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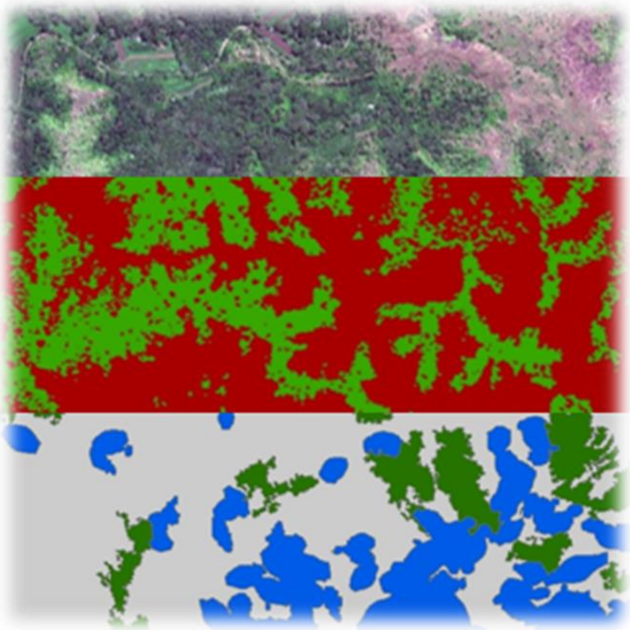
Object-Oriented Forest Stratification for REDD-readiness in Fiji

An object-based image analysis approach for the implementation of policy definitions to the Fijian forests

Jonas van Duijvenbode



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Abstract

For REDD-readiness the government of Fiji needs to develop a national carbon monitoring system. For this monitoring system it is necessary to develop a framework and method to stratify the Fijian forest according to chosen FAO forest definitions. In this research a method is proposed to go from a Worldview-2 satellite image, through a forest canopy map, to a forest density map. A definition-dependent, object-based method is evaluated for the delineation of the areas of closed, open and non-forest. This method resulted in a density map that indicates a forest canopy cover less than 10% different from the actual canopy cover, an improvement compared to the results of other pixel-based methods. It has also been explored whether mangrove and pine can be distinguished spectrally, but this was not validated due to a lack of ground reference data. The parameters used for segmentation and classification of the canopy map proved to be usable independent of geographic aspects, showing that methods developed in one area can be applied on different areas without a significant loss in accuracy. The red band was used for segmentation and the NDVI, hue, saturation and maximum difference in brightness were shown to be the features most influential for the classification of the forest canopy. The automatic classification with a Bayesian classifier had an average overlap of 84% with visual interpretation and 76% with ground reference data.

Keywords: remote sensing, GEOBIA, forest density mapping, FAO forest definitions, Worldview-2

1 Introduction

1.1 Fiji's REDD-readiness

Fiji is an archipelago that comprises of two main islands and several hundred small islands, laying about 3000 km north-east of the coast of Australia. The main land mass of Fiji consists of two islands, Viti Levu (56% of total land mass) and Vanua Levu (30%). The climate is tropical with small seasonal temperature changes of a minimum of 22°C in July and 26°C in February. Rainfall is on average 2000-3000 mm per year with over 5000 to 10000 mm in mountainous regions (Ash 2000).

Since 2011 the Fijian government has adopted a national REDD+ (Reducing Emissions from Deforestation and forest Degradation) policy for the reduction of emissions from deforestation and forest degradation (Fiji Forestry Department 2011). One of the activities for the REDD-readiness of the country is the design and initial implementation of a national forest carbon monitoring programme. The amount of carbon can be monitored through carbon pools, which consist of above-ground biomass, belowground biomass, litter, dead wood and soil organic carbon (Smith et al. 2007). The amount of above-ground and below-ground biomass is heavily dependent on the type and amount of forest that is present in that area. Therefore it is necessary for the country to make an inventory of the forest and its major contributing forest types to the national carbon stock (FCPF 2013). Two such attempts to make a forest inventory for Fiji have been made in the past, one in 1991 and one in 2007 under supervision of the FAO (FCPF 2013). These were not considered satisfactory for REDD-readiness. They also did not envelop all the definitions set up by the FAO, who has its own specific definitions of forest. These two aspects lead to a need for an improved forest inventory.

1.2 Problem definition

The forest stratification in Fiji is dependent on definitions set up by the FAO regarding what constitutes a forest. Translating these definitions into quantifiable definitions, benchmarks and thresholds that can be quantitatively analysed can be a challenge. For the FAO definitions specifically this has been investigated by Magdon et al. (2014) but as it was put by Bartholomé & Belward (2005): "As international forest definitions are negotiated in a policy process rather than being based on scientific analysis only, conflicting constraints are put on land cover mapping".

A spatial difference in reflected radiance that is not dependent on the actual reflectance characteristics of the observed object can result in a misclassification if this change in reflected radiance is not recognised and corrected. Such a change can be caused by a change in any of the components of the bidirectional reflectance distribution function (BRDF) (Schaepman-Strub et al. 2006), like the illumination angle, the view angle or the solar irradiance intensity. A first reason for such a change is the use of multiple satellite images within one study area without a good atmospheric correction for every image (Du et al. 2002). Another reason is the measurement of a non-flat surface. In hilly or mountainous areas there can be a large difference in the reflected radiance of the objects between the shadow side and the illuminated side of the hill or mountain (Dubayah 1992; Lübker & Schaab 2008). Since Fiji is originally a volcanic island there are many relief differences, so differences in reflected radiance independent of reflectance characteristics are to be expected during the image analysis and can complicate automatic classification.

To do a stratification through classification it is first of all necessary to be clear what the classes of interest are. The flora of Fiji consists of hundreds of different species, varying for a great number of forest types (Keppel et al. 2006; Kirkpatrick & Hassall 1985; Kirkpatrick & Hassall 1981) and it is virtually impossible to classify every single one of them. This problem requires a focus on species that are well distinguishable and important for the biomass estimation in the area. Whether the species are distinguishable depends on the quality and spatial and spectral resolution of the images. In Fiji the main forest type is deciduous forest. Deciduous forest is more difficult to distinguish from grassland and also on an individual tree level more difficult to delineate than coniferous forest (Hussin et al. 2014; Ke & Quackenbush 2011). Also the forest is not homogeneous (Keppel et al. 2006) and the intensive spatial mixing of tree species will make it more difficult to distinguish different species or species groups. Although the forest in Fiji is very mixed different groups of species will occur in certain geographic niches, like areas with a high or low precipitation level and a certain altitude.

In most areas in Fiji there are a lot of human-induced disturbances on both small and medium scales (Ash 2000) that have taken place for over hundreds of years. These disturbances can result in a large variety of areas with distinct texture, shape and spectral characteristics. There is no consensus on some levels to what extent such a disturbance can still (or again) be part of a forest. Clear definitions are therefore needed to what is forest and what is not (FAO 2005) and this needs to be translated into quantifiable rules that can be interpreted through software. These definitions and corresponding rule sets again are dependent on the spatial scale of the segmentation and classification (Marceau & Moreno 2008).

1.3 Research objectives and questions

"The overall objective of this thesis is to stratify the forest in Fiji for major forest classes through object-based image analysis"

The detailed research objectives that accompany this general research objective are:

- Stratify a sample of the Navosa province on Viti Levu in closed forest, open forest and non-forest.
- Stratify within the forest distinct species or species groups that are distinguishable and important in the vegetation of Fiji.
- Analyse the need for different rule sets dependent on geographic information.
- Apply an accuracy assessment based on reference data and transferability of the rule sets to analyse the quality of the stratification.

The general research question that goes along with the research objective is:

"What are the distinct forest classes and species and on what characteristics can they be identified through very high resolution imagery?"

The detailed research questions that accompany this general research question are:

- What are the spectral characteristics of these species and classes?
- In what way do these species and classes differ from each other and can they be distinguished?
- In what way can the forest be delineated dependent on the framework and definitions of the FAO?
- To what extent can thematic/geographic data help improve the accuracy of the stratification?

In this research very high resolution images are used to stratify different forest types present in Fiji through object-based image analysis. In the next chapter (2) methods and principals of geographical object-based image analysis (GEOBIA) and the relation to forest stratification in Fiji based on the vegetation in Fiji are gathered from literature. In the methodology chapter (3) methods are proposed for the initial classification and subsequent density stratification. These methods are applied on a case study accompanied with image and reference data, also discussed in this chapter. In chapter four (4) the results of this stratification are shown, along with the expected accuracy with the developed rule sets for the forest classification and the effects of the chosen methods for density stratification. In the following chapter (5) the implications of these results and how they relate to other research are discussed followed by a general conclusion (6). In the last chapter (7) recommendations are given based on the findings for following research and the application of these findings.

2 Literature review

2.1 Forest inventory: policy to mapping

For a forest inventory certain standards and definitions need to be used that state what encompasses a forest. To give an insight of the importance of rigid definitions: A list of all definitions of forests, deforestation, afforestation and trees as noted in literature has been continually updated since 1998, already comprising hundreds of different definitions (Lund & Gyde 2014). The FAO definitions for forest were designed as to be applicable to countries all over the world. There is a rather long list of the specific rules and exceptions on what defines a forest which need to be incorporated into the model for forest inventory mapping. However, the main definition is as follows: Land spanning more than 0.5 hectares with trees higher than 5 meters and a canopy cover of more than ten percent, or trees able to reach these thresholds in situ. It does not include land that is predominantly under agricultural or urban land use (United Nations 2010a).

Individual countries are free to adapt these definitions to their policies. Fiji has done this by incorporating separate definitions for low density forest (open forest) and high density forest (closed forest), having a respectively 10-40% and a 40-100% canopy cover. These definitions are mentioned in their REDD-readiness proposal (FCPF 2013). It is not clear where these definitions stem from, besides that these classes are also used in the Philippines (United Nations 2010b). It is reasonable to assume that due to the high level of forest cover in Fiji there was a need for more density classes so as to better represent the forest through maps and statistics. Fiji has not adopted the definition that a forest cannot include land that is predominantly under agricultural or urban land use; it is not found in its forest definition in the national REDD-readiness proposal (FCPF 2013).

There are many aspects of these stated definitions, and especially the extra explanatory notes (United Nations 2010a) that are difficult if not impossible to translate to quantitative features that can be translated to an automatic wall-to-wall mapping procedure. An example of such a definition: “It also includes areas that are temporarily unstocked due to clear-cutting as part of a forest management practice or natural disasters, and which are expected to be regenerated within 5 years.” (United Nations 2010a). The problem with such definitions has already been extensively covered by Magdon et al. (2014). The result of their paper is a flowchart that goes from a pixel-based classified land cover map through an FAO defined land use map to a FAO forest map, having the classes Forest, Non-Forest and No Data. The decision tree used to go from land cover map to FAO defined land use map is shown in Figure 1.

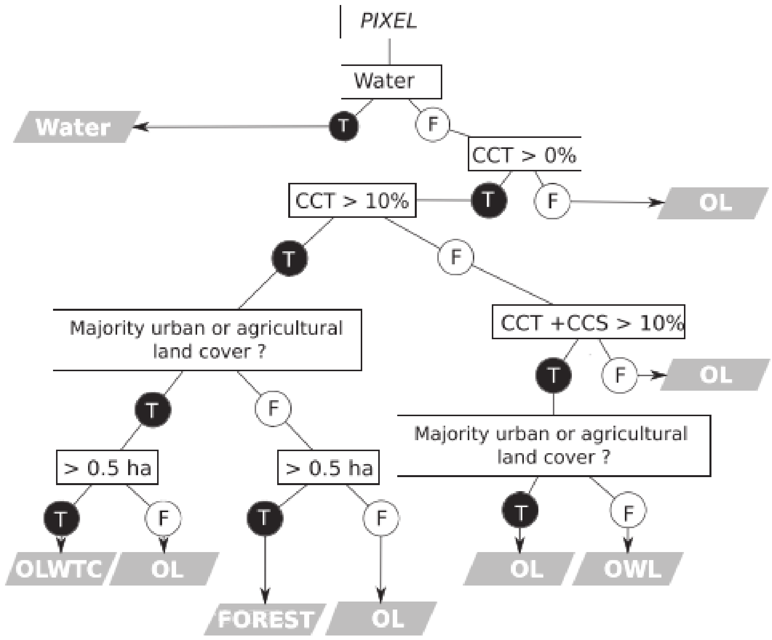

Figure 1 Decision tree to differentiate FAO land use classes: forest (FOREST), other land (OL), other land with tree cover (OLWTC) and other wooded land (OWL) using the criteria crown cover trees (CCT) and crown cover shrubs (CCS) and majority of land cover type in the reference area; T= true, F= false.(Magdon et al. 2014)

This decision tree can be used as a model for a similar object-based method for forest inventory mapping for Fiji by at least incorporating the open and closed forest thresholds of 10-40% and 40-100%.

One of the problems in Fiji is that there are a large number of minor disturbances, meaning forest converted to small-scale agricultural land (Ash 2000; FCPF 2013). The small scale of these disturbances can make it difficult to distinguish between land cover that is agricultural and land cover that is natural. Since for REDD-readiness only a forest map is required and not a land use map this is not a problem; other land, other wooded land and other land with tree cover are eventually all classified in the above decision tree as non-forest. Therefore they do not need to be incorporated into the decision model for the forest stratification of Fiji.

Many of the country reports that use the FAO definitions are based on mapping with low resolution satellite imagery, like Landsat data (FAO & JRC 2012). However, the current research uses high resolution satellite data for its forest inventory -namely Worldview-2 data-.

