Stock Volume Using SAR Data and OBIA: Effects of Scale Parameter and Textural and Geometrical Features. *Journal of Remote Sensing Technology*, *2*(c), 108–117. Retrieved from http://www.researchgate.net/profile/Soner_Uereyen/publication/261174720_Modeling_Growing_Stock_Volume_Using_SARtrica/links/00b7d5336d3f753925000000.pdf

Wang, L., Gong, P., & Biging, G. S. (2004). Individual Tree-Crown Delineation and Treetop Detection in High-Spatial-Resolution Aerial Imagery. *Photogrammetric Engineering & Remote Sensing*, *3114*, 351–358. Retrieved from http://info.asprs.org/publications/pers/2004journal/march/2004

Wang, O. (2012). *Forest canopy shadow exttraction using aerial photographs in the Ecuadorian Amazon* (pp. 174–179).

White, J. C. (2012). Digital high spatial resolution aerial imagery to support forest health monitoring: the mountain pine beetle context. *Journal of Applied Remote Sensing*, *6*(1), 062527. doi:10.1117/1.JRS.6.062527

Whitmore, T. C. (2014). Canopy Gaps and the Two Major Groups of Forest Trees. *Ecological Society of America*, *70*(3), 536–538.

Wulder, M. A., LeDrew, E. F., Franklin, S. E., & Lavigne, M. B. (1998). Aerial Image Texture Information in the Estimation of Northern Deciduous and Mixed Wood Forest Leaf Area Index (LAI). *Remote Sensing of Environment*, *64*(1), 64–76. doi:10.1016/S0034-4257(97)00169-7

Yan, G., Mas, J. F., Maathuis, B. H. P., Xiangmin, Z., & Van Dijk, P. M. (2006). Comparison of pixel based and object oriented image classification approaches—a case study in a coal fire area, Wuda, Inner Mongolia, China. *International Journal of Remote Sensing*, *27*(18), 4039–4055. doi:10.1080/01431160600702632

Yao, T., Yang, X., Zhao, F., Wang, Z., Zhang, Q., Jupp, D., … Strahler, A. (2011). Measuring forest structure and biomass in New England forest stands using Echidna ground-based lidar. *Remote Sensing of Environment*, *115*(11), 2965–2974. doi:10.1016/j.rse.2010.03.019

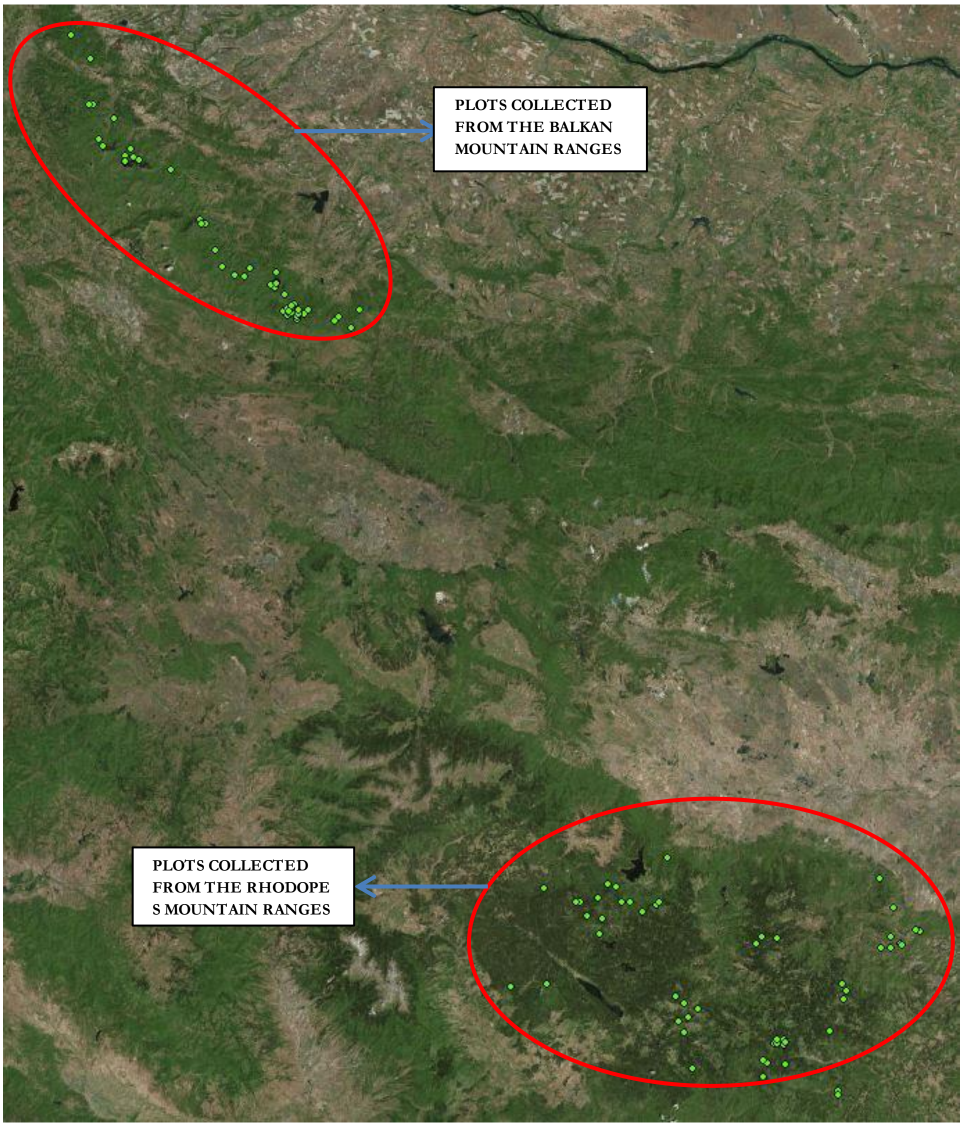
Zeibig, A., Diaci, J., & Wagner, S. (2005). Gap disturbance patterns of a Fagus sylvatica virgin forest remnant in the mountain vegetation belt of Slovenia, *80*, 69–80.

