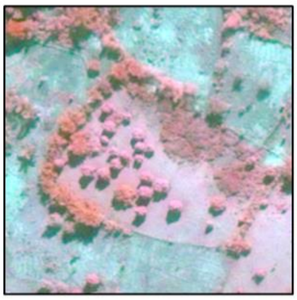
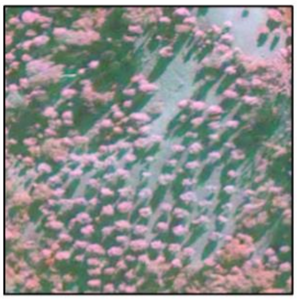
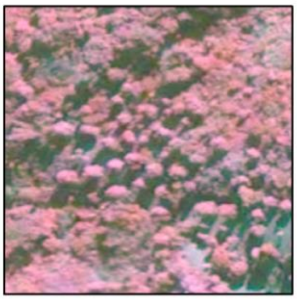
Automated Detection of Single Clove Trees for Yield Quantification in North-Eastern Madagascar based on Multi-Spectral Satellite Data







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Cover Very high resolution panchromatic satellite image and schematic representation of the three clove production type systems, pasture, clove plantation and agroforest.

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Automated Detection of Single Clove Trees for Yield Quantification in North-Eastern Madagascar based on Multi-Spectral Satellite Data

GEO 610 MASTER'S THESIS

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Abstract

The aim of this master thesis was to investigate the potential of remote sensing methods for classifying clove production systems in north-eastern Madagascar. This study was embedded in the framework of the Swiss Programme for Research on Global Issues for Development (r4d - research for development), within the project 'Managing telecoupled landscapes for the sustainable provision of ecosystem services and poverty alleviation'. To reliably classify clove production systems, information on the individual tree level as well as extensive information about the entire study area is required. Remote sensing enables obtaining this combination of information even in regions otherwise difficult to access.

The classification of the clove production systems in this thesis is based on very high resolution multi-spectral satellite imagery. A total of four sometimes complex steps were necessary for the final classification. The four steps were: 1) the detection of individual potential clove trees, 2) the classification of clove trees, 3) the classification of land cover and land use classes (LULC) and 4) the distinction of productive clove production systems from the unproductive LULC classes.

The complex structure of the Madagascan tropical rainforest, in particular complicates steps 1) and 2). Our investigation found existing tree detection and classification algorithms to perform insufficient in the tropical rainforest. Here, for the first time, we applied the Circular Hough Transform algorithm (CHT) for tree detection. With the CHT algorithm, we detected 97.9% of the reference clove trees in the study area. Using a combination of spectral and structural information, it was possible to distinguish the clove trees from the other tree species. The classification, which was carried out applying a Random Forest (RF) classifier, resulted in a producer accuracy of 70.7% and a user accuracy of 59.2% for the class of clove trees. The third processing step was to reliably distinguish the partly spectrally similar LULC classes from each other. Tree occurrence information was used in addition to the spectral information for the classification. This step resulted in an overall accuracy of 87.5%. The fourth step of the classification into the three prevalent clove production systems pasture, clove plantation and agroforest was based on a threshold approach. Only LULC classes containing a previously defined number of clove trees were considered active clove production systems. This final classification resulted in a total accuracy of 77.9%.

This study was the first time that clove trees and clove production systems were classified and mapped over a larger area. Based on these new findings, it was possible to calculate a yield estimate for the cloves produced in the entire study area. In conclusion, the study demonstrates that remote sensing is a suitable means of classifying clove production systems in Madagascar. However, it was also found that the limited availability of reliable reference data on clove trees per se and clove yields led to high uncertainties in the yield estimates. The collection of better in situ data is therefore a prerequisite for more reliable statements about the clove production systems and their respective yields.

Zusammenfassung

Ziel dieser Masterarbeit war es, das Potential von Fernerkundungsmethoden zur Klassifizierung von Nelkenproduktionssystemen im Nordosten Madagaskars zu untersuchen. Diese Studie wurde im Rahmen des Schweizerischen Forschungsprogramms für globale Entwicklungsfragen (r4d - research for development) im Rahmen des Projekts "Managing telecoupled landscapes for the sustainable provision of ecosystem services and poverty reduction" (Management von telecoupled Landschaften zur nachhaltigen Bereitstellung von Ökosystemdienstleistungen und Armutsbekämpfung) erstellt. Um Nelkenproduktionssysteme zuverlässig klassifizieren zu können, sind Informationen auf der einzelnen Baumebene sowie umfangreiche Informationen über das gesamte Untersuchungsgebiet erforderlich. Die Fernerkundung ermöglicht es, diese Kombination von Informationen auch in sonst schwer zugänglichen Regionen zu erhalten.

Die Klassifizierung der Nelkenproduktionssysteme in dieser Arbeit basiert auf hochauflösenden multispektralen Satellitenbildern. Insgesamt waren für die endgültige Klassifizierung vier teilweise komplexe Schritte notwendig. Die vier Schritte waren: 1) die Erkennung von einzelnen potenziellen Nelkenbäumen, 2) die Klassifizierung von Nelkenbäumen, 3) die Klassifizierung von Landbedeckungs- und Landnutzungsklassen (LULC) und 4) die Unterscheidung von produktiven Nelkenproduktionssystemen von den unproduktiven LULC-Klassen.

Die komplexe Struktur des madagassischen tropischen Regenwaldes erschwert insbesondere die Schritte 1) und 2). Unsere Untersuchungen ergaben, dass die existierenden Algorithmen zur Erkennung und Klassifizierung von Bäumen im tropischen Regenwald nicht ausreichend sind. Hier haben wir zum ersten Mal den Circular Hough Transform Algorithmus (CHT) zur Baumdetektion eingesetzt. Mit dem CHT-Algorithmus haben wir 97,9% der Referenz-Nelkenbäume im Untersuchungsgebiet entdeckt. Durch die Kombination von Spektral- und Strukturinformation konnte man die Nelkenbäume von den anderen Baumarten unterscheiden. Die Klassifizierung, die mit Hilfe eines Random Forest (RF) Klassifikators durchgeführt wurde, ergab eine Produzentengenauigkeit von 70,7% und eine Benutzergenauigkeit von 59,2% für die Klasse der Nelkenbäume. Der dritte Schritt bestand darin, die teilweise spektral ähnlichen LULC-Klassen zuverlässig voneinander zu unterscheiden. Zusätzlich zu den Spektralinformationen für die Klassifizierung wurden auch Informationen über das Vorkommen von Bäumen verwendet. Dieser Schritt führte zu einer Gesamtgenauigkeit von 87,5%. Die vierte Stufe der Einteilung in die drei vorherrschenden Nelkenproduktionssysteme Weide, Nelkenplantage und Agroforst basierte auf einem Schwellwertansatz. Nur LULC-Klassen, die eine vorher festgelegte Anzahl von Nelkenbäumen enthielten, wurden als aktive Nelkenproduktionssysteme betrachtet. Diese endgültige Klassifizierung ergab eine Gesamtgenauigkeit von 77,9%.