"The crown cover percent for a pixel is inferred from the intensity of vegetation response over the pixel area. The potential of analysing individual tree crowns for large areas arises from a new generation of H-resolution satellite sensors with pixel sizes in the meter (e.g., RapidEye, Ikonos, SPOT 5, TerraSAR-X, Radarsat) and submeter (e.g., Worldview I&II, Quickbird, Ikonos) range. Using H-resolution sensors, individual tree crowns can be identified and crown cover measured; this is contrary to the application of L-resolution sensors. Therefore, when changing from L- to H- resolution imagery for forest mapping, not only the spatial resolution is relevant but also a second scale component needs to be considered: the reference area which will be elaborated in the following section."(Magdon & Kleinn 2013).

The problem of finding the right reference or support area is called the modifiable area unit problem (MAUP).

To put this modifiable area unit problem in an example, imagine an island of one hectare with half the area covered by trees. If the reference area is submeter, then the map will show that the forest cover of the island is 50%. On closer inspection the areas classified as forest have a 100% canopy cover, far more than 10% as defined by the FAO. At the other extreme, if the reference area is one hectare, then the whole island is classified as forest, with within the as forest classified area an average canopy cover of 50%, still more than 10%. The first method results in a forest area half that of the second method.

Magdon & Kleinn (2013) show through a spatial modelling technique that depending on the reference area -within reasonable sizes- the forest cover depending on the FAO definitions can differ indeed over 50%. Magdon et al. (2014) state that till now there is no conclusive answer to the MAUP and an FAO definition is needed to create a method that is applicable and similar for all forest inventories.

One thing that all the studies mentioned in the research of Magdon et al. (2014) have in common is that they use a pixel-based approach. The current research uses an object-based approach (for object-based image analysis, see (Blaschke et al. 2008) and related to this study see section 3.3). This technique could provide a more logical solution to the MAUP than an arbitrarily chosen reference area.

2.2 Fiji’s vegetation

Automated forest stratification requires an algorithm that can distinguish between the necessary strata based on the reflectance of an object. It is therefore important to know what kind of objects are to be expected in the images and what the reflectance characteristics of said objects are. In this section the major forest types are discussed and problems for the stratification that could occur because of other vegetation types.

The vegetation of Fiji consists of hundreds of different species. Although the island group is relatively small it still has a wide variety of geographically different regions due to its mountainous character. This allows for large variations in rainfall and with this possible moisture uptake for vegetation. As discussed in the introduction Fiji has an average annual rainfall of 2000-3000 mm, but this can vary between 5000-10000 mm for mountainous areas and only about 1500 mm for the northwest coasts of the larger islands. The mountainous/hilly characteristic of large parts of Fiji increases the presence of large local differences in possible soil moisture available for vegetation. This leads to expect large local differences in vegetation species.

Multiple case studies have been done on the vegetation of Fiji for different areas, for instance of a mesic forest in Vanua Levu (Keppel et al. 2006), in the sand dunes in the south-west of Viti Levu (Kirkpatrick & Hassall 1981) and an altitudinal transect along mount Korobaba in the south-east of Viti Levu (Kirkpatrick & Hassall 1985). These studies have shown that the forests in Fiji are generally very mixed (see also Ash (2000)) and searching for one dominant type would not be useful or probable as a method for forest classification for all species.

However, there are some species types that occur homogeneously in larger areas. The reason for this is on the one hand human-induced and on the other hand caused by ecological niches. First of all in Fiji there are hardwood plantations for industrial purposes that consist mainly of mahogany trees (FCPF 2013). A second type is pine trees, and then especially Pinus Caribea (Caribbean pine) (Ash 2000) being planted as pine plantations in more drier/steeper areas in Fiji. These plantations can consist of just a couple of trees, as a minor economic activity for a village, or on a larger scale. Both pine and mahogany are exotic species for Fiji and are mostly managed and monitored by logging companies.

Another species is coconut trees. These are indigenous to Fiji and grow originally in areas close to major water bodies and the coast. In other areas they are planted for multiple uses nearby villages.

These trees have very little canopy cover and due to this their spectral characteristics are especially in low resolution imagery determined by the undergrowth, making them possibly difficult to map.

The last major tree type is mangrove. These trees grow in vast areas along the coast, being tolerant to salt water. In Fiji there are multiple species of mangrove, namely: "Bruguiera gymnorhiza, Excoecaria agallocha, Lumnitzera coccinea, Rhizophora stylosa, R. samoensis [plus infertile hybrids between the Rhizophora species], and Xylocarpus granatum" (Ash 2000). Rizophora dominates the seaward mangrove areas. This mangrove species proves even in laboratory very difficult to differentiate from other mangrove species (Vaiphasa et al. 2005) and this species is also present in the inlands of Fiji (Ash 2000).

The four tree types discussed here are also the main forest types as distinguished in the REDD-readiness document of Fiji (FCPF 2013), with a relative land cover for pine of 5%, hardwood plantations of 3%, mangrove forests of 3% and coconut plantations of about 1.5%. The other land use types are closed forest (mixed species), attaining to 32% of all land cover, open forest (mixed species) 20%, and the rest of the land mass being non-forest and inland water bodies (FCPF 2013). There is no known documentation as to how the open and closed forest cover percentages were determined.

The mixed open and closed forest in Fiji consist mainly of indigenous species and some exotic species like the African tulip (Meyer 2000). The occurrence of individual species may vary according to aspects like precipitation, slope or soil type but as stated before these niches do not result in larger homogeneous areas with one species. This means that these forests need to be classified as mixed forest, perhaps accompanied with a label like lowland or upland forest based on its geographical aspects. This is also the current method in Fiji as applied in the stratifications in 1991 and 2007 (Tokalauvere 2012; FCPF 2013).

One of the greatest expected problems for optic classification of the forest is a creeping vine called Merremia Peltata. As described by ISSGS (2006):

"Merremia Peltata is a vine that strangles vegetation and invades forest strands. It may provide rapid ground cover following land disturbance reducing erosion and nutrient loss. There is debate over the extent to which external factors such as cyclones and land clearing drive the invasiveness of the species. It may be a successional component of regenerating forest in its native range."

Figure 2 Merremia Peltata overgrowing a forest. It grows both on the trees and on low vegetation and bare soil. Image courtesy: SPC

This species can overgrow even larger trees and drops from these trees, seemingly covering the forest like a blanket. Merremia grows over trees and over shrubland, grassland and bare soil. It is therefore very difficult to distinguish whether underneath the Merremia there is forest canopy or not. Because it covers like a blanket there is no abrupt shadowing at the edges of trees.

Shrubs can further complicate the classification. The most well-known example is the Macropiper Aduncum, known in Fiji as the Yanggona Ni Onolulu. This plant is described as a shrub or slender tree, can have a height between 1.5 and 8 meters and is in Fiji generally accepted as a shrub (Smith 1981).

Areas with these species should not be classified as forest. It could be expected that there are many shrub types like the macropiper aduncum. It is not in the scope of this research to change policy definitions to improve optical classification and thus this species and species alike shall be handled in a field validation accuracy assessment as non-forest.

There is to date no reliable method to estimate accurately the height of a bush or tree through photogrammetric non-stereographic image analysis, although some methods have been proposed; e.g. based on the shadow of a tree (Ozdemir 2008) or the NDVI (Carlson & Ripley 1997). Imagery with higher spatial resolution will definitely contribute to better estimations of the tree height in the future but no conclusive methods were found that were usable within the scope of this research. Therefore it has to be visually estimated if an object is a tree or a bush, based on its spatial context and texture along with field verification.

Figure 3: macropiper aduncum, also known as spiked piper, bamboo piper and yanggona ni onolulu (Fijian name)

2.3 GEOBIA

GEOBIA, or object based image analysis for geo-related purposes (Hay & Castilla 2008) is the analysis of remote sensing images through segmentation and classification of meaningful objects within the image. The use of objects in remote sensing arose from the dawning of more and more high and very high resolution satellite data. The term high resolution depends on this case of the objects of interest; if the pixel size is smaller than the objects of interest, we speak of high resolution imagery, otherwise of low resolution (Magdon & Kleinn 2013). The general procedure in GEOBIA is first the segmentation of the image into objects, creating so-called geons. A geon can be defined as a homogeneous geospatial referencing unit, specifically designed for policy-related spatial decisions (Lang 2008). The creation of these geons allows for a whole new range of features that allow for better classification, since any geon contains a number of pixels.

Ecognition is probably the most well-known software package for GEOBIA (Trimble 2014b). It has been around since 1995 and is accessible to new users with a simple interface, an extensive reference book for its functions and an upcoming active user community. The most important aspect of GEOBIA software is probably its segmentation algorithm. Its multiresolution segmentation algorithm scores quite high when compared to other segmentation algorithms (Marpu et al. 2010; Neubert & Herold 2008). It is based on the works by Baatz & Schäpe (2000) and they state it to be "an universal high-quality solution applicable and adaptable to many problems and data types". The software offers analysis on multiple levels (scales) and has a great amount of possibilities for object analysis based on the reflectance, texture, context and hierarchy. Besides segmentation the objects can also be classified in Ecognition based on single-dimensional, multi-dimensional and fuzzy classification. Available classification algorithms are: support vector machine (Tzotsos & Argialas 2008), random forest (Immitzer et al. 2012), decision tree, Bayes (Rish 2001) and K-nearest neighbour classification. The software also offers accuracy assessment functions like classification stability (the difference between the first choice for classification and second choice, based on chosen features and samples) and error analysis with validation data.

For the choice of features a feature space optimization toolbox is available. The user gives as input multiple classes with samples and an array of candidate features. Based on these features and these samples the algorithm calculates which configuration is best depending on the best separation distance. Ecognition calculates this separation distance as follows:

"Calculation of the Separation Distance d_{ij} of class i to class j: 'Take each sample of class i and find this sample of class j with the smallest Euclidean distance to it. Take each sample of class j and find this sample of class i with the smallest Euclidean distance to it. Average these Euclidean distances over all (i+ j) samples (i.e. $d_{ij} = d_{ji}$)'"(Ecognition n.d.). This Euclidian distance is then normalized by √d so as not to overestimate the separation distance in a feature space with many dimensions.

3 Methodology

3.1 Study area and data

The area of interest in this study is the Navosa province on Viti Levu and then especially the area around the Sigatoka river. The satellite imagery consists of one stitched image encompassing 650 square kilometres, shown in Appendix 1. This image was acquired with the Worldview-2 satellite in the beginning of July 2013. Within the image coastal areas, hilly areas and wetland areas are present, which creates ideal circumstances for this project since basically all main geographical areas are present here. Within the area coconut, pine and mangrove are present. Large areas of coconuts as plantations and naturally occurring are present in the river and coastal areas. These coconut trees all stand solitary and have different undergrowth, like forest, grassland, no vegetation (beach), or shrubland. Pine is present in dense forest stands and scattered in the hilly areas further away from the river. Mangrove is present in the coastal areas.

The satellite image used for this research has been ortho-rectified although no metadata is available on how this has been done. No cloud mask has been applied to the image. There is no known atmospheric correction applied meaning that it cannot be compared to other images taken under different circumstances. The data has been pan sharpened through a technique called hyperspherical colour sharpening (HCS), as developed by Padwick et al. (2010). Worldview-2 images have an expected horizontal inaccuracy of 5-10 meters (Eckert 2012) which should not be a major problem in this research.

Worldview-2 is up till now the only one of its kind with as much as 8 multispectral bands and it has a pan-sharpened resolution of 0.5 meters (2m unsharpened) (DigitalGlobe 2009). This offers new possibilities; the first one, as discussed previously, is the fact that the resolution is much higher than many objects of interest in the field -like trees-. This enables the possibility of GEOBIA, offering derivatives of reflectance information like the standard deviation and skewness of distribution of a geon. The second advantage is the larger number of bands compared to other commercial satellite sensors.

From the larger Worldview-2 image four subsets are selected from the satellite image. Two of these subsets are used for the canopy classification and density stratification: one lowland image and one highland image, both two by two kilometres. Lowland in this case refers to a low-lying area relatively close to the river and with little height differences within the area. The highland image has large height differences and is higher up in a drier area. These two areas are selected based on a digital elevation model (DEM) of Fiji. There is no known written metadata available about this DEM or an expected accuracy. Therefore this DEM is only used in the most basic way, by visually selecting the highland and lowland area. These two images are further referred to as the lowland and highland image, respectively. The other two images are subsets in which large areas of mangrove or pine are present. The highland and lowland image with close-up of the DEM, as well as the images of mangrove and pine are shown in appendix 1.

During fieldwork on the 8th and 9th of July 2014 70 points were taken in the field in a lowland area with, according to the optimal classification as given by sections 4.1.2.1 to 4.1.2.2, equal areas of canopy and non-canopy. This area had relatively low and few slopes, thus making it better accessible than areas in the highland image. The points were taken with a Garmin Juno 3B with an expected accuracy with differential correction of 2-5 meters (Trimble 2014a). The points were classified as being either canopy or non-canopy, depending on whether there was canopy of a tree straight above (excluding species like the Macropiper Aduncum (section 2.2) which were classified as non-canopy).

No Merremia (section 2.2) was found in the area and also no pine, mangrove, coconut or mahogany. The validation points were then compared to the canopy map as classified with the optimal classifier, feature space configuration and scale parameter, which were calculated in the former two sections. On closer inspection there seemed to be a spatial shift in either the validation or satellite imagery: one of the points (41, see Appendix 4) was taken under a solitary tree on a hill that can clearly be seen from the satellite image. All points were shifted accordingly (10 meters south, 5 meters east).