Zhang, C., Franklin, S. E., & Wulder, M. (2004). Geostatistical and texture analysis of airborne-acquired images used in forest classification. *International Journal of Remote Sensing*, *25*, 859–865. doi:10.1080/01431160310001618059

http://ec.europa.eu/environment/nature/legislation/habitatsdirective

APPENDICES

Appendix 1 Location of sample plots



Appendix 2 Field and image data of the Needle leaved forest type

Plot	Forest_type	SP_5	SP_7	SP_11	SP_15	SP_21	MW5_R	MW7_R	MW11_R	MW15_R	MW21_R
5	Needle	19.31	23.12	23.01	26.18	22.74	4.68	5.98	3.63	3.58	1.53
26	Needle	44.11	50.04	50.04	50.04	47.90	31.05	21.45	9.02	18.71	9.87
49	Needle	52.57	59.59	59.51	59.41	52.77	28.81	28.06	28.35	25.60	25.10
50	Needle	50.49	62.08	62.13	62.05	62.26	55.15	30.32	54.14	45.49	50.48
52	Needle	30.76	40.14	35.72	35.69	39.82	14.59	10.23	12.57	11.78	6.93
55	Needle	46.76	52.78	46.91	46.94	52.76	20.46	28.45	18.49	17.21	13.85
57	Needle	56.72	61.45	61.40	61.40	61.29	27.98	36.21	32.50	25.10	23.50
63	Needle	35.26	28.39	28.36	28.41	28.39	23.81	19.24	18.68	16.70	10.63
64	Needle	40.91	40.92	37.16	32.74	32.69	26.67	20.00	19.57	17.44	10.46
65	Needle	16.59	16.52	13.78	11.00	11.09	8.64	5.54	6.11	5.59	1.93
66	Needle	47.82	40.75	37.11	37.05	36.55	23.28	18.49	17.26	13.71	8.30
67	Needle	61.32	64.98	61.41	55.61	56.92	83.38	36.72	52.44	33.69	25.16
68	Needle	65.65	65.66	61.98	61.79	63.31	47.79	45.47	66.09	36.10	29.95
69	Needle	64.61	64.82	64.94	64.98	64.86	67.59	51.29	55.94	41.93	43.27
70	Needle	48.32	48.42	48.40	48.28	44.75	26.45	21.29	14.29	20.93	10.12
71	Needle	47.87	51.09	52.86	47.87	48.04	15.03	17.03	12.06	11.57	6.88
72	Needle	67.89	71.38	68.09	67.95	70.83	76.47	75.36	68.67	47.50	49.40
73	Needle	59.84	59.88	59.82	59.87	59.85	31.82	33.76	28.50	24.99	21.97
74	Needle	51.49	59.15	51.52	51.65	41.43	43.43	24.61	60.40	42.67	31.61
75	Needle	21.05	23.63	23.65	20.94	12.61	11.03	8.91	6.63	10.10	2.22
76	Needle	27.41	27.42	27.28	24.13	17.46	16.40	13.10	11.93	9.68	5.15
77	Needle	47.02	51.89	46.80	51.90	46.81	45.06	34.78	33.19	29.59	21.41
78	Needle	35.57	35.63	31.01	35.54	35.64	28.13	20.89	20.58	18.41	12.00
79	Needle	38.49	38.52	38.41	35.00	34.72	28.78	23.60	22.76	19.54	13.24
80	Needle	23.23	23.20	20.71	17.62	17.71	15.09	12.14	10.96	8.77	4.74
81	Needle	45.30	50.41	45.23	45.30	45.15	43.47	37.02	41.00	31.55	22.51
85	Needle	56.96	56.94	56.91	49.58	49.66	27.73	20.10	26.90	25.95	22.13
88	Needle	44.97	44.98	44.90	44.74	44.48	36.57	28.80	27.69	23.93	16.57
89	Needle	33.21	37.24	39.12	32.90	32.70	25.09	13.06	19.29	15.67	10.46
93	Needle	45.96	46.01	40.05	40.12	45.91	50.25	38.71	41.44	34.11	29.53
99	Needle	51.64	61.82	59.24	55.99	55.51	84.23	64.01	56.16	53.04	45.65