Diese Studie war das erste Mal, dass Nelkenbäume und Nelkenproduktionssysteme klassifiziert und flächendeckend kartiert wurden. Auf Basis dieser neuen Erkenntnisse konnte eine Ertragsschätzung für die im gesamten Untersuchungsgebiet produzierten Nelken berechnet werden. Die Studie zeigt, dass die Fernerkundung ein geeignetes Mittel zur Klassifizierung der Nelkenproduktionssysteme in Madagaskar ist. Es wurde jedoch auch festgestellt, dass die begrenzte Verfügbarkeit verlässlicher Referenzdaten über Nelkenbäume und Nelkenerträge zu hohen Unsicherheiten bei den Ertragsschätzungen führten. Die Erfassung besserer in situ Daten ist daher eine Voraussetzung für zuverlässigere Aussagen über die Nelkenproduktionssysteme und deren Erträge.

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Thank you all!

Contents

List of Figures

List of Tables

Abbreviations

CHT	Circular Hough Transform
FAO	Food and Agriculture Organization of the United Nations
LiDAR	Light Detection And Ranging
LULC	Land Use/Land Cover
OA	Overall Accuracy
PA	Producer Accuracy
r4d	Research for Development
RF	Random Forest
UA	User Accuracy
VHR	Very High Resolution

1 Introduction

In times of ongoing transformations induced by climate and global socio-economic processes, monitoring land use and land cover (LULC) changes enables to better understand how these processes affect our planet. Earth observation techniques allow gathering global and comprehensive data providing cross-thematic information about these transformations.

1.1 Subordinate frame of the project

This master thesis was conducted in the framework of the 'Swiss Programme for Research on Global Issues for Development' (r4d programme n.d.). The findings will be of further use for the r4d project 'Managing telecoupled landscapes for the sustainable provision of ecosystem services and poverty alleviation'.

This project focuses on forest frontier landscapes in the humid tropics in Laos, Madagascar and Myanmar. It is these landscapes which exemplary show the consequences from the difficulty of maintaining human and economic development in balance with limited natural resources (Managing telecoupled landscapes n.d.). These socio-ecological systems on the one hand have to meet increasing global demands for agricultural expansion but on the other hand these systems are expected to provide worldwide environmental benefits (Managing telecoupled landscapes n.d.). 'Telecoupling' describes this phenomenon of combined socio-economic ('globalization') and environmental ('teleconnection') interactions between two or more distant socio-ecological systems (Managing telecoupled landscapes n.d.).

One such 'telecoupled' landscape is the study site of this master thesis, which is located in north-eastern Madagascar. There, most farmers are smallholders who mainly cultivate crops for subsistence (Harvey et al. 2014). In order to secure products which cannot be produced on their plots, Madagascan farmers aim to earn money with the cultivation of so-called 'cash crops' such as for example coffee, vanilla or cloves (Lobietti 2013, Danthu et al. 2014, Thomson 2016). The amount of money that can be made by selling these cash crops depends on the amount produced and the global market price (Lobietti 2013, Thomson 2016). Due to the lack of reliable government statistical data, it is not possible to make accurate statements about the amount of cash crops produced in this region. It is therefore not possible to predict the effects of changes in global demand on

Figure 1 – Clove tree in the study site
(Photo credit: E. Celio)

local production volumes and the local population. But it is exactly this interaction between the global and the local system, which is of interest for the r4d project. In order to better understand the relationship between the two systems, the r4d project is investigating one of these cash crops, the clove tree, in more detail.

Clove trees are mainly grown for production purposes in Indonesia, Madagascar and Tanzania (Lobietti 2013). For historical reasons cloves are farmed in three different production types. These are pasture, clove plantation and (complex) agroforest systems (Lobietti 2013, Danthu et al. 2014, Levasseur et al. 2012).

Figure 2 – Picture taken on the study site showing some pasture in the front and plantation and agroforest in the back. Note the clove tree's characteristic round form. (Photo credit: E. Celio)

The two main products from clove cultivation are the dried flower buds and the essential oil (Danthu et al. 2014). As the global demand for both of these products is rising, cloves are of increasing importance on the world's trading markets (FAOSTAT n.d.) and for the national economies of the producer countries. This is especially the case for Madagascar, being the world's second largest producer and even the world's leading exporter of cloves (FAOSTAT n.d.).

Thus, the increasing global demand for cloves makes them also more important on a local scale for the farmers cultivating them as cash crops (Danthu et al. 2014). In order to assess both future social and ecological changes along with the increasing significance of cloves, it is deemed necessary to investigate on today’s production situation. This is where this master thesis takes up: A method has been developed to produce an estimate of the clove production based on Earth observation data.

1.2 Traditional methods to map and characterize areas with clove trees

A general challenge in Madagascar is the lack of reliable government statistical data. Although there is the ‘National Institute of Statistics’ (INSTAT) from the ‘Ministry of Agriculture and the Population’ its data is considered outdated and unreliable (Rakotondrasoa and Olitina 2014). In addition, Waldner et al. (2015) state Madagascar as one of the priority countries for cropland identification as there is little accurate and current data available.

However, more reliable data is provided by the ‘Food and Agriculture Organization of the United Nations’ (FAO) and the FAO’s ‘World Food Programme’ (FAO/WFP). The FAO is actively collecting data in Madagascar (Rakotondrasoa and Olitina 2014). Their data is most valuable to assess a countries’ overall situation in the agricultural sector. However, this data is too coarse when data about a specific region or a specific crop is needed. Thus if such specific data is needed, it must first be collected by researchers in the field.

In regard to clove production in Madagascar there are almost no data and few studies at hand. In terms of available large scale data there is only the above mentioned official data of the FAO (FAOSTAT n.d.). This data is informative about general trade indicators, such as Madagascar’s total clove production or its trading balances. However, no official data exists about regional clove production systems.

Recent studies about the clove production in Madagascar can be counted on one hand (Michels et al. 2011, Pfund et al. 2011, Lobietti 2013, Danthu et al. 2014, Levasseur et al. 2012). These studies assess the different types of clove production systems by conventional fieldwork and interview techniques in relatively small sampling areas. Such methods are time consuming, costly, and potentially subjective. These downsides of fieldwork are intensified by the remoteness of the area and the impassibility of the tropical terrain.

It is therefore difficult to find sufficient information about possible interactions between the global and local systems due to today's data availability. For this reason, the r4d project hopes to use remote sensing to generate more comprehensive and meaningful data for their research area(s).

1.3 Advantages of remote sensing

As can be seen from the above description of the current situation, new approaches have to be taken into consideration to obtain large-scale, quantitative data collections about clove trees and production systems. When it comes to gathering data of remote or inaccessible areas, remote sensing often is a useful solution. Remote sensing in general allows acquiring data for large areas in rather short time. Furthermore, different sensor systems are available enabling measuring different aspects and thus solving certain questions with an even broader range of information (Wulder and Franklin 2003). Another advantage of remote sensing data is the large temporal extent of certain products (Lefsky and Cohen 2003).