3.2 Forest canopy classification

3.2.1 Segmentation

The right segmentation scale enables the software to delineate the trees at its boundaries and ensures that the geons as calculated by the GEOBIA software package (Ecognition in this case) align the physical objects on the image. Oversegmentation (more geons per physical object) causes less problems in the analysis than undersegmentation (more physical objects per geon), since multiple geons can later be merged but a geon encompassing multiple objects cannot be correctly classified. Therefore a maximum permitted scale is established for segments so that there is as little undersegmentation as possible.

Defining the optimal scale for segmentation is done through the ESP-tool developed by Drăguţ et al. (2010). This tool looks at the rate of change of the local variance for segments of multiple scales. A local maximum in the rate of change means a relatively large variance between segments which indicates that meaningful segments and segment boundaries are established at this scale. The result of this step will be a segmentation with a scale that does not allow for undersegmentation but is as large as possible within this range so that the resulting segments/geons can provide more meaningful data like the standard deviation of a spectral band within one segment.

Other parameters that need to be set for a segmentation are the layers that will be used to determine homogeneity per segment, the relative importance of colour compared to shape of an object and the relative importance of smoothness compared to compactness of the shape parameter. The combination of these parameters needs to ensure that canopy and other land cover types are not mixed within one segment.

Of the original eight layers and the NDVI the only layer that shows two distinct peaks in the layer histogram (indicating two land use types) is the red band. After trial-and-error this seems to be the layer that delineates best the borders of a forest (based on visual inspection). Therefore this layer is used for the segmentation. The colour/shape parameter is set to 0.3. This means that the relative importance of shape is 3/7 of that of colour. In principle it is possible for a tree and especially a tree in a dense forest to have any shape, which means that the shape aspect is not that important. However, during the trial-and-error for segmentation it was showed that for individual trees, which tend to have a round canopy, a small factor for the shape parameter can significantly improve the segmentation. A value of 0.3 for this parameter turned out to give the best results. Individual trees and trees in forests almost never have smooth edges and therefore the smoothness/compactness parameter is set to 0.1/0.9.

3.2.2 Classification

In this research a multi-dimensional sample-based classification technique is used for the initial canopy classification. Multiple classification algorithms (section 2.3) are tested and evaluated in the accuracy assessment to determine the best algorithm for this project.

The features chosen for the classification depend on the results of the feature space optimization, which is based on the feature values of the samples. A selection of features that might be valuable for the classification of canopy are used as input for the feature space optimization. The samples are selected in an iterative procedure: the test images are classified and segments that are classified incorrectly are added to the sample until visually satisfactory results are attained. Note that the chosen features will not relate to geographic/thematic factors like closeness to water bodies or altitude; the focus of this study is on a classification through reflectance characteristics only.

Most experts agree that the more instances/subjects/objects there are the better. There are however many opinions about the minimum subjects-to-variables (STV) ratio. In this study the subjects are the segments selected for sampling. The variables are the features of the objects that are chosen to be used in the classification. Zhao (2009) gives an overview in what literature describes as the minimum STV ratio. The opinions are sundry and range between at least 500 samples regardless of the amount of variables to an STV ratio of 2:1. To conclude, it is up to the researcher, depending on the quality of the data and the possibility to gather more samples, to determine the STV ratio. In this research always the best ten features are chosen from the feature space optimization. Samples are selected till all visually different instances of a class have been covered.

3.3 Forest density stratification

The modifiable area unit problem (MAUP) has a great influence on the resulting forest inventory while no final solution has been given by the FAO and cannot be logically derived through a pixel-based approach. This research suggests an object-based approach that combines characteristics of the definition set by the FAO to find the most logical reference area that best represents the forest as it is in the field. The updated flowchart derived from the flowchart in Figure 1 is given in Figure 4. This flowchart is converted in Ecognition in a ruleset that segments and classifies the image into a forest canopy map (see previous section) and then uses this canopy map to derive a forest density map. Note that water is not included in the classification in this study; in both the highland and lowland image there are no water bodies present and as was shown in the flowchart in Figure 1 this class does not interact with the forest density classes.

The delineation of forest is two-fold. Closed forest is classified as being an area with a connected canopy through branches or internal shadowing larger than 0.5 hectares. For smaller forest areas a buffer is used. The two definitions that are used for this buffer-based approach are that (1) the minimum area to be considered is 0.5 ha and (2) the minimum canopy cover is 10%. This means that in an area of 5000 m^2 there needs to be at least 500 m^2 canopy. When there is one large tree or a connected forest stand of 500m^2 then, given a circle-shaped plot, the maximum distance from the canopy is given as the radius of the half-hectare plot minus the radius of the tree stand canopy. With two trees or forest stands of 250 m^2 the maximum distance is roughly halved. This can be quantified as the maximum distance from a tree stand based on the size of said tree stand. The distance from the tree stand in such a half-hectare plot is given according to the following formula (Equation 1):

$$d = \sqrt{\frac{5000}{\pi}} - \sqrt{\frac{A}{\pi}} \qquad \text{Equation 1}$$

Where d is the distance to the tree stand and A is the area of the tree stand.

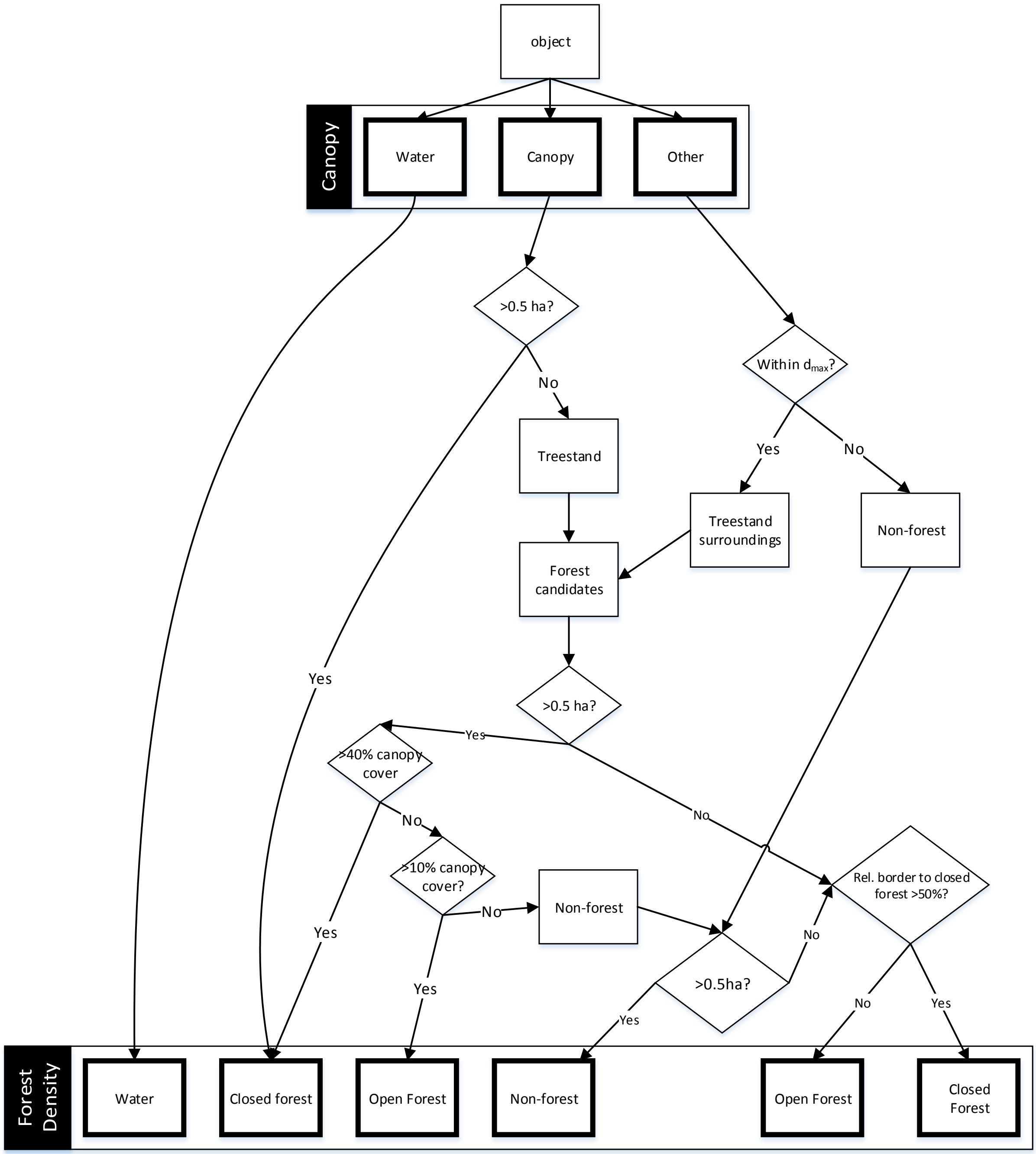

Figure 4: Decision Tree for the stratification of objects into open, closed and non-forest. d_{max} is calculated by the formula in Equation 2. The first container displays the classes of the forest canopy classification. The second container holds the classes of the forest density classification. The tree stands that do not meet the half hectare criterion are joined with its surroundings based on d_{max} and are then again evaluated on the minimum area and canopy cover criteria. Patches of non-forest that do not meet the area criterion are incorporated in the open or closed forest with which it shares the largest boundary. The result of this flowchart are areas that all meet the area criterion and forest (open and closed) patches that also meet the canopy cover criterion.

For simplifying purposes we will assume a linear relationship between forest stand size and maximum distance to forest stand. Furthermore we can say that if we have a tree stand larger than 500 m^2 then the tree stand can be part of an area larger than half a hectare, which means that 500 m^2 is our largest possible tree stand for one area unit of half a hectare. This can be formulated as follows:

$$d_{MAX} = \frac{\sqrt{\frac{5000}{\pi}} - \sqrt{\frac{A}{\pi}}}{(\frac{500}{A})} \; where \max(A) = 500 \qquad \text{Equation 2}$$

Where d_{MAX} is the maximum distance from the tree stand in meters with area A of said tree stand in square meters.

With this formula a buffer is created around each tree and tree stand with a radius dependent on the size of the object, the tree (stand). The advantage of this method is that (1) the definition of maximum distance is derived from the FAO definitions for minimum crown cover and area and (2) the reference area is dependent on the size of the tree stand.

After merging all areas that have been found to be within the maximum distance of a tree (stand) and the tree (stand) itself the decision tree as shown in Figure 4 can be followed to determine whether the area is open, closed or non-forest, dependent on the canopy cover fraction and the land use included in the buffer.

To some extent it would be logical to create a buffer around closed forest larger than 0.5 ha as well, with the radius as given by max(A) (Equation 2). However, this would artificially increase the size of the closed forest while decreasing the canopy cover fraction within said closed forest without any added value to the clearness of the boundary of the forest, especially in the field.

3.4 Stratification of individual species

It was mentioned in the introduction that an improved forest inventory -especially when focusing on REDD+ subjects like carbon stocks based on biomass- needs to include species that contribute on a different level to carbon monitoring in Fiji since different species can have huge differences in its carbon content.

The purpose here is to develop a method to incorporate distinct species into the flowchart presented of Figure 4. Mangrove and pine are the best and most interesting species to differentiate. These species are an important part of REDD+-activities (FCPF 2013), they generally occur in large homogeneous areas (Green et al. 1998) and they are the most widespread species in Fiji (FCPF 2013). Although coconut trees are also much present in the landscape of Fiji there are no large areas to be found that are dominated by coconut which makes classification even more difficult and without good ground reference data this is not within the scope of this research to investigate. This part of the research is an example/explorative study to show how to incorporate distinct species into the decision flowchart shown in Figure 4. The result will not be a classified image since there are no ground validation points of mangrove and pine and it is not in the scope of this research to obtain such points. The method consist of (1) finding information in literature about a

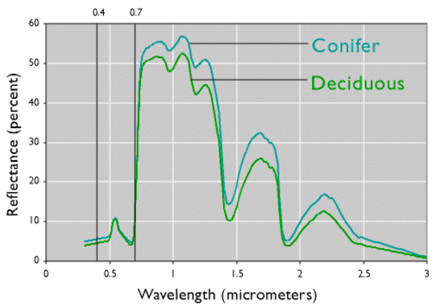

Figure 5: average spectral response for coniferous vegetation compared to deciduous vegetation (DiBiase & Dutton 1999)

species (as was shown in section 2.2 and this section), (2) determining through this literature review what the problems could be and to a certain extent the plausibility of the classification of the species, and (3) through inductive methods –sampling through visual interpretation and feature space optimization- determining if the species are separable from the other species. The fourth step, namely finding points in the field for training and validation is not included in the current research.

As was already mentioned in section 1.2, coniferous forests are easier to map than deciduous forest and therefore the mapping of Caribbean Pine should be possible. There was no literature to be found on the specific spectral characteristics that could aid in distinguishing Caribbean pine. A general spectral response of coniferous trees compared to deciduous trees is shown in Figure 5. This shows that the most differences can be expected in the near-infrared bands.

There are many mangrove species in Fiji (section 2.2). Thus it seems very difficult to differentiate between individual mangrove species. The main features (spectra) that seem most useful for discrimination between mangrove types are at 720 nm, 1277 nm, 1415 nm, and 1644 nm (Vaiphasa et al. 2005). Only the former (720 nm) can be found in the Worldview-2 data, namely in the red edge band. Green et al. (1998) showed that through a supervised classification, as applied in this research, an accuracy of more than 70% can be obtained with Landsat TM data. Given that this research uses Worldview-2 data, which has a higher spectral and spatial resolution, it should be possible to get a similar or higher accuracy when classifying mangrove from other types.