Appendix 3 field and image data of the Broadleaved forest type

Plt	Forest_type	SP_5	SP_7	SP_11	SP_15	SP_21	MW5_R	MW7_R	MW11_R	MW15_R	MW21_R
1	Broadleaved	43.92	48.86	48.89	48.84	48.88	27.65	24.10	28.16	23.33	20.85
2	Broadleaved	3.55	8.83	6.33	5.21	4.26	1.34	0.96	0.92	0.63	0.36
3	Broadleaved	11.82	11.63	12.84	14.77	13.21	2.09	1.18	1.47	1.18	0.67
4	Broadleaved	24.86	28.05	27.98	27.97	26.31	9.42	13.70	13.22	7.68	9.06
6	Broadleaved	11.93	11.86	11.76	11.81	14.14	2.42	2.86	1.86	1.77	0.95
7	Broadleaved	28.11	28.06	27.94	26.63	27.83	12.76	14.00	11.24	11.52	8.38
8	Broadleaved	20.11	24.19	19.93	19.93	19.71	6.29	6.95	5.38	3.15	4.23
9	Broadleaved	7.00	10.01	9.89	9.61	13.85	1.80	2.07	1.14	1.02	0.35
10	Broadleaved	31.14	34.99	31.08	33.60	34.72	19.88	21.55	18.27	17.05	14.42
11	Broadleaved	14.88	20.71	20.60	17.87	17.63	6.83	4.80	5.72	4.97	3.36
12	Broadleaved	7.22	10.18	10.07	12.94	12.70	2.01	1.11	1.43	1.09	0.51
13	Broadleaved	19.50	24.88	24.71	24.67	24.44	4.88	3.60	3.73	3.58	1.95
14	Broadleaved	11.94	15.75	15.76	18.59	15.48	3.47	2.26	2.66	2.49	1.28
15	Broadleaved	9.60	9.55	12.07	9.35	11.81	1.11	0.52	0.65	0.47	0.23
16	Broadleaved	33.15	37.11	33.55	38.67	33.40	15.45	12.19	13.57	13.90	9.41
17	Broadleaved	18.37	18.38	21.44	21.42	21.27	7.69	5.05	5.82	4.86	3.22
18	Broadleaved	12.27	16.82	13.69	13.70	13.65	5.41	3.07	4.22	2.87	2.23
19	Broadleaved	45.59	50.05	45.72	45.75	46.73	35.99	24.30	36.73	16.93	27.31
20	Broadleaved	14.19	19.11	13.61	18.92	13.48	2.31	1.84	2.76	2.36	0.93
21	Broadleaved	16.78	24.04	17.39	20.39	20.42	6.70	3.40	4.15	3.75	1.97
22	Broadleaved	29.02	28.99	28.83	33.96	28.56	7.42	3.89	6.52	5.23	3.33
23	Broadleaved	32.83	32.79	32.87	32.90	32.67	20.07	12.92	16.85	12.65	5.97
24	Broadleaved	31.53	42.53	31.40	35.69	31.34	18.66	10.50	15.13	15.68	10.74
25	Broadleaved	48.91	59.35	56.47	56.48	54.94	61.33	20.57	49.79	34.52	40.05
27	Broadleaved	39.55	42.57	42.55	42.49	42.44	22.26	12.42	19.70	17.70	14.93
28	Broadleaved	33.21	35.21	35.09	35.24	34.99	17.70	11.50	15.21	13.24	10.91
29	Broadleaved	55.47	63.76	60.53	60.56	60.56	28.87	25.15	50.53	24.19	21.62
30	Broadleaved	32.57	36.31	31.53	31.65	33.51	14.13	15.94	19.04	18.42	13.21
31	Broadleaved	31.68	37.78	31.59	37.80	37.61	10.96	8.53	9.15	8.58	5.79
32	Broadleaved	51.52	51.46	51.48	51.57	52.66	21.38	19.98	20.63	25.09	16.39
33	Broadleaved	54.91	58.75	54.80	54.67	52.17	12.38	21.79	32.34	20.62	23.43
34	Broadleaved	25.07	33.20	27.99	30.75	30.73	13.36	9.80	11.07	10.75	7.07
35	Broadleaved	26.83	29.36	26.80	29.23	23.91	16.25	13.15	12.96	12.04	8.89
36	Broadleaved	44.68	49.66	49.51	44.72	49.43	34.84	21.33	26.64	26.00	19.48
37	Broadleaved	14.47	17.37	14.31	14.22	14.02	5.94	3.83	4.45	4.26	2.48
38	Broadleaved	21.75	24.04	21.75	24.04	26.26	7.48	4.38	5.73	5.33	3.30
39	Broadleaved	40.65	46.72	40.72	40.61	40.55	23.23	20.26	20.69	19.11	15.52
40	Broadleaved	33.18	36.99	32.99	33.06	28.96	18.87	11.58	14.67	13.53	10.97
41	Broadleaved	18.46	20.46	18.43	16.03	18.38	6.06	3.88	4.48	3.89	2.25
42	Broadleaved	37.44	40.19	37.57	40.18	37.36	20.22	23.73	18.37	22.92	13.92
43	Broadleaved	22.06	27.56	22.09	21.97	21.81	7.42	4.45	5.08	4.65	2.14