This specific advantage as well as the general practicability of remote sensing as data source is also shown by Zaehringer et al. (2015). This study is the first and only of its sort so far for Madagascar mapping land cover and land use changes for a study area of more than 24’000km^2. The study was based on Landsat 5 Thematic Mapper (TM) and Landsat 7 Enhanced Thematic Mapper Plus (ETM$^+$) data whose combination resulted in covering a long period of time allowing the monitoring of change over time.

While a 30 x 30 m or a 15 x 15 m (using the panchromatic channel of ETM$^+$) spatial resolution (National Aeronautics and Space Administration n.d.) is very suitable to fulfil the above mentioned task of detecting LULC and its changes over large regions, distinguishing different small-area clove production types is not possible as this requires information on the individual tree level for which their respective spatial resolution is too coarse. Remote sensing is therefore not per se the ideal solution to obtain more data on local clove production. Especially today’s availability of a wide suite of remote sensing data sources and products makes it essential to carefully choose the most suitable data for the planned application in the research field of this study (Lefsky and Cohen 2003, Wulder and Franklin 2003).

The choice of system in this case is for example limited by the large extent of the study area, the frequent cloud cover in the area as well as the very limited financial resources available. Such resources are mainly limited as the outputs of this r4d project are intended to be potentially applicable by the local agencies in Madagascar. Thus data which is either available at no charge or at low price is preferred. Hence, LiDAR (light detection and ranging) as well as imaging spectrometer (‘hyperspectral’) or other airborne data is not considered as it is too expensive (Fassnacht et al. 2016). UAV (unmanned aerial vehicle, drone) data is unsuitable as well due to the vastness of the study area to be covered.

The only remaining suitable data sources are satellites providing multi-spectral data. This has the advantages of large areas being covered and very often suitable satellite images are readily available in data archives. Thus no long and cost intensive data acquisition campaign is necessary. Furthermore VHR (very high resolution) satellite data enabling single tree detection (e.g. Pu and Landry 2012) can be acquired for a decent price nowadays thanks to technological progress and competition between data providers (Fassnacht et al. 2016, Ørka and Hauglin 2016).

Although multi-spectral satellite data actually meet all user requirements of the r4d project, one has to be aware that the almost permanent cloud cover over the study area limits the applicability of this data. However, if there is a cloudless scene like the one used for this thesis, it was shown that VHR multi-spectral satellite data is suited to detect single clove trees and classify clove production systems on large areas. With suitable data, remote sensing is thus a sustainable data source for the r4d project.

1.4 Remote sensing methods and studies related to tree species classification

Despite of little data on the study object itself, a comprehensive amount of literature is available regarding the methodological parts of this thesis. As this master thesis aimed to develop a method to produce an estimate of clove bud production in the study site, two parameters are of major interest. First, the number of clove trees growing in the study area. Second, the surroundings within which they grow.

The first parameter is of interest because it allows yield data per tree to be extrapolated to the entire study area. To obtain this parameter, two main methodologies had to be applied. First, potential clove trees had to be identified. This was achieved by a single tree detection method (see section 2.3.1). Second, the clove trees had to be distinguished from the remaining detected trees. This was done by a tree species classification (see section 2.3.2).

The second parameter is required to determine which of the detected and classified clove trees are used for the production of clove buds. Only those trees that grow in a clove production system (pasture, clove plantation and agroforest) were considered to be contributory trees. These clove production systems were found using a two-step classification of the LULC classes present in the study area (see section 2.3.3).

The following subsections provide an overview of the functionality and applications of the above-mentioned methods.

1.4.1 Single tree detection

As multi-spectral satellite data are considered the best choice for this thesis, only single tree detection methods using passive optical data will be taken into account for this methodological overview. Nevertheless, single tree detection is also possible with other sensor systems as for example LiDAR (Brandtberg et al. 2003, Koch et al. 2006, Kaartinen et al. 2012).

Crown delineation algorithms

Focusing on passive optical sensor systems, single tree detection is mainly performed using VHR data (for applications of satellite VHR data see e.g. Gougeon and Leckie 2006, Ke and Quackenbush 2007, dos Santos et al. 2017). Culvenor (2003) defines VHR imagery in this specific case as "[…] imagery that facilitates the direct recognition of […] individual tree crowns."

While individual trees can and have been detected manually from large scale aerial photography in the past, today's studies aim to automate tree crown delineation in order to obtain reliable large scale tree inventories. "A fundamental assumption inherent in crown delineation algorithms is that the center of a crown is brighter than the edge of the crown, or more particularly, the boundary between crowns" (Culvenor 2003). Based on this essential feature, Culvenor (2003) groups tree crown delineation algorithms in three different algorithm groups. They are 'bottom-up', 'top-down' and 'template-matching' (Culvenor 2003).

'Bottom-up' crown delineation algorithms

'Bottom-up' algorithms are focusing on the shadows around the trees. These 'valleys' are mostly found by searching the scene for local minima which in the end form a separating line around the individual trees. Such approaches have the disadvantage that they are based on the assumption of every tree having a more or less encircling shadow. Thus such approaches are less suited for very dense and complex forests and under certain circumstances even for sparse forest stands. Furthermore, the result becomes dependent on the solar zenith angle as shade varies depending on the position of the sun (Gougeon 1999, Culvenor 2003).

'Top-down' crown delineation algorithms

'Top-down' algorithms are detecting trees by searching for radiometric maxima representing tree crown's centers. These centers are then used as seeds to mathematically grow the tree crown. The stop criterion for tree crown growth in general is defined by a global minimum threshold or a minima boundary as created in the 'bottom-up' algorithms. This approach works rather well for dense forests. Problems occur in less dense and homogenous forests when there is large background brightness variation. This could result in the identification of bright soil pixels as local maxima as well (Brandtberg and Walter 1998, Culvenor 2002, Culvenor 2003). Another 'top-down' algorithm proposed by Pinz (1991) focuses more on the tree's position, as well defined by a local maximum, but does not aim to find the tree's exact boundaries. Instead, successive concentric circles centering on the local maximum are created for which the average brightness of the pixels within is calculated. If the shape of this brightness distribution corresponds with the user-set threshold an estimate of the crown's radius is calculated. The advantage of this approach is that it only requires little user input. On the other hand, it is unclear how substantially the user-set threshold influences the final output (Pinz 1991, Culvenor 2003).

'Template-matching' crown delineation algorithms

The last of the three algorithm groups, the so-called 'template-matching', tries to find trees in forests featuring variable spacing of the trees and having differently sized tree crowns. Furthermore, 'template-matching' algorithms do not require tree boundaries which makes them applicable for situations where there is no or very little shade around the trees as for example in sparse forests. "The algorithm involves matching a three-dimensional synthetic image model (or template) of tree crowns with radiometric values in the image" (Culvenor 2003). This makes this algorithm computationally rather expensive and also dependent on the a priori created model of the trees. Another challenge of these algorithms is that they indeed can cope with different crown sizes but not with different crown forms as they then do not match the template. Thus it makes it hard to use this kind of algorithm in mixed species forests (Culvenor 2003).