The stratification of mangrove and pine can be easily incorporated in the flowchart shown in Figure 4: after determining that an area is open or closed forest the canopy within this area can be classified as mangrove/pine or mixed forest. If more than half of the area is mangrove/pine, then the open or closed forest can be classified as respectively open or closed mangrove/pine forest. Since a large area (several hectares) can be classified as a forest it would be more representable for the actual forest to first segment this larger forest into smaller parts of half a hectare. Then it can be determined for any of these segments whether it is more than 50% mangrove or pine and can then be classified accordingly.

For the analysis of the possibility to distinguish and classify pine and mangrove two subsets of the Navosa area images are chosen with known larger areas of pine and mangrove. These are shown in Appendix 1. From the image areas were selected together with trained interpreters with knowledge of the area of which they are sure that mangrove or pine is present or not. These areas are used as samples for the classification. The best separation distance and the classification stability can then give an indication on the possibility for separation of these classes and inclusion in the forest density of Fiji.

3.5 Accuracy assessment of canopy classification and density stratification.

The only aspect of the forest stratification that can be assessed on accuracy is the automatic classification of canopy; the forest density stratification is a derivative of the canopy map and thus cannot be wrong when the canopy map is correct. The accuracy of the canopy map is assessed through comparison with visually interpreted data and through ground truthing. Visual interpretation cannot be used as a final benchmark since it is still unknown whether this interpretation is correct and in principle a computer can be better at classifying an object than a visual interpreter can, for various reasons (e.g. a visual interpreter can only see three bands at a time). The visually interpreted data is used to measure the transferability of the classification parameters such as the chosen classifier algorithm and the classification features. The final accuracy with optimal algorithm and feature space is then determined through ground reference data comparison.

This ground truthing is done by focusing on a small area of the lowland image and taking several points there through a systematic sampling method. The lowland image was chosen since the highland area is practically inaccessible, especially on its steeper slopes. The chosen area in the lowland image has roughly 50% canopy, to ensure that both classes are well represented in the accuracy assessment.

There are some quality indicators that can give more insight in the used method for density stratification. First of all a good stratification will give a good representation of the actual amount of forest in an area, both for the total area and per class. This means that it would be more representative if the class open forest would have an average of about 25% canopy cover (average of 10-40%) and the closed forest class an average of 70% (average of 40-100%). If such was the case then this would be an extra argument in favour of the used delineation method as proposed in section 2.1 although it is not a necessity, since it is not part of the definitions set up by the FAO.

4 Results

4.1 Forest canopy classification

4.1.1 Segmentation

The results of the estimator of scale parameter on the red band of the image subsets are shown below in Figure 6 and Figure 7. The optimal scale is easy to see for the highland image: there is a very distinct local maximum at a scale parameter of 25. For the lowland image this is not so distinct: the smallest local maximum is found at 23, while others are found at 33, 37 and 46. Application of all four of these scales on the image shows that only with a scale parameter of 23 the smaller individual trees can be delineated without undersegmentation. The presence of more local maxima could mean that there are distinct object types that have a certain size which are well delineated at the scale parameter sizes of 33, 37 and 46, such as houses or agricultural parcels (present in the lowland image, not in the highland image).

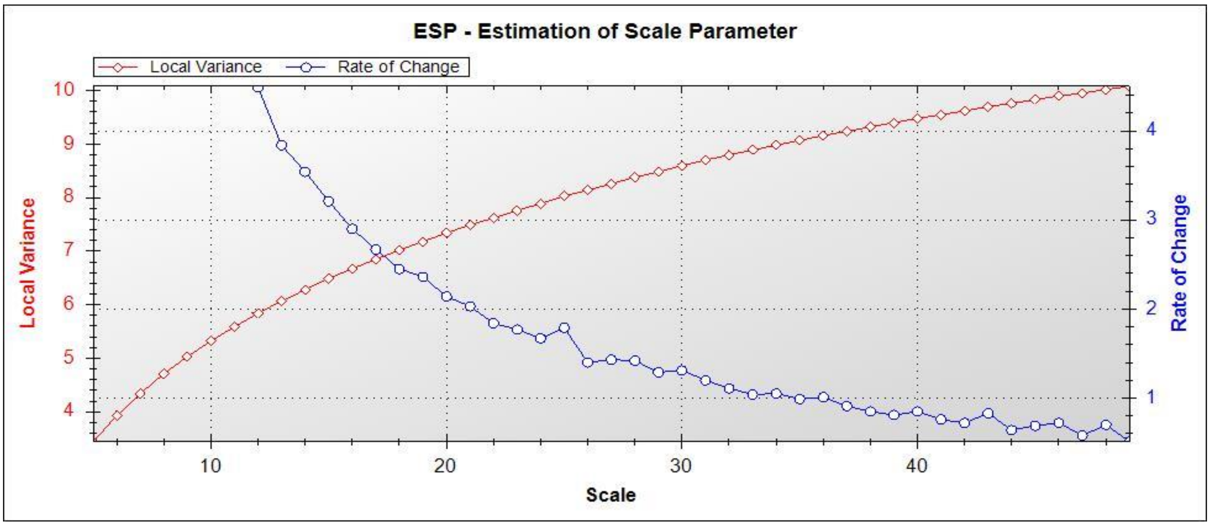

Figure 6: Local Variance and Rate of Change of the objects in the highland image. There is a clear peak of the rate of change at a scale parameter of 25. This means that there are objects present that are best delineated with this scale parameter.

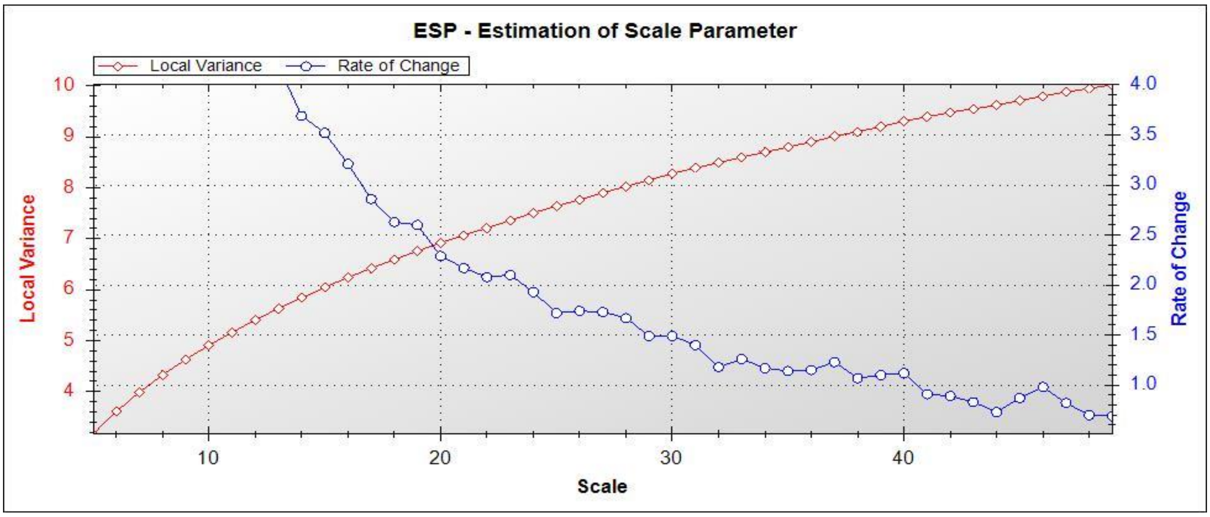

Figure 7: Local Variance and Rate of Change of the objects in the forest subset of the lowland image. There is a smaller peak at a scale of 23, not as clear as for the highland image. There are other local maxima at 33, 37, 40 and 46 but with these scales there was undersegmentation at the tree level.

4.1.2 Classification

4.1.2.1 Optimal feature configuration

The original configuration used for feature space optimization consists of 53 possible features. Texture features are not included. Besides taking a disproportionate amount of computing power an exploratory analysis showed that there is not much added value in these features for the classification of canopy/non-canopy. The features that were used for the initial configuration are:

- Any combination of [Blue, Green, Yellow, Red, Red Edge, NIR1, NIR2, NDVI] and [Mean layer value, Standard deviation of Layer value, Skewness of distribution, Minimum pixel value, Maximum pixel value, Absolute difference to neighbouring objects]. The coastal blue band was not included since it was not designed for land cover purposes and has a low signal-to-noise ratio. This gives a total of 8 layers times 6 features (48 features).
- The Hue, Intensity and Saturation, of the Red, Green and Blue band combination (3 features).
- The Brightness and the maximum difference in brightness within one object. The brightness is the sum of the original 8 Worldview-2 band layers (2 features).

Four sets of samples (two for canopy, two for non-canopy) per image were visually identified with supervision of a skilled interpreter. For all four combinations (canopy sample 1 with non-canopy sample 1, etc.) the optimal configuration with ten features was calculated. A summary of the occurrence of the features in these configurations are shown in Figure 8.

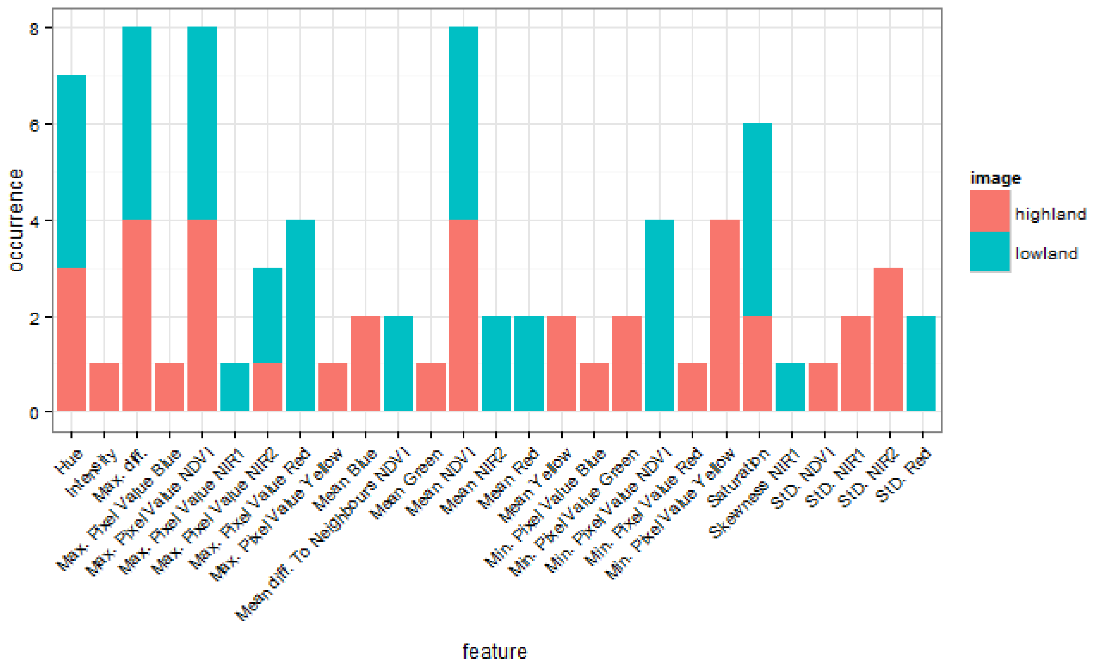

Figure 8 Occurrence of features in the optimized feature configuration of ten features for the highland and lowland image. The NDVI is most represented as an important feature for the classification of canopy, with all its features besides skewness represented in the table.

It is clear from the figure that the NDVI is the most influencing layer for the classification of canopy, although it was not best at delineating trees, which was the red layer (as explained in section 3.2.1). Furthermore it is interesting to see that the three extra bands of Worldview-2 are not much present. The Red Edge is not present at all, while it was designed to aid in vegetation analysis, though not specifically to differentiate between vegetation and other land use types (Digitalglobe 2010). It is also important to note that the features maximum pixel value of the red band, minimum pixel value of the

NDVI and the minimum pixel value of the yellow band occur in all combinations within one image but not in the other image. For the lowland image this can be explained by the presence of buildings and agricultural fields, for the highland image this must be caused by other, unidentified objects.

The features that are present in three or four of the configurations per image are used in the following sections. This means for the lowland image the hue, max. diff., max. pixel value NDVI, max. pixel value red, mean NDVI, min. pixel value NDVI and the saturation. For the highland image these are the hue, max. diff., max. pixel value NDVI, mean NDVI, min. pixel value yellow and the standard deviation of NIR2.

4.1.2.2 Classifier

The Bayesian classifier scores best overall regardless of on which image it was trained (Figure 9). This means that the Bayesian classifier with whichever chosen configuration of features can be applied to both highland and lowland areas, wet and dry areas and areas with slopes or without. It is important to note that accuracy in this section is used in the context where the classification of visual interpreters is the benchmark/correct. This does not necessarily have to be the case.

The average accuracy of the Bayesian classifier is the highest, with an average of 0.86, compared to 0.81 for the second highest, which is the decision tree. The Bayesian classifier trained on the highland with the features selected in the feature space optimization for the highland image scored highest as well, with an average accuracy of 0.82 compared to 0.73 for the lowland. For some reason the classification accuracy of the support vector machine classifier trained on the lowland image has a very low accuracy; on visual inspection it shows that the classification seems inverted, meaning that the canopy is classified as non-canopy and vice-versa. This is not an error in the input (tested with different samples and on different occasions) but might be an error in the software or in the classifying algorithm. Unfortunately the process behind the algorithm in Ecognition is a black box and it cannot be said why exactly this has happened. When the support vector machine classifier is not taken into account the quality of the average classifier of the lowland image is 0.83, compared to 0.82 for the highland image. The classification of the highland image is overall higher (0.84 compared to 0.80).