44	Broadleaved	18.66	16.89	16.83	14.80	14.77	6.47	4.42	4.68	4.25	2.26
45	Broadleaved	14.23	14.18	11.70	14.16	14.13	3.95	2.72	2.88	3.13	1.53
46	Broadleaved	24.63	24.63	24.48	24.60	24.40	7.34	6.37	5.32	4.79	2.58
47	Broadleaved	14.17	14.14	14.03	13.94	13.80	4.37	3.61	3.27	3.10	1.90
48	Broadleaved	21.38	25.58	25.65	22.91	22.85	5.50	6.35	6.76	6.34	4.04
51	Broadleaved	22.93	22.91	28.45	22.84	23.09	10.35	6.12	6.42	8.52	5.11
58	Broadleaved	17.79	17.79	17.76	17.79	17.61	6.12	4.31	0.30	4.37	0.09
59	Broadleaved	24.82	24.80	24.85	19.66	19.55	13.81	8.88	10.93	10.93	5.11
60	Broadleaved	35.17	40.63	35.10	35.14	34.96	20.77	22.89	22.26	20.75	14.62
61	Broadleaved	28.41	28.38	21.36	24.64	24.55	24.07	17.29	17.92	17.16	10.43
62	Broadleaved	22.32	19.24	19.28	16.27	16.36	10.00	6.38	6.54	5.68	2.28
82	Broadleaved	26.86	24.10	26.68	29.46	26.87	7.72	10.07	5.44	5.35	2.46
84	Broadleaved	41.89	41.92	41.99	41.96	42.13	12.63	12.05	12.29	12.08	10.24
90	Broadleaved	41.79	39.78	36.70	30.48	30.57	24.32	17.60	16.03	13.14	6.89
91	Broadleaved	29.08	29.03	29.01	24.48	18.93	10.84	7.52	6.43	4.61	2.07
92	Broadleaved	51.12	51.15	51.24	51.24	51.12	74.74	58.95	66.95	42.37	33.78
94	Broadleaved	16.31	14.27	10.01	10.32	10.24	1.88	1.09	0.80	0.42	0.10
95	Broadleaved	43.81	43.83	43.71	42.23	39.34	49.87	46.58	46.41	26.91	32.67
96	Broadleaved	35.90	35.86	35.86	35.58	35.38	16.65	12.01	12.75	12.33	8.33
97	Broadleaved	45.25	45.32	45.30	35.26	37.00	38.64	27.03	25.39	22.35	14.68
98	Broadleaved	39.30	39.19	35.00	38.99	31.26	37.84	29.39	26.12	24.54	14.97

Appendix 4 Scatter plot of scale parameters with field data