Single tree detection in tropical forests

Irrespective of which group the algorithm belongs to, most approaches to detect single trees were developed for temperate and boreal forests (Pinz 1991, Gougeon 1995, Brandtberg and Walter 1998, Culvenor 2002, Pouliot et al. 2002, Wang et al. 2004, Gougeon and Leckie 2006, Hirschmugl et al. 2007, Wolf and Heipke 2007, Wang 2010). Others have focused on detecting specific trees in orchards or plantations (Daliakopoulos et al. 2009, Aksoy et al. 2012, Srestasathiern and Rakwatin 2014, Mahour et al. 2016). However, applications in tropical forests are few as tropical forests pose a range of challenges regarding single tree detection. Mainly, the closed canopies of tropical forests make automatic tree crown delineation almost impossible as tree crown boundaries often are barely recognizable (Culvenor 2003, Clark et al. 2005). Also, template algorithms are not particularly suitable for the detection of single trees in the tropics, since the trees there are uneven in shape and size due to the high diversity of species (Culvenor 2003, Clark et al. 2005, Baldeck et al. 2015). Hence, there is a clear gap to fill by finding an algorithm which is capable of detecting single trees in tropical forests. However, various tests have shown that this gap cannot be filled with the standard procedures mentioned above. For this reason, a method was developed in this thesis which to some extent is a combination of the ‘bottom-up’ and the 'template matching' approach (see section 2.3.1).

1.4.2 Tree species classification

Developing a reliable method to detect individual trees also in tropical forests is moreover important for tree species classification. An accurate classification result is dependent on two principles. First, there has to be a high similarity of features within a class, and second, there has to be a high dissimilarity of features between the different classes (Ren and Malik 2003). Hence, accurate single tree delineation will improve the spectral signatures of each tree species as there are fewer pixels from outside the actual tree crown impurifying the signature. This is especially the case when averaged spectra for crown objects are calculated (Fassnacht et al. 2016).

The most used remote sensing sensor systems for tree species classification are hyperspectral systems. Multi-spectral systems are widely used for tree classification purposes especially because they allow covering larger forest areas and are less cost intensive than hyperspectral systems. These passive optical sensor systems have several advantages to distinguish different tree species. According to Fassnacht et al. (2016), the reflected fraction of solar irradiation at the different sensor wavelengths provide information about the tree canopy’s chemical properties of the plants tissue, leaf morphology, canopy structure, and tree size. Furthermore, crown texture information can be analyzed as well as information source of the tree phenology. All these information strongly enhance the possibility to distinguish different tree species as these parameters vary between different species. Thus, the more of such information can be gathered the more likely is a low misclassification in the classification outcome.

Tree species classification algorithms

An important part of the species classification process is the classification algorithm itself. To start with, there is no ultimate classifier for tree species. As important as the choice of a classifier is the quality of the data and that the data matches the requirements of the classifier. For instance, the well-known classifiers such as maximum likelihood classifier or LDA (Linear Discriminant Analysis) both require the data to be normally distributed. Hence, classifying the data with one of these classification algorithms will only succeed if the input data is normally distributed. Still, they are rather popular for tree species classification as there are many software implementations (Franklin et al. 2003, Fassnacht et al. 2016).

Gaining more and more popularity in tree species classification approaches are the so-called non parametric approaches such as Support Vector Machine (SVM) or Random Forest (RF). Advantages of such algorithms are that the data can be distributed in any given way. Furthermore, they are capable of dealing with high-dimensional data and especially RF algorithms are robust and not very sensitive to the number of input variables. While RF is rather easy to apply SVM requires the user to set the kernel function parameters which can be rather demanding and highly influence the classification output (Franklin et al. 2003, Fassnacht et al. 2016).

Tree species classification in tropical forests

Although there are many sensor systems and classification algorithms to choose from, automated tree species classification in tropical forests is a mainly unresolved problem (Baldeck et al. 2015).

One reason for this is that a high quality crown delineation is a necessary prerequisite in order to be able to classify trees based on crown-mean spectra (Baldeck et al. 2015). As already mentioned in section 1.4.1, both the closed canopies and the change in scale of the target features lead to the problem that automatic tree crown delineation in tropical forests is almost impossible (Clark et al. 2005, Baldeck et al. 2015). It is therefore mainly the dependence on the detection of individual trees, which makes tree species classification difficult.

Another major challenge in tropical forests is the high species diversity of sometimes more than 300 species per hectare. Although there are several studies showing that it is possible to distinguish und properly classify several species based on their spectral differences, mapping these species was not successful (Cochrane 2000, Clark et al. 2005, Asner et al. 2008, Asner and Martin 2011, Immitzer et al. 2012, Asner et al. 2017). That is because the investigated species could be distinguished from each other but not from all the hundred other spectrally unknown species surrounding them.

Baldeck et al. (2015) have identified a potential cause of the above challenge to distinguish analyzed tree species from unknown species in the classification approach. In all these studies the classification approach was a multi-class approach. Such an approach entails representative training data for all model species present in the scene. And although for example (Asner et al. 2008) showed that it is possible to analyze more than a thousand species for their leaf reflectance and transmittance spectra, finding all species present in the scene is not very promising as classification accuracy decreases with increasing number of classes (Baldeck and Asner 2014).

Instead, Baldeck et al. (2015) propose a single-class classification approach as this kind of approach improves classification accuracy for the focal class and not the average accuracy for all the model classes. Furthermore, single-class classification requires far less training data and allows species mapping in the area as this method explicitly tries to distinguish the focal species from the background comprised of all other species. Still, this approach is not limited to one species but several species can be classified with this approach by combining the single-class models of different species. Baldeck et al. (2015) were able to show that this approach works for at least three tree species and Ferreira et al. (2016) did so for eight species.

Although the approach of Baldeck et al. (2015) cannot be adopted as a whole, since they have delineated the tree crowns manually and not automatically, the tree classification approach in this thesis is also based on the principle of binary classification (see section 2.3.2).

1.4.3 Production type classification

Clove production types as such have so far never been classified based on remote sensing data. The difficulty of classifying clove production types lies in the classification of land use classes. Cihlar and Jansen (2001) define land use as the ways land covers are used by humans. The three clove production systems (pasture, clove plantation and agroforest) are therefore to be seen as land use classes used by humans for the production of cloves.

According to Foody (2002), "the production of thematic maps, such as those depicting land cover, using an image classification is one of the most common applications of remote sensing". However, since land uses cannot be derived directly from a satellite image based on the spectral information (Aplin 2003) their detection and classification is much more difficult and therefore less common in the literature (Lackner and Conway 2008).

As studies (e.g. Barnsley and Barr 1996, Zhang and Wang 2003, Lackner and Conway 2008) show, the difficulty in the land use classification is, among other things, that the classification requires an intermediate step. The generally used method is that first the land cover classes are classified (mostly purely on the basis of spectral properties) and in a second step with various additional, often object based information, the classification of the land use classes takes place.

Cihlar and Jansen (2001) express this challenge of deriving land use from a land cover map with the following function

$$LU_i = f(LC_j, e_1, \ldots, e_n, sc_1, \ldots, sc_n)$$

where e and sc are environmental and socio-economic or cultural variables and j and i are specific land use (LU) and land cover (LC) types (Cihlar and Jansen 2001).