The results of the optimal classification with the Bayesian classifier for both lowland and highland images can be observed in respectively the top-right image of appendix 2 and appendix 3.

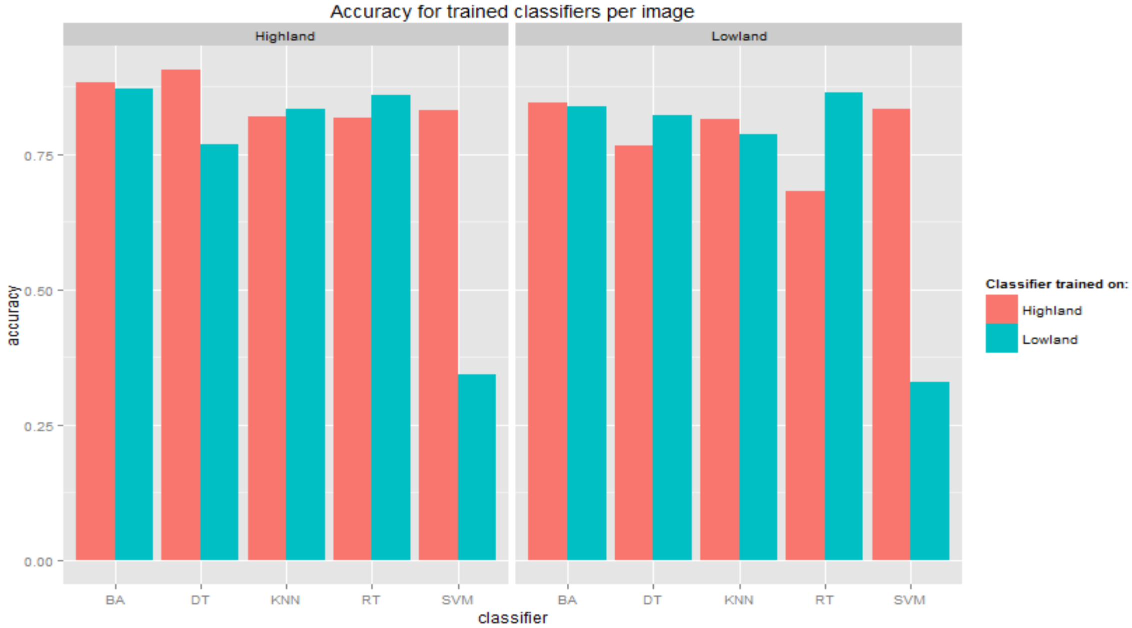

Figure 9: Accuracy for the classifiers trained on the lowland and highland image and applied on both images (BA=Bayesian, DT=Decision tree, KNN=K-Nearest neighbour, RT=Random Trees, SVM= Support vector machine).

4.1.3 Ground validation of forest canopy classification

The result of the comparison between automatic classification and ground reference data is shown in Appendix 4. In Table 1 a summary is given of the results. With an overall accuracy of 75.7% the classification is not nearly as good as the comparison to the visual interpretation as shown in Figure 9. This lower accuracy can have multiple reasons besides the obvious that visual interpretation is also not perfect and that both automatic classification and visual interpretation were wrong on some interpretations. Other reasons could be the spatial inaccuracy of the GPS or the Worldview-2 image or due to the post-processing of this image. Minor spatial inaccuracies could play a large role especially valid in this ground validation test: the area was selected to have roughly 50 percent canopy and therefore there were a great number of transition zones where a few meters can make a difference between a good classification and a wrong one. Visually it can thus be observed that some points were classified in the field as canopy or other while from the satellite image it seems that they are not so, for instance at points 14, 15, 26 and 36 and especially at point 55 and 41.

Table 1: Results of ground validation of the canopy classification of the lowland image. Especially the producer's accuracy scores high with almost 85%, which means that the samples for which the classifier was trained covered almost the whole scale of tree vegetation and was able to differentiate these classes from the non-forest land cover types.

		AUTOMATIC CLASSIFICATION		
		Canopy	Other	Sum
FIELD VALIDATION	Canopy	33	6	39
	Other	11	20	31
	Sum	44	26	70
	producers' accuracy	84.6%	64.5%	
	users' accuracy	75.0%	76.9%	
	overall accuracy	75.7%		

Important to note are the wrongly automatically classified points 20, 31 and 38. These seem to be taken under vegetation with a white-tinted canopy in true colour (forest or bush, see Figure 10), but this was not noted in the field. Therefore it is not possible to add it to the sample data to train the classifier. A right classification of this forest type could have resulted in a potential 4.5% increase in accuracy.

The areas with Macropiper Aduncum were in general classified correctly as non-canopy since they were added to the sample to train the classifier. Merremia was not found in the area so whether these would be classified correctly or not cannot be said.

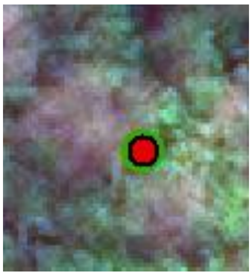

Figure 10: Point 20 of the ground validation data with a white-tinted (true colour) canopy at that location.

4.2 Forest density stratification

In the bottom-left images of appendix 2 and 3 the final density stratification is shown of the lowland and highland image, respectively. Furthermore in Figure 11 and Figure 12 the boxplots of the relative area of canopy for the objects in these images is shown. Especially the Closed Forest class has a much higher average canopy cover than would be expected from the definitions of the FAO (respectively 0.92 and 0.90 for the highland and lowland image compared to 0.7 for the FAO definition). This is caused by the fact that in this research the closed forest has been defined as an entity with trees connected through shadows and branches; the only reason that it is not fully 100% canopy cover is that the open non-forest patches within the forest that were smaller than half a hectare were integrated in the closed forest object. If a buffer of 27.28 meter would be added to the closed forest as well (maximum of Equation 2, see section 2.1) then the average canopy cover fraction would be much lower and perhaps more representable for the FAO definition. However, this method would artificially adapt the numbers and would have no added value for any forester in the field or for any other reason. Another aspect that is clear from the two figures is that the average for Non-Forest is in both images lower than 5% canopy cover and for Open Forest lower than 25%. This could be adapted by changing the buffer area (the linear relation between tree stand area and buffer distance).

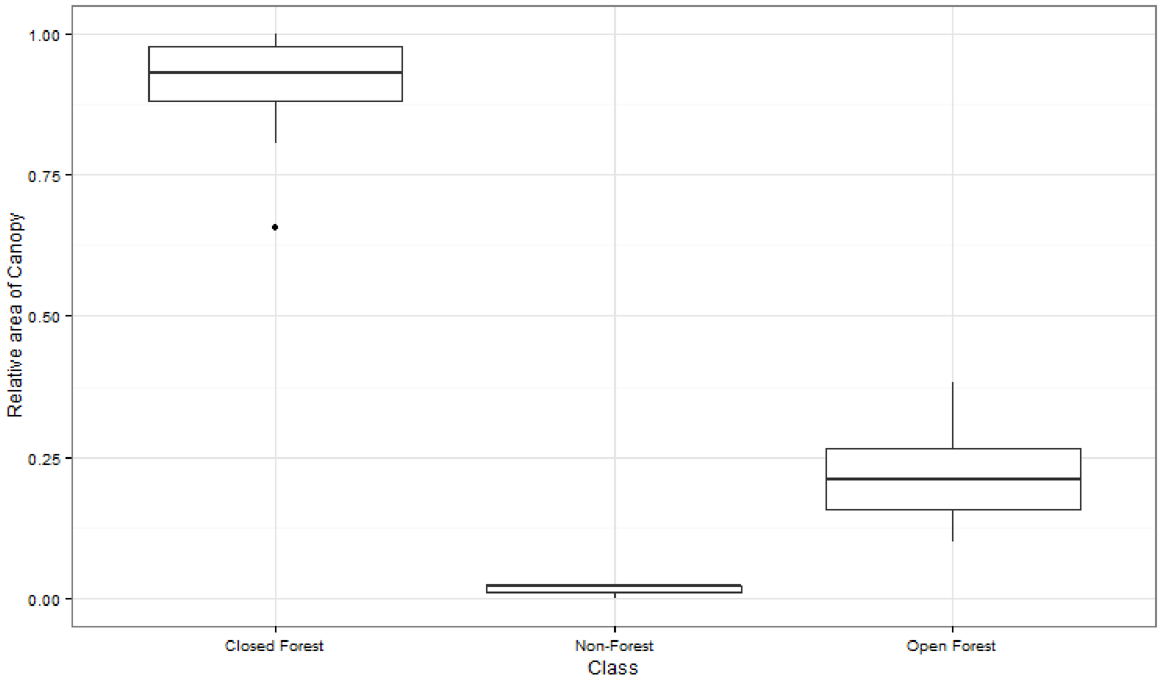

Figure 11: The relative area of canopy per class for the highland image. For closed forest the average canopy cover fraction is 0.92, minimum is 0.66 and maximum 1.00. For open forest the average is 0.21, minimum is 0.10 and maximum is 0.38. For Non-Forest the values are 0.016 average, 0.000 minimum and 0.023 maximum. Especially the Closed Forest class is thus not a very good representation of its definition (70% as an average of 40-100%).

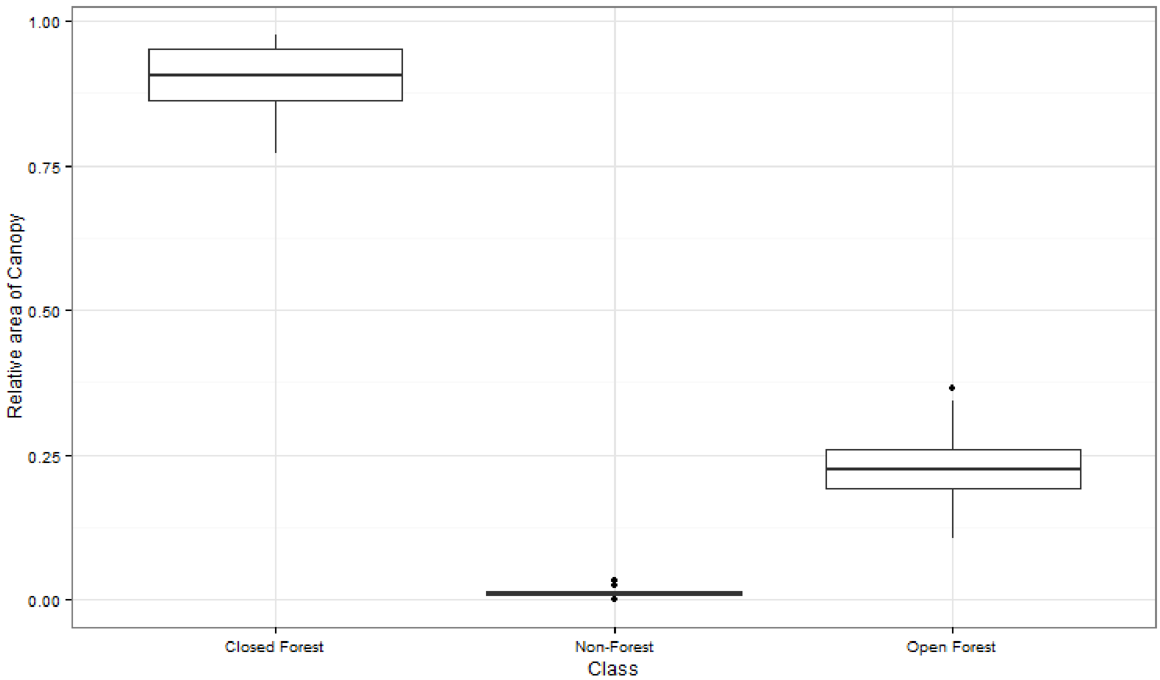

Figure 12: The relative area of canopy per class for the lowland image. For closed forest the average canopy cover fraction is 0.90, minimum is 0.77 and maximum 0.98. For open forest the average is 0.22, minimum is 0.11 and maximum is 0.36. For Non-Forest the values are 0.01 average, 0.00 minimum and 0.03 maximum. Here as well the average values of the closed forest class are not a good representation of the FAO-definition.

The ideal total canopy cover was calculated by multiplying the area for each class with the average for that class as given by the FAO definitions. The formula for the calculation of this ideal canopy cover is given in Equation 3

$$CC_{ideal} = 0.7 * \sum_{i=1}^{n} ACF_n + 0.25 * \sum_{i=1}^{n} AOF_n + 0.05 * \sum_{i=1}^{n} ANF_n \qquad \text{Equation 3}$$

Where CC_{ideal} is the ideal canopy cover, ACF, AOF and ANF are the area in square meters of respectively closed, open and non-forest and n is the number of instances (areas) for each class in the study area.

The actual canopy cover is given by the formula in Equation 4

$$CC_{actual} = \sum_{i=1}^{n} ACF_n * CCCF_n + \sum_{i=1}^{n} AOF_n * CCOF_n + \sum_{i=1}^{n} ANF_n * CCNF_n \qquad \text{Equation 4}$$

Where CC_{actual} is the actual canopy cover, ACF, AOF and ANF, and CCCF, CCOF and CCNF are the area in square meters and the canopy cover fraction of respectively closed, open and non-forest and n is the number of instances (areas) for each class in the study area.

It turns out that the ideal canopy cover fraction given the area of the forest classes for the lowland image would be 0.286 (28.6%) of the area, while the actual canopy cover fraction is 0.320 (32.0%). For the highland image the ideal canopy cover fraction would be 0.210 (21.0%) while the actual cover fraction is 0.222 (22.2%). For both images the ideal fraction is lower than the actual fraction, indicating a systematic underestimation of the forest cover with this method. If both images are representable for the whole of Fiji then the national forest density map would give an indicative canopy cover 8.75% lower than the actual forest canopy cover.

4.3 Stratification of individual species

Images of both a pine and mangrove area (Appendix 1) with other forest surroundings have been classified based on the segmentation parameters (scale 23) used in the canopy/non-canopy images, the feature space optimization and the sampling as explained in section 3.2. The chosen features are shown in Table 2. It is clear that the skewness of different layers is the most important differentiating type of feature for mangrove and pine. What is also noticeable is that the Red Edge is not present as an important layer for differentiation for mangrove, although literature indicated that this should have been the case (section 3.4). The Red Edge is an important feature to distinguish pine, although based on the information from section 3.4 there was no difference with other deciduous vegetation expected in the Red Edge and more difference in the near-infrared bands.

Table 2: ten optimal features to distinguish between mangrove and mixed forest and pine and mixed forest as calculated through feature space optimization.

mangrove	pine
Skewness NIR2	Standard Deviation of Red Edge
Skewness Green	Max. pixel value of Red Edge
Hue	Min pixel value NIR1
Absolute mean difference to neighbours of NIR2	Standard Deviation of Blue
Skewness NDVI	Absolute mean difference of neighbours of Red Edge
standard deviation NIR2	Skewness NIR1
Skewness Red	Mean Red Edge
Max pixel value NIR1	Standard Deviation NIR2
Skewness Blue	Skewness Red
Skewness NIR1	Skewness NDVI

The best separation distance for mangrove based on these 10 features is 1.37 and for pine 2.41. This is not nearly as high as for the canopy/non-canopy and it might prove difficult to differentiate between these two classes and other mixed forest. In Table 3 and Table 4 the classification stability for the two classified maps of mangrove and pine are shown. What is clear is that the classification stability is not very high; e.g. there is no object that was classified as pine for which the software is sure that it is actually pine (maximum of 0.73). The explorative study shows that although literature states that the two classes can de classified, inductively it is shown that this might not be the case. However, the only conclusive method would be based on ground reference data.

Table 3: Classification stability summary of the classification of pine and mixed forest.

CLASS	OBJECTS	MEAN	STDDEV	MINIMUM	MAXIMUM
PINE	253	0.270653	0.190478	0.002227	0.733195
MIXED FOREST	1460	0.424745	0.211387	0.000214	1

Table 4: Classification stability summary of the classification of mangrove and mixed forest.

CLASS	OBJECTS	MEAN	STDDEV	MINIMUM	MAXIMUM
MANGROVE	331	0.166503	0.17107	0.000264	1
MIXED FOREST	1616	0.226966	0.152416	0.000652	1

5 Discussion

The literature review showed that there are just a very limited number of species in Fiji that occur in great numbers in homogeneous areas. The species that have these characteristics are mahogany, pine trees and mangrove. Explorative research showed that the latter two showed overlap with other not yet identified species and that it is not straightforward to stratify them, especially not without good ground reference data. These species were selected based on the fact that in the REDD-readiness proposal they were mentioned as covering major parts of the land-mass of Fiji. However, in the field other species were observed that covered in total a large areas, although they were not homogeneously found over larger areas. A mentioned example that occurred wide-spread in the field was the African Tulip (Meyer 2000). African Tulip displays a canopy covered with red flowers, which could make it very well distinguishable from other species (though these flowers are seasonal). This is just an example of one among many other species that could be interesting to classify, as long as good ground reference data is available. In this research high-resolution imagery was used and this type of imagery is especially useful for mapping these species that occur individually, since there are still multiple pixels per individual tree. The major problem with getting ground reference data for individual trees could be the spatial inaccuracy, a problem that might also have occurred during the acquisition for ground reference data as shown in section 4.1.3. Although at the onset of this research it was the idea to map a larger number of species this turned out to be impossible; even the two species that were mapped experimentally could not be validated and the classification stability was on average 0.17 and 0.27 (Table 3and Table 4) for respectively mangrove and pine, on a scale between 0.0 and 1.0. The ground reference data that was used in this research was only for the mapping of mixed forest (section 4.1.3). The image data used for the accuracy measurement was taken one year before the acquisition of this ground reference data (July 2013 and July 2014 respectively) and although this probably did not have a major impact it could have had a minor one. Much more would be possible with remote sensing and especially with stratifying individual species with solid ground reference data including metadata taken on an appropriate temporal interval. It was already stated in 1991 and is still valid: "It is obvious that in order to adequately assess the accuracy of the remotely sensed classification, accurate ground, or reference data must be collected. However, the accuracy of the ground data is rarely known nor is the level of effort needed to collect the appropriate data clearly understood." (Congalton 1991). Nonetheless, explorative research as was done on pine and mangrove can give better insight into what is possible with remote sensing before investing great amounts of time and money in solid ground referencing.

From the results in section 4.1.2 it seems that there are limited differences in the quality that would be obtained when applying certain classification algorithms trained on one geographical area on a different geographical area. The implication of this finding is that geographical aspects do not have a large effect on the expected quality of a classification and that one trained classifier can be applied on a whole range of areas, as long as the quality of the satellite images used for these areas is similar. It needs to be noted that the geographical features were only used on a very course scale, by selecting two areas that were geographically very different. Since the quality of the DEM was not known the information of this dataset could not be used on such a small scale at e.g. tree level.

The selection of features through optimal feature space configuration in section 4.1.2.1 showed that there are a few features that are most important for classifying mixed forest canopy (namely the hue, saturation, maximum difference in brightness, maximum value of the NDVI and the mean NDVI). The NDVI has already proven to be useful in the classification of tree canopy, for instance in the research of Zeche (2003); Meneguzzo et al. (2013); Mallinis et al. (2008) among many others. The latter also uses the hue in his research to delineate forest and mentions another research in which both hue and saturation are used for the classification of aspen forest. The maximum difference in brightness is used in the research of Gao et al. (2003) for mapping sparse and dense temperate forest and tropical dry forest. The selection of the Bayesian classifier is purely inductive; there was no distinguished reason found in literature to base this decision on. There are a number of articles that use the same classifier in GEOBIA but the same goes for random forest or support vector machine. The classifier was chosen based on the overall accuracy. Many other accuracy measures are available, but according to a comparative study by Labatut & Cherifi (2012) the overall accuracy (overall success rate), is still the favourite method for the choice of classifiers. It is also important to note that the Bayesian classifier did not score that much higher than the other classifiers. Therefore it could be favourable to choose a classifier that is more transparent, for practical reasons, like the decision tree.

The segmentation of objects is a very important step in GEOBIA. In this research the only tool used that was based on prior research was the estimator of scale parameter. The other parameters were more or less based on trial-and-error, which means that it is possible that not the optimal configuration was chosen. Unfortunately, since GEOBIA is still a relatively new field of research, there are no alternatives till now and most researches mention a trial-and-error approach (Meneguzzo et al. 2013; Neubert & Herold 2008). Marpu et al. (2010) offer a solution to this problem by creating reference polygons and applying different segmentation configurations on the image to see which configuration is best at delineating these reference polygons. This method has not been applied in this research for various reasons, the major one being that no reliable reference polygons of trees were available.

The accuracy of ground validation of 75.7% means that there is still a lot of space for improvement, regardless of some points not being entirely reliable (4.1.3). The first most obvious method is to improve the samples for the training of the classifier, favourably from ground reference data and not visual interpretation. The second part is the feature space optimization. To exclude chance the features were chosen as a combination of different optima based on different sample combinations. However, the ten optimal features were chosen as a combination and do not need to be the best configuration solely because they are most often represented in a different configuration. Again this can be improved by being sure that the samples are the correct ones, so that no different configurations need to be tested; this can be attained by using sample data through ground referencing.

The delineation of the forest into forest density classes was implemented through GEOBIA, a method that has not yet been applied when trying to incorporate REDD+ policy definitions of the FAO. Since the delineation has not been defined by the FAO, this method was open for discussion and it is not possible to objectively measure whether a delineation method is wrong or right. In section 4.2 this was still attempted by seeing if the data was representable for what would be expected when using the same FAO definitions. It showed that overall the current used method showed an underestimation of the forest canopy cover of 8.75%. As was put by Magdon & Kleinn (2013), a small difference in methodology can result in a change of over 50% of the expected forest canopy cover. With an underestimation smaller than 10% the results of the currently used method are quite good. Furthermore, the methods proposed in the current research are a derivative of the FAO definitions and reference area sizes were thus not chosen arbitrarily and also based on the data itself. Because of these rigid definitions the same results would be obtained when using a smaller, larger or shifted study area and is not dependent on a specific starting point like the focal statistics method used in current research on this topic by Magdon et al. (2014). The method can however still be perfected, for instance by changing the constant value of the linear relation between area and buffer size (Equation 2) or by also applying a buffer on the closed forest (although this would be unpractical from a users' point of view).

There was no part of this research that focused on the added value of the Worldview-2 data compared to lower spatial or spectral resolution data. From the results in section 4.1.2.1 it was shown that there is not that much added value from the three/four extra bands: the three bands were chosen 13 times out of 40. This is confirmed by Collin & Planes (2011) who state that the most added value can be found when a larger number of classes needs to be differentiated. The added spatial resolution of Worldview-2 will of course improve the delineation of forest significantly when compared to for instance Landsat images. However, according to Magdon & Kleinn (2013), this spatial resolution has only a small effect on the relation between forest canopy and forest density mapping (at least according to the pixel-based methods used in their research). It has not been investigated in this research how large the effect would be when for instance Landsat images were used. However, their pixel-based findings can be just as relevant for the methods used in this research and when a satellite image with a lower resolution is just as capable in classifying forest canopy then it would offer more opportunities when also these low-resolution imagery would be used, for instance for time-series, which are a major aspect of the eventually needed carbon monitoring system for Fiji.

6 Conclusion

Based on the literature review in this research it was chosen to identify the forest class mixed species and to explore the possibilities of identifying plots of pine and mangrove. The best features for mixed forest canopy classification were the hue, saturation, NDVI and maximum difference in brightness. The red band was best at delineating forest canopy and was therefore used for segmentation. The accuracy of this classification was 75.7% based on ground validation data and it had an average overlap of 86% with per-segment visual interpretation for the Bayesian classifier, which is a good score. Some incorrectly classified points were located on top of an object (tree, bush) that was not identified in the field and the classifier could therefore not be improved for these specific objects. The four extra bands of Worldview-2 had no major influence on the quality of this classification. The features that deduced from literature to be influential for classification of pine and mangrove did not turn up in the optimized feature space through the inductive method. The expected quality of the classification of these species is not expected to be high but this cannot be said with certainty due to a lack of ground reference data. The mixed forest canopy classification was later on converted to a forest density map. This object-based conversion method based on the FAO definitions proved to be solid. The closed forest class shows an underestimation with an actual canopy cover of 91% compared to an expected 70% based on the FAO definitions. The open forest class scores best in this category, since the expected canopy cover is virtually the same as the actual canopy cover (±25%) and showed an average underestimation of the actual forest canopy cover of 8.75%, which, in light of other researches, proves it to be a very suitable method for forest stratification. There were no significant differences in the expected quality (based on visual interpretation) of the mixed forest canopy map when the image was trained on a certain geographic area and applied on a different geographic area, which shows that there is no need for individual classifiers for different geographic areas. Ground-based observations did show that using high-resolution, high-quality geographic information could aid in the classification as a feature. In general it can thus be concluded that with the methods provided in this research solid, good quality forest density maps can be created based on classified mixed forest canopy maps through object-based classification with high-resolution satellite imagery within the FAO-defined framework.

7 Recommendations

7.1 Software alternatives

Ecognition does a very good job at object-based image analysis. It is accessible for non-experts and has the largest user-based community along many other advantages. There are however some downsides of the software and alternatives should be explored by researchers with a different budget or interest also working on forest density stratification or related topics.

First of all there are open-source alternatives for object-based image analysis or at least less expensive alternatives. Some of the open-source alternatives are:

- Saga GIS(saga-gis.org)
- Opticks (opticks.org)
- ORFEO toolbox (orfeo-toolbox.org)
- OpenCV (opencv.org)

Ecognition does not offer the possibility to show and compare spectral signatures; especially with imagery data with higher spectral resolution this is a limiting factor. Therefor it is advisable to use separate software like Erdas Imagine or IDL ENVI to analyse the spectral signatures and determine important bands and band ratios for supervised classification with a larger number of bands.

The classification of open, closed and non-forest was based on a method involving a buffer. Although Ecognition offers through somewhat complicated ways the option to create buffers and create objects accordingly it is not the best software to do so. When the classification does not involve features based on reflectance or on the shape of the original segments then a researcher can choose to continue with a more GIS-related software package like ArcGis. For instance the forest density classification could have been done based on the canopy/non-canopy polygon dataset which would probably decrease the processing time as well.