In case of clove production types, only the increased and targeted occurrence of clove trees ($= e$), distinguishes clove production types ($= LU_i$) from the land covers ($= LC_j$) present in the study area.

For this reason, a production type classification approach was developed, which distinguishes the production types from the surrounding land covers based to the number of detected clove trees (see section 2.3.3).

1.5 Research questions

In order to find ways in which insufficient official data on clove trees and their production can be enhanced, this thesis attempts to find answers to the following research questions:

1) How can single tree crowns in tropical forests be detected and delineated in an automated way using multi-spectral satellite data?
2) How can clove trees be classified in an automated way using the spectral properties of the canopy?
3) How can clove production types be classified and what are the respective production rates quantified on a regional level?

The methods used in this thesis and the results obtained are explained in the following manuscript of a scientific publication. The discussion and conclusion in the manuscript relate above all to the methods and the insights gained from them. The discussion at the end of this thesis will then address the above-mentioned research questions and put the results in a broader context.

2 Manuscript of the scientific publication

Automated detection of single clove trees for yield quantification in north-eastern Madagascar based on multi-spectral satellite data

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Contribution:

Design	80%
Materials & Methods	95%
Results & Conclusion	95%

Abstract

The demand for clove products, mainly dried buds and essential oil, is increasing on the global markets. Consequently, the importance of clove trees is also increasing on the local level for smallholders cultivating them as cash crops. Due to the limited official data on the local production, it is of major interest to investigate alternative approaches, such as remote sensing based methods, to quantify today's production situation. To estimate clove bud yields in our study area in north-eastern Madagascar, the amount of clove trees had to be determined. Therefore, a single tree detection and tree species classification were performed. We propose using Circular Hough Transform (CHT) for the automated detection of individual clove trees in the tropical forests of Madagascar. Tree species classification, based on the extracted features for every detected circular tree crown, was performed by using a Random Forest (RF) classifier. We then classified and mapped the different production types (pasture, clove plantation and agroforest) within which the detected clove trees are growing. Based on the number of detected clove trees growing in clove production systems we provide a clove bud yield estimate. Our results show that 97.9% of all reference clove trees were detected by the CHT. Classifying clove and non-clove trees resulted in a producer accuracy of 70.7% and a user accuracy of 59.2% for the clove trees. The classification of the clove production types resulted in an overall accuracy of 77.9%. By averaging different clove tree yield estimates obtained from the literature we calculated an average total yield of approximately 575 tons/year for our 25'600 ha study area.

Keywords: Circular Hough Transform, tree species classification, clove bud yield estimation, LULC classification, random forest, very high resolution satellite image, Pléiades satellite

2.1 Introduction

Obtaining statistical information about crops is of wide interest. In the developed countries, where industrial agriculture is the dominant form of farming (Bowler 2014), this information is often available due to official data collections and close monitoring of the crops by the farmers. Thus, relatively accurate projections about crop health and yields are possible.

85% of the world's farms are smallholder farms which often produce for subsistence purposes and are not officially overseen (Nagayets 2005). Often, no agricultural census data or agricultural statistics are available in less developed countries, where most of these smallholder farms are located (Nagayets 2005). Thus, it is of high relevance to find methods to collect large scale information about crops cultivated on smallholder farms.

Remote sensing offers a practicable approach to gain insights about cultivated crops and land use changes on a large scale (Nellis et al. 2009). Information about plant traits and the plant's health (Haboudane et al. 2002, Reyniers and Vrindts 2006, Haboudane et al. 2008, Chen et al. 2010, Homolová et al. 2013), but also about crop distribution or crop yield (Doraiswamy et al. 2003, Ferencz et al. 2004, Yang et al. 2004, Ye et al. 2006, Yao et al. 2008) can be gathered.

The crop to be investigated in this study, using remote sensing data, is cloves (*Syzygium aromaticum*). Cloves are mainly produced in Indonesia, Madagascar and Tanzania (Lobietti 2013). The two main products from clove cultivation are the dried flower buds and the essential oil (Danthu et al. 2014). As the global demand for both of these products is rising, cloves are of increasing importance on the world's trading markets (FAOSTAT n.d.) and for the national economies of the producer countries. This is especially the case for Madagascar, being the world's second largest producer and even the world's leading exporter of cloves (FAOSTAT n.d.).

Most farmers in Madagascar are smallholders who mainly cultivate crops for subsistence (Harvey et al. 2014). In order to secure products which cannot be produced on their plots, Madagascan farmers aim to generate revenue with the cultivation of cash crops such as for example coffee, vanilla, or cloves (Lobietti 2013, Danthu et al. 2014, Thomson 2016). The increasing global demand for cloves makes cultivating them also more important on the local scale (Danthu et al. 2014). For historical reasons, cloves are farmed in three different production types. These are pasture, clove plantation, and agroforest systems (see Table 1 for the definitions) (Lobietti 2013, Danthu et al. 2014, Levasseur et al. 2012).

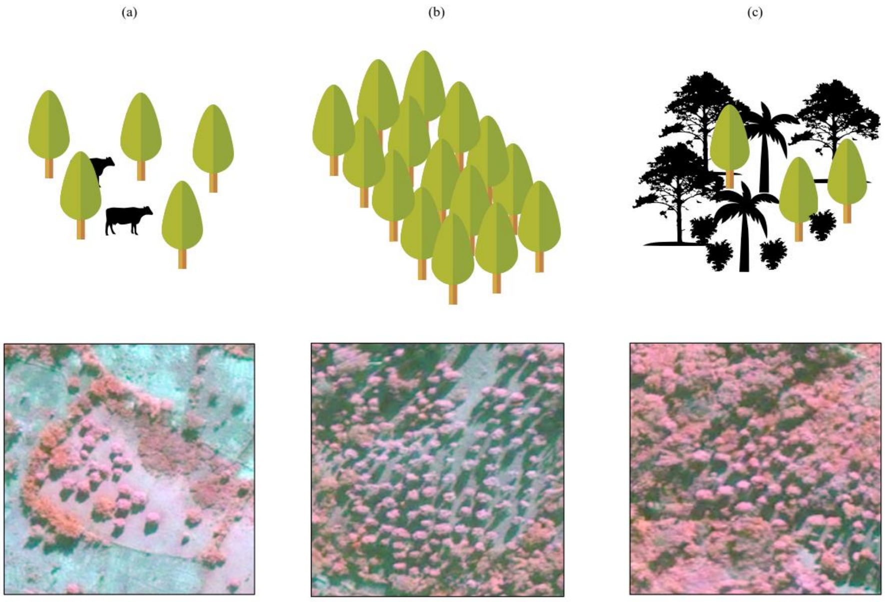

Figure 3 – Schematic and false-color satellite image representation of the three clove production type systems, (a) pasture, (b) clove plantation and (c) agroforest.