7.2 Data quality control

During this project different datasets have been used: Worldview-2 image, a DEM and acquired ground reference data. Of the DEM no information was written down about the acquisition and about both the satellite image and DEM there was no information about the (pre)processing of this data. All relevant information like the pan-sharpening of the satellite image and the original resolution of the DEM were given informally and it just had to be assumed that this was true (which was done for the satellite image in that it was fully used; the DEM was only used for orientation). This resulted in a very limited use of the DEM, while it could have offered many advantages, as discussed in the Discussion chapter. For the satellite image the lack of metadata about geo-rectification resulted in doubts about the validity of the location of the ground reference data. A lot of literature deals with the organisation of metadata, data quality control and spatial data infrastructure in general, e.g. DSD Infrastructures (2004) and Masser (2005) among many others.

7.3 Geographical data as feature in GEOBIA

Based on observations in the field distinct species like reed and Macropiper grow in very specific niches on a slope. The same goes for species like mangrove, which always grows alongside water and especially along the coastline; pine trees that were never observed in the field growing in wetter regions and almost always on a slope; other species like bamboo, mahogany, Rain trees and African Tulip growing in areas which are richer in water, caused by local geographic differences. A good example is the gallery forest which can also be observed in the highland image (see appendix 3), where thinner strips of forest vegetation grow in the lowest point between two hills. All these aspects are overlooked when only spectral information is used, while GEOBIA is very much tailored for handling this type of information. For instance, in a research of Ke (2007) the slope and elevation were two of the thirteen most important features for the classification of different forest species. A prerequisite for especially this elevation information is the availability of a DEM for which the quality is known to be good. An aspect that has not been studied in this research is the use of thematic data. During explorative fieldwork it was shown that certain species grow mainly near villages or roads, since they are mostly planted. A named example was coconut trees further from rivers and the ocean, since these trees depend on transportation through water for dispersion and when these vectors are not present they have to be planted. The use of such information can be used in GEOBIA with sufficient supporting data and it could be interesting to look further into this in future research.

7.4 Unification of MAUP protocol

In this research a new method for handling the modifiable area unit problem was proposed, implemented and analysed. Regardless of how rigid it is and how well it reflects the actual forest canopy, it is still a method among many others, though the other methods are all pixel-based. Since REDD+ focuses on monitoring carbon stocks, the quality of time-series is just as important as the estimation of the forest cover in one timeframe. The quality of such time-series is very much dependent on the rigidity in time and space, which means that the methods used for the forest density stratification need to remain similar over the entire time-series and favourably also comparable to other parties involved in the same project (i.e. other countries with a carbon monitoring system). Magdon et al. (2014) have proposed a solid methodology for the forest density stratification except for the modifiable area unit problem. Their solution is arbitrary and only applicable to low-resolution imagery and therefor this reference unit needs to be officially defined favourably by the same institution (FAO) that has created the other definitions of forest. The same urgency has already been expressed in a different paper by Magdon & Kleinn (2013): “if maps are analyzed quantitatively, such vagueness is difficult to handle, and in cases where forest area is directly linked to high economic values, as it is the case for example in the Reducing Emissions from Deforestation and Forest Degradation (REDD) Program, vagueness is hardly acceptable as an element of a methodological approach.”

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9 Appendices

9.1 Appendix 1: Fiji, Navosa area, and the satellite image subsets.

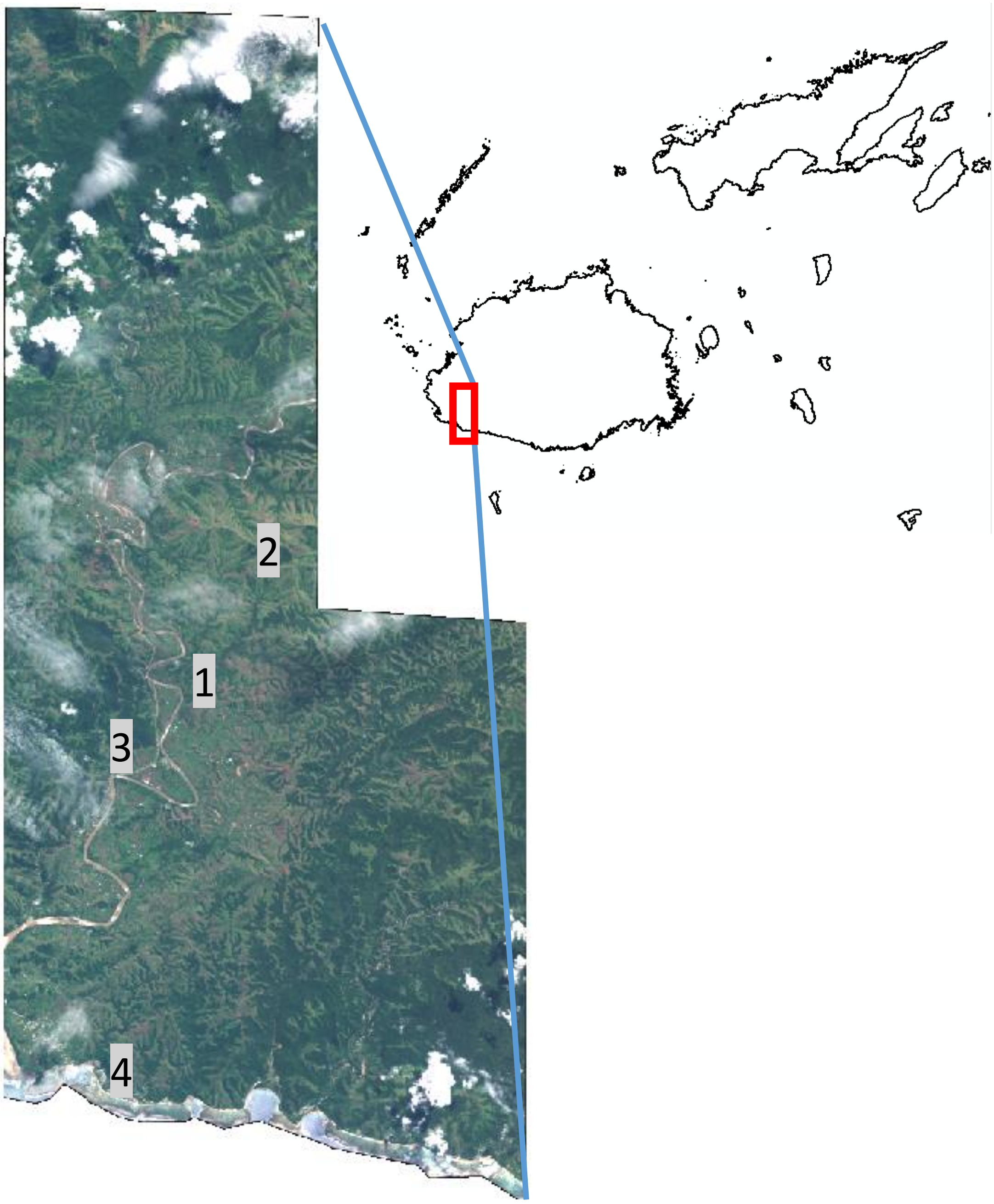


Figure 13: The stitched satellite image in true colour in the context of Fiji and Viti Levu. The numbers refer to the images used in this research and corresponding DEM close-up for the lowland and highland image shown in Figure 14 below.

Left: lowland image(1)/right: highland image(2)

Left: lowland image DEM/right: highland image DEM

Fiji DEM

Height (m)

1042.58

0.303572

Left: Pine subset(3)/Right: mangrove subset(4)

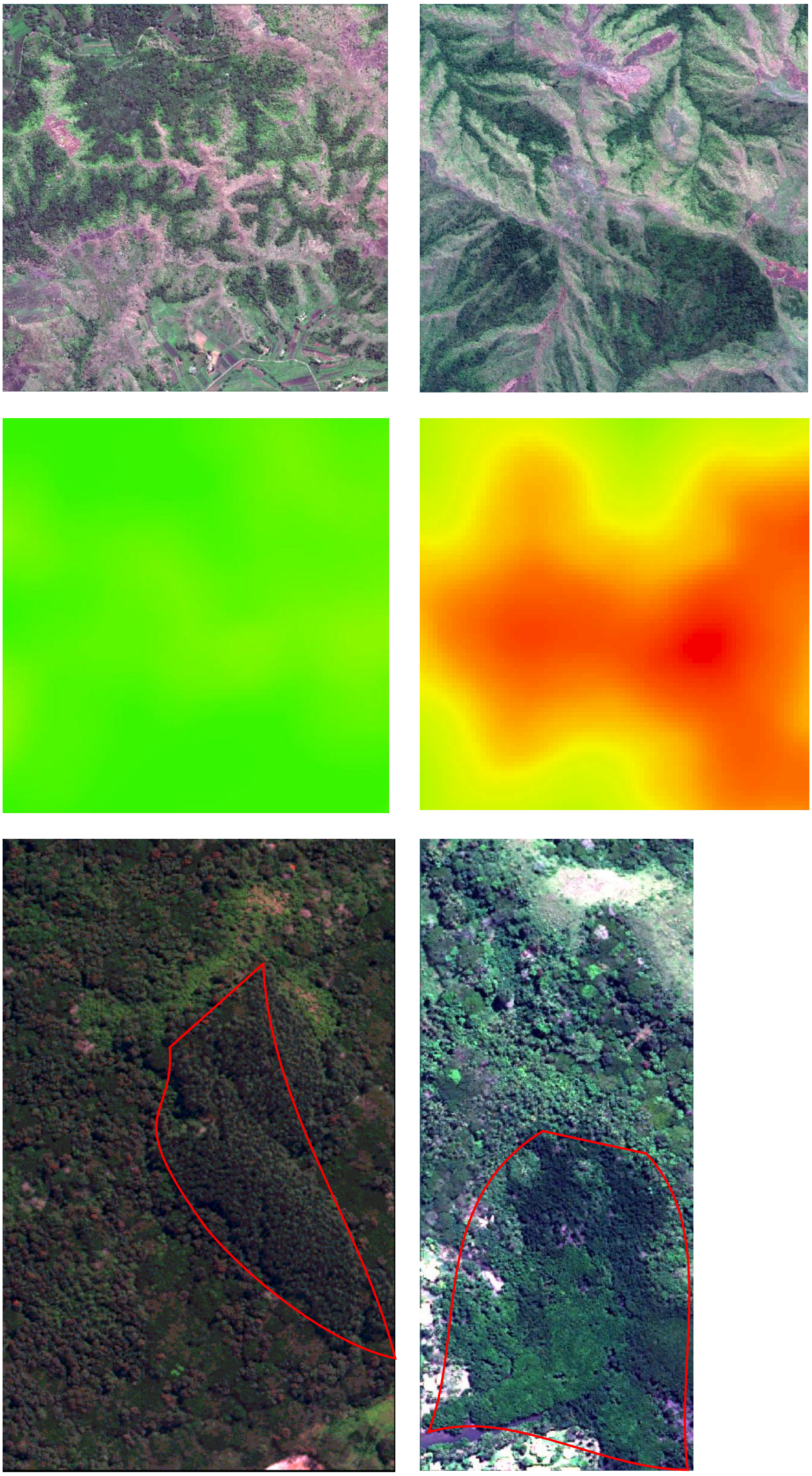
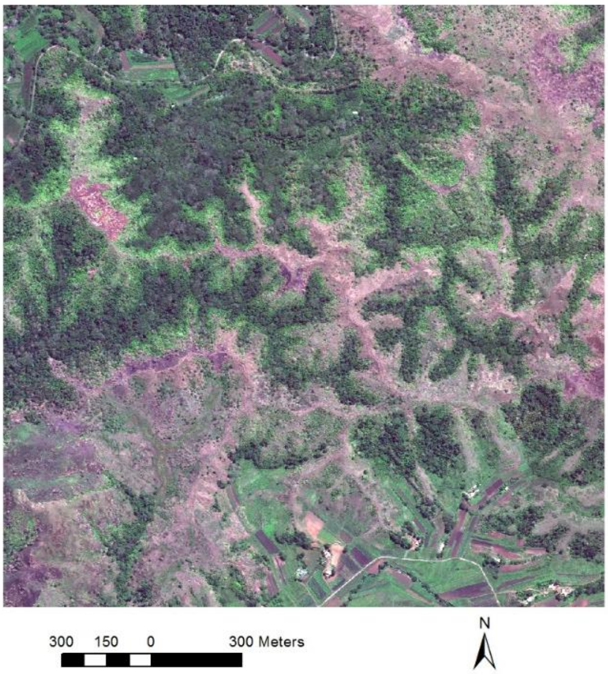
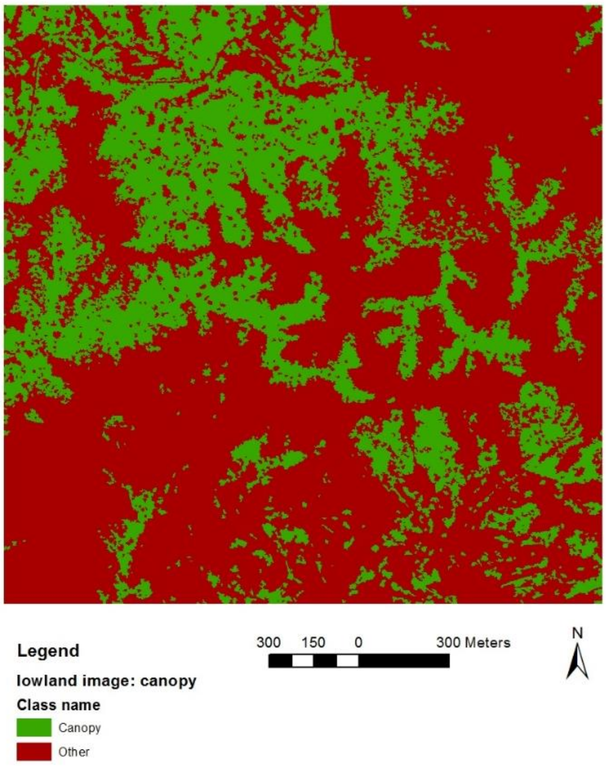
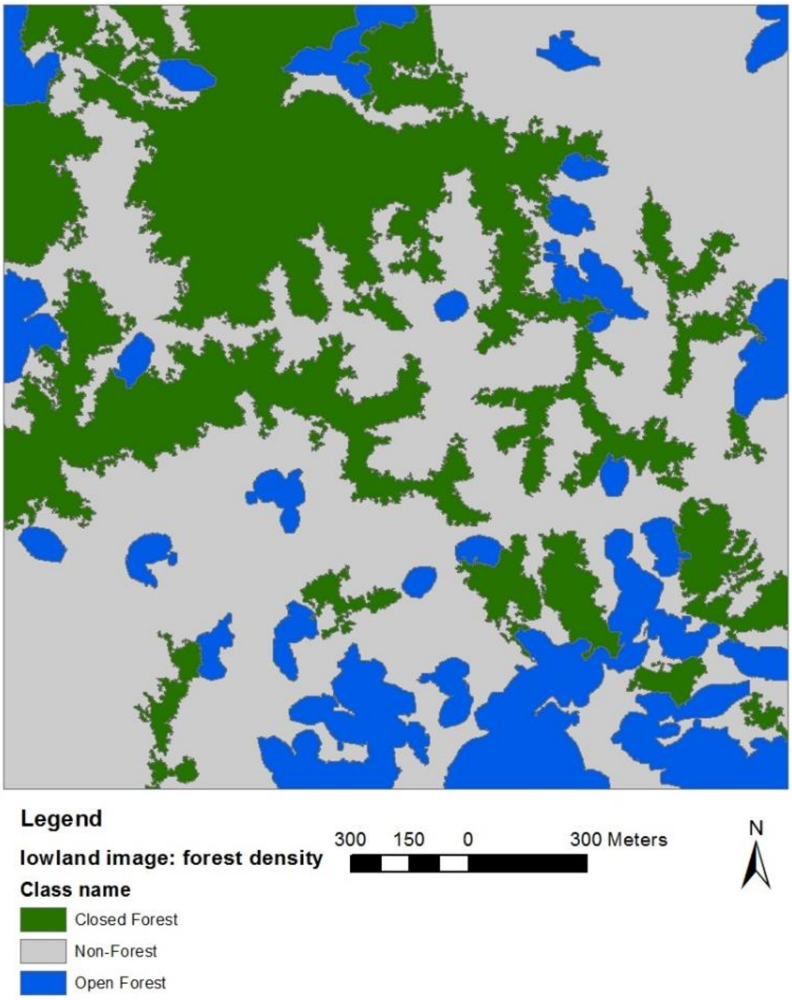


Figure 14: Used satellite images of the lowland (1; top left), highland (2: top-right), pine forest (3; bottom-left) and mangrove forest (4; bottom-right). In the middle the DEM of the lowland (left) and highland (right) image, with legend on the left in meters for indicative purposes. The pine in the bottom-left image and the mangrove in the bottom-right image can be found roughly within the red polygons, although this has not been ground-referenced.

9.2 Appendix 2: lowland image: original, canopy classification and density stratification

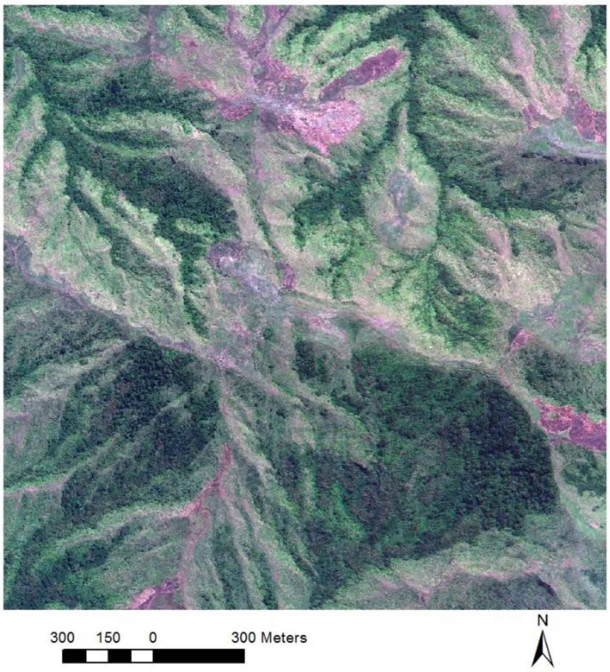


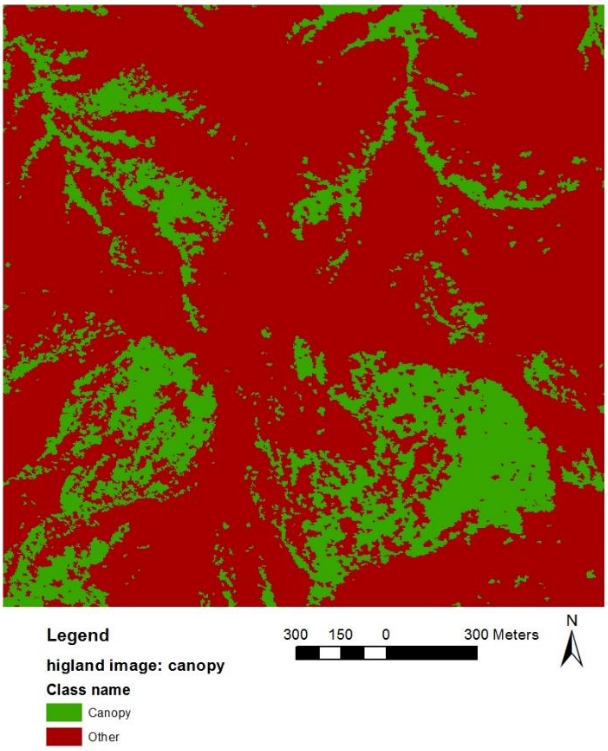


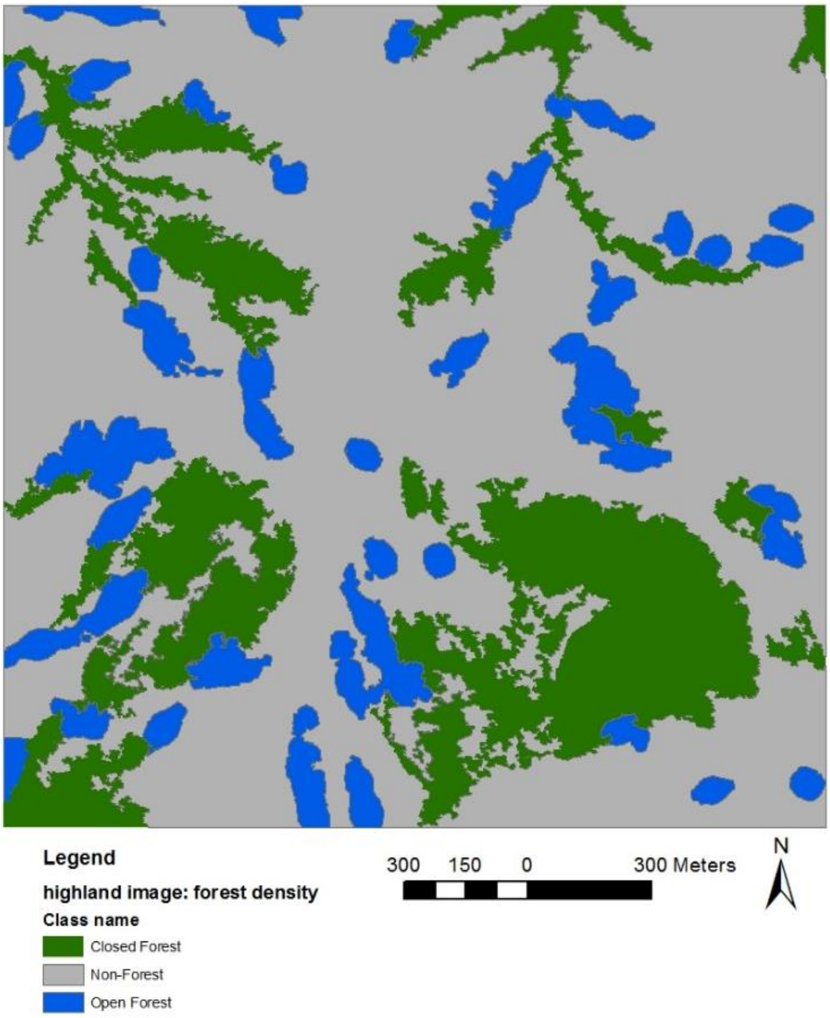


On the top-left the subset of the original satellite image in true-colour. On the top-right the classification of the image with a Bayesian classifier and the features as chosen through feature space optimization for the lowland area (sections 4.1.1 and 4.1.2). On the bottom-left the image as a forest density map.

9.3 Appendix 3: highland image: original, canopy classification and density stratification







On the top-left the subset of the original satellite image in true-colour. On the top-right the classification of the image with a Bayesian classifier and the features as chosen through feature space optimization for the highland area (sections 4.1.1 and 4.1.2). On the bottom-left the image as a forest density map.

9.4 Appendix 4: Field validation and automatic classification points

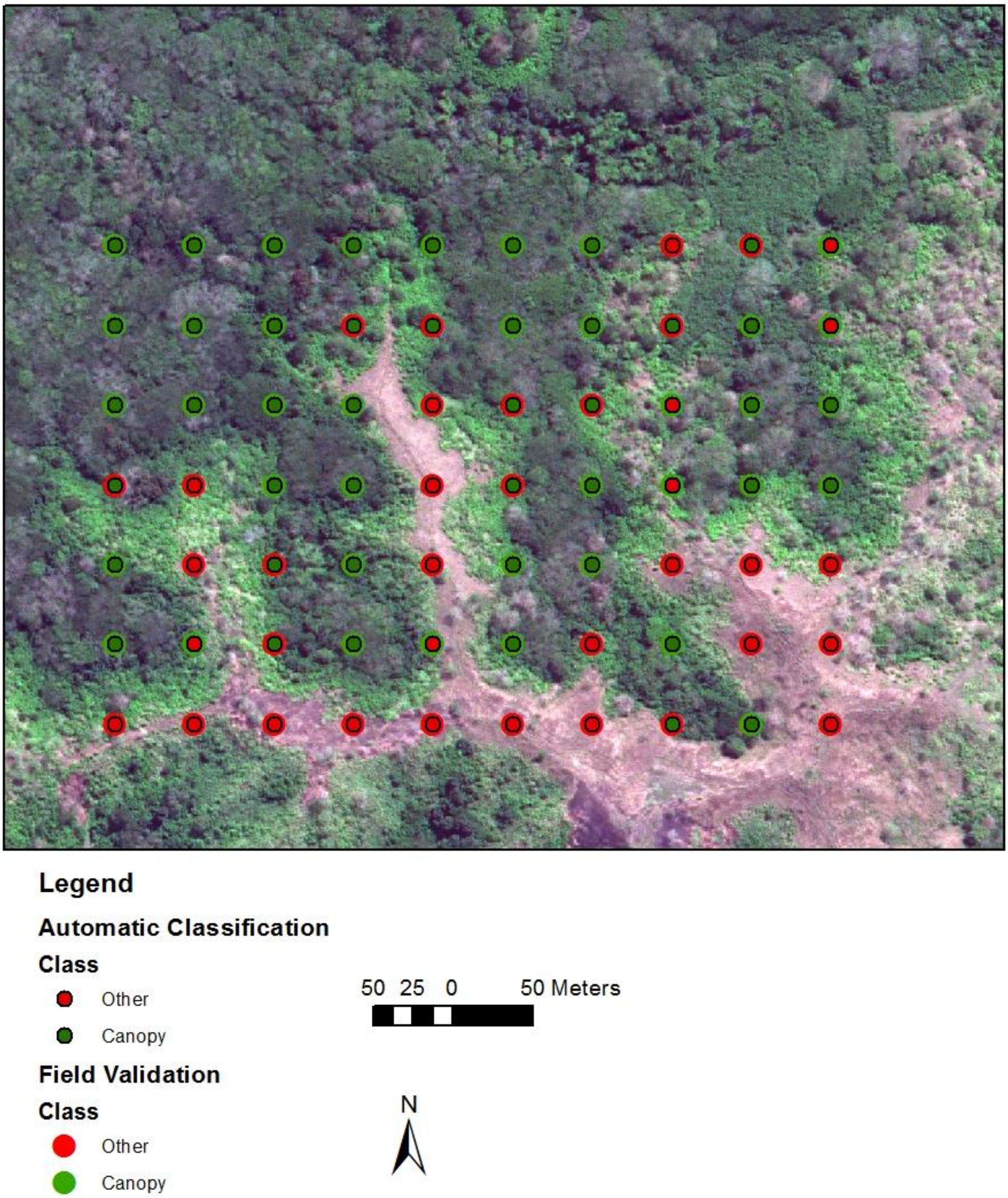


Figure 15: The points that were validated in the field on the 8th and 9th of July 2014. The larger circles are the classification values as determined in the field, the smaller circles are automatically classified with the methods discussed in the methodology section. Points 1-10 are the points in the upper row, from left to right, 11-20 for the second row etc. till point 70 in the bottom-right corner.