To estimate the clove production in the study site, two main parameters are of interest: The number of clove trees and in which production type they grow in. Therefore, this study focuses on the following three aspects: detecting and classifying single clove trees and classifying the clove production types within which the detected trees grow.

Several studies have successfully shown the potential of single tree detection or tree crown delineation in temperate and boreal forests (Pinz 1991, Gougeon 1995, Brandtberg and Walter 1998, Culvenor 2002, Pouliot et al. 2002, Wang et al. 2004, Gougeon and Leckie 2006, Hirschmugl et al. 2007, Wolf and Heipke 2007, Wang 2010). Others have focused on detecting specific trees in orchards or plantations (Daliakopoulos et al. 2009, Aksoy et al. 2012, Srestasathiern and Rakwatin 2014, Mahour et al. 2016). With the rapid progress in LiDAR techniques also LiDAR data is successfully used to detect single trees in such environmental settings (for an overview and further information see e.g. Kaartinen et al. 2012). Until today, delineating individual trees in tropical forest, however, is a challenging task as the tree delineation is mainly hindered by the closed canopies and the variability of crown shapes and sizes (Clark et al. 2005, Baldeck et al. 2015).

A reliable method to detect and delineate individual trees is also important for the tree species classification (Baldeck et al. 2015). Several studies have already successfully classified different tree species based on remote sensing data (e.g. Boschetti et al. 2007, Ørka et al. 2009, Dalponte et al. 2012, Shang and Chisholm 2014). For tropical forests, however, an automated tree species classification is a mainly unresolved problem (Baldeck et al. 2015). Besides facing the challenge of hampered tree delineation to obtain spectrally pure training data, one of the major challenges in tropical forests is the extremely high species diversity of sometimes more than 300 species per hectare (Baldeck et al. 2015). Thus classification approaches used for temperate forests cannot be easily adapted to tropical forests. Although there are several studies demonstrating the possibility to distinguish und properly classify several species in tropical forests based on their spectral differences, mapping these species was not overly successful (Cochrane 2000, Clark et al. 2005, Asner et al. 2008, Asner and Martin 2011, Immitzer et al. 2012, Asner et al. 2017). The investigated species could be distinguished from each other but not from all of the hundred or so other spectrally unknown species surrounding them. Baldeck et al. (2015) have identified a potential cause of the above challenge in the classification approach itself. All of these studies used a multi-class classification approach. Instead, Baldeck et al. (2015) proposed a single-class classification approach as this kind of approach improves classification accuracy for the focal class and not the average accuracy for all the model classes. Still, this approach is not limited to one species but several species can be classified by combining the single-class models of different species. Baldeck et al. (2015) were able to show that this approach worked in tropical forests for at least three tree species and Ferreira et al. (2016) did so for eight species. Although not naming it that way, Baldeck et al. (2015) performed a decomposition of a multi-class problem into a binary classification problem (Aly 2005).

Clove production types as such have never been classified on the basis of remote sensing data. However, this is a form of land use classification. The three clove production systems (pasture, clove plantation and agroforest) are land use classes that are used by humans for clove production. While the creation of land cover maps is one of the most common applications of remote sensing (Foody 2002), the detection and classification of land uses is far more difficult and therefore less common (Lackner and Conway 2008). The main difficulty in classifying land use is that land use cannot be derived directly from the spectral information of a satellite image (Aplin 2003, Lackner and Conway 2008). In order to classify land use, a land cover map is usually required first. The challenge then lies in finding additional, meaningful information to classify the land use classes in a second step (e. g. Barnsley and Barr 1996, Cihlar and Jansen 2001, Zhang and Wang 2003, Lackner and Conway 2008).

2.1.1 Objectives of this study

In order to assess both future social and ecological changes coming along with the increasing significance of cloves, it is necessary to get an overview of today's production situation.

Thus, this study aimed to 1) find a way to detect single trees and to delineate their crowns in the tropical forest in the north-eastern part of Madagascar based on very high resolution (VHR) passive-optical, multi-spectral satellite data, 2) to identify clove trees in order to 3) classify different clove production types, and 4) to estimate the clove bud yield in the study area.

These outputs are especially of interest regarding the possibility to create a comprehensive map of the different clove production systems in order to monitor future local land use and land cover changes.

2.2 Study site, study object and data

2.2.1 Study site

The study site is located in the north-eastern part of the Analanjirofo region in Madagascar. Analanjirofo, literally meaning 'forest of cloves', is Madagascar's main clove production region (Levasseur et al. 2012). The study site is roughly 16 x 16 km (25'600 hectares) including the environs of the villages of Mahavelona and Anjanavana (Figure 4). Bordering the study site is the Masoala National Park, being the last large continuous tropical rainforest on Madagascar and containing 1% of the world's biodiversity (Därr and Heimer 2015).

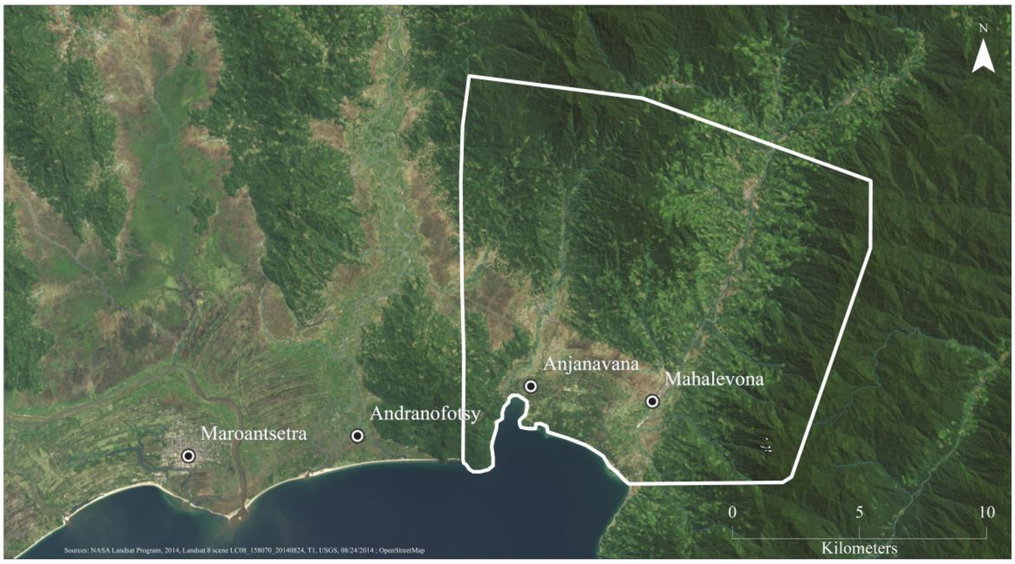

Figure 4 – The study site in the north-eastern part of Analanjirofo region, Madagascar.

Besides the urban areas and rice fields which are either located on Antongil Bay or along the rivers, the hillsides mostly contain agroforest systems, pastures with some individual trees or a few small rice paddies. Continuous dense primary forest is getting rare and can almost exclusively be found further away from human settlements.

Due to the south-east trade wind hitting the island on its east coast, there is rain all over the year resulting in an annual precipitation of over 2000 mm in this region (Kägi 2008). This, combined with warm temperatures, leads to abundant growth of tropical vegetation.

2.2.2 The clove tree and clove production types

Although not originating from Madagascar, the clove tree (*Syzygium aromaticum*) is perfectly adapted to Madagascar's tropical climate. Clove trees have consistent leafage of a shiny green. The tree is characterized by circular crowns with diameters of up to about 10 m and tree heights ranging from 12 to 15 meters, resulting in narrow-oblong to almost round crown shapes (Lobietti 2013, Danthu et al. 2014).

The clove tree is mainly cultivated for its flower buds and its eugenol-containing essence extracted mostly from the leaves. In general, clove buds are produced for the first time at the age of around six years, high harvests can be expected from trees being twenty years or older (Ministère des Affaires étrangères 2012). The harvesting season is from October until December (Lobietti 2013). Clove yield undergoes a triennial cycle. A year of high yield is generally followed by two mediocre or even poor yield years (Levasseur et al. 2012, Ministère des Affaires étrangères 2012). On average, balancing age and cycle related yield fluctuations, a clove tree yields 2-3 kg of dry clove buds per year (Locatelli 2000, Clove Crop Cultivation Guide n.d., Horticulture Spice Crops n.d.). To gain the eugenol-containing essence, the young leaves are cut. This can be done once every four years and results in approximately 80 kg of leaves per tree. The harvest of clove buds is incompatible with the harvest of leaves (Ministère des Affaires étrangères 2012).

There are three main production systems to cultivate the clove tree in Madagascar. They are *Silvo-pastoral systems* (hereafter called 'pastures'), *Monoculture clove plantations* (here after called 'clove plantations') and *Multicrop-multilayer agroforestry systems* (hereafter called 'agroforest') (Celio 2016). These three production types are part of the following five major land use and land cover (LULC) classes of which the study area consist (Table 1).

Table 1 – Definitions of the five major LULC classes and the tree production type systems present in the study area.

LULC class	Definition
Grassland	Grasslands are areas of grasses for livestock grazing. These patches of grassland are often surrounded by bamboo tree hedges and have only a few trees (one or two) in the patch (often a mango or litchi tree) (Celio 2016).
	Silvo-pastoral production systems ('pastures') are defined as grasslands with mainly clove trees in which other trees such as mango or litchi can be found sporadically. Clove trees can be either planted in straight lines or are scattered over the pasture (Celio 2016).
Plantation	Plantations are areas that have been planted for the production of food or cash crops. These crops make up approximately 75-100 percent of the cover. Only clove plantations are considered in the study site (The USGS Land Cover Institute (LCI) n.d.).
	Monoculture clove plantations ('clove plantations') are densely planted clove stands with no other use found on the same plot (Celio 2016).
Forest	Forests are characterized by tree cover which, together with woody vegetation, makes up the largest part of the area. Madagascar's forests consist of evergreen species resulting in a year-round green canopy (Kägi 2008).
	Multicrop-multilayer agroforestry production systems ('agroforest') in general are composed of three layers of vegetation. They include clove trees, fruit trees, primary forest trees, and coffee plants (in decreasing occurrence) (Michels et al. 2011, Celio 2016).
Bare soil/Rice paddies	Areas with little or no "green" vegetation. Rice paddies were non-vegetated at the time of the satellite overpass as they are harvested in January (seeded in August) and May/June (seeded in October/November). Bare soil results mainly from slash-and-burn activities (Celio 2016).
Urban areas	Areas containing artificial, human made structures such as buildings or roads.

The detection and classification of land use classes, as the three production types are, however, is not trivial (see 2.1). In order to separate the clove-producing land use classes (pasture, clove plantation and agroforest) from the remaining non-clove-producing LULC classes in the study area (Table 1), additional information about features which enable a distinction of the two groups are required. The only known feature that distinguishes productive from non-productive LULC classes is the increased occurrence of clove trees.

To date, the only available information on cloves and clove production systems come from local fieldwork utilizing interview inquiries carried out in different regions of Madagascar (Locatelli 2000, Lobietti 2013, Levasseur et al. 2012, Celio 2016). These studies provide information on the density of cloves per hectare, the distance between individual clove trees and clove yield estimates. However, values vary greatly between the different studies, as they were collected in different places in Madagascar. In particular, the number of clove trees per hectare, which is of importance to us in this context, is rather diverse. For this reason, we calculated clove densities per production type based on manually detected reference clove trees and reference production type areas (Figure 5).

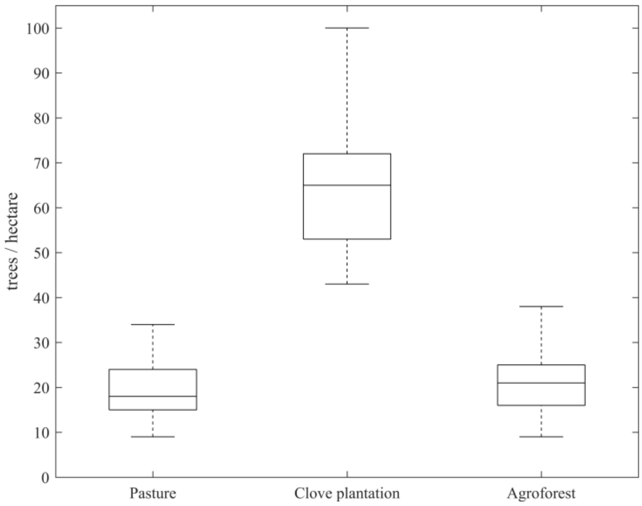

Figure 5 – Box plot displaying the reference clove tree density per hectare for each clove production type.

For our study area we chose the lower whisker values (excluding outliers) as delimitation between a productive versus the natural (non-productive) occurrence of clove trees. Pastures were defined as grasslands with a minimum of 9 trees per hectare, clove plantations as plantations with at least 43 clove trees per hectare and agroforests as forests surpassing the limit of 9 clove trees per hectare. LULC classes with fewer clove trees per hectare are considered as non-clove-producing classes.

2.2.3 Data

The two satellite image strips used were recorded from the Pléiades 1A satellite platform on the 9th of July 2014. The delivered product has the following properties:

Table 2 – Spectral bands properties of the Pléiades 1A satellite (ASTRIUM 2012)

Spectral range	Channel	Spatial resolution
0.43-0.55 µm	Blue	2 x 2 m
0.50-0.62 µm	Green	2 x 2 m
0.59-0.71 µm	Red	2 x 2 m
0.74-0.94 µm	Near infra-red	2 x 2 m
0.47-0.83 µm	Panchromatic	0.5 x 0.5 m

Both images were delivered as ‘ortho products’ which are georeferenced and corrected from acquisition and terrain off-nadir effects (ASTRIUM 2012). Due to the perfect cloud free conditions, no further processing such as atmospheric correction or cloud masking was applied.

To enhance the image’s information content, pan-sharpening was performed. Regarding the importance of the spectral information to later distinguish the clove trees from surrounding trees, the Principal Component Analysis (PCA) pan-sharpening was chosen. This method has virtually no spectral distortion and still performs well relating to the spatial resolution (Zhang et al. 2014, Pushparaj and Hegde 2017). All analyses were either performed on the original panchromatic image or the processed pan-sharpened multi-spectral image.

The vastness and inaccessibility of most parts of the study site challenge the gathering of a sufficient amount of in-situ reference data. Thus, the reference data was acquired manually on the satellite image by an expert in forest inventories who is specialized in aerial image interpretation.

Two types of reference data were collected. On the one hand, production type reference data to validate the clove production type assignment and on the other hand clove reference data to validate the single tree detection.

To assess the correctness of the clove production type classification, 20 square polygons encompassing an area of 1 hectare (ha) were distinguished for the three clove production types. Within this total of 60 polygons, all visually detectable clove trees were marked, resulting in a total of 2194 reference clove trees. Furthermore, another 20 square polygons encompassing an area of 1 ha were distinguished for each of the remaining LULC classes, rice paddies/bare soil and urban areas in order to validate the LULC classification.

2.3 Methods

2.3.1 Single tree detection and crown delineation

Tree crown delineation using passive-optical sensor data, as it is used in this study, is based on the fundamental assumption that a crown’s center is brighter than its edge (Culvenor 2003). Hence, single tree detection algorithms traditionally either search for the shadows surrounding an individual tree (e.g. Gougeon 1999, Leckie et al. 2003) or for the bright crown centers, with the second approach being more common. The crown centers are found by searching for local radiometric maxima and using them as ‘seeds’ to grow the crown until a certain stop criterion such as a global minimum threshold or a minima boundary is reached (Brandtberg and Walter 1998, Culvenor 2002, Culvenor 2003, Wulder et al. 2004, Hirschmugl et al. 2007). Such approaches have the disadvantage that they are based on the assumption of every tree having a more or less encircling shadow and a clearly identifiable center. Thus, they are less suited for very dense and complex forests such as tropical forests (Clark et al. 2005). Furthermore, it makes the result dependent on the solar zenith angle as shade varies depending on the position of the sun (Gougeon 1999, Culvenor 2003).

Another widely used single tree detection approach is to match a three-dimensional synthetic tree crown image model to radiometric values in the image (Pollock 1996, Culvenor 2003). Such algorithms mainly try to generalize the shape of the crown for example based on the shape of an ellipsoid (Pollock 1996, Wolf and Heipke 2007). Although such algorithms are shadow-independent, they have difficulties dealing with varying shapes of tree crowns as it is the case in mixed species forests or tropical forests (Culvenor 2003).

Although the choice of a single tree detection method depends mainly on the type of forest to be classified and the data available, it is also important to consider the further use of the data. In our case, we must be able to determine the tree species based on the data from the automatic single tree detection. According to Chubey et al. (2006), a higher amount of information can be gained from image objects consisting of several pixels, compared to individual pixels. Thus, it is not only possible to calculate aggregative statistics regarding the spectral values, but also information about the size, shape or texture of the object can be obtained (Chubey et al. 2006).

Due to the complex interweaving of different LULC classes in the investigated area, the general difficulty of single tree detection in tropical rainforests and the fact that image objects facilitate tree species classification, we advocate a completely new approach to single tree detection.

Taking advantage of the almost perfectly circular crown shape of clove trees, we propose to apply the well-known Circular Hough Transform (CHT) to detect clove trees (Duda and Hart 1972, Atherton and Kerbyson 1999, Rizon et al. 2005). To our knowledge, Circular Hough Transform has not been used for automated single tree detection so far. However, its use looks promising as it combines all of the above mentioned approaches to detect single trees to a certain degree. Namely, this approach provides an approximation of the trees boundary as well as its centre in one pass by generalizing the tree crown as a circle.

CHT is a common method for circle detection which aims to find circles of a given radius R in images (Atherton and Kerbyson 1999). The CHT is said to be robust to the presence of noise, varying illumination conditions as well as to occlusion (Atherton and Kerbyson 1999).

CHT transforms a set of feature points from the x, y-plane to the parameter space. The equation of a circle in parameter space is:

$$R^2 = (x - a_x)^2 + (y - a_y)^2$$

Where (a_x, a_y) is the circle centre and R is the radius. CHT basically consists of two major steps. First, the image is searched for pixels of high gradient representing the edge points which then contribute a circle of the predefined radius R to an output accumulator space. Second, the circle centre location is estimated. Circle centres tend to be at the place where most contributed circles overlap, indicated by a peak in the accumulator space. Hence circle centres can be found by detecting peaks in the accumulator space. In case a radius range instead of a single radius is applied, the radii of the detected circles are calculated in a further step (Atherton and Kerbyson 1999, Rizon et al. 2005, The MathWorks Inc. 2012).

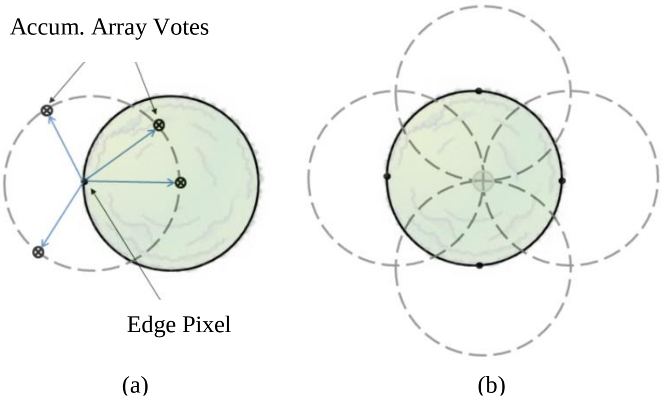

Figure 6 – (a) shows a candidate pixel lying on the edge of an actual circle (solid circle) with the CHT voting pattern (dashed circle) for the candidate pixel, (b) is an example of candidate pixels (solid dots) whose voting patterns (dashed circles) coincide at the centre of an actual circle (solid circle) (The MathWorks Inc. 2012, Oryx Digital Ltd. n.d.).

We used MATLAB's readily implemented 'imfindcircles' function (The MathWorks Inc. 2012) to perform CHT and to automatically detect individual tree centres. As 'imfindcircles' works with grayscale images it was applied on the original panchromatic image which was normalized and contrast enhanced beforehand. Object polarity was set to 'bright' causing the function to search for circular object which are brighter than the image background which is the case for the clove trees. As most clove trees in the scene do not exceed a diameter of 8 meters, the radius range was experimentally optimized to span from 1 to 4 meters. Different radius ranges were investigated but the detection rate did not improve. The values for the sensitivity and edge threshold were also found experimentally. The sensitivity value was set to the maximum value of 1 in order to increase the amount of detected circular objects and therefore increase the chance of finding as many clove trees as possible. As the clove trees will be separated from all other detected trees in the tree species classification step, a high number of false positives can be accepted. The edge gradient threshold, which determines the edge pixels in the image by setting a gradient threshold, was set to 0.2 on a scale from 0 to 1. Lower edge threshold values lead to a higher amount of detected circular objects as objects with weak as well as strong edges are detected (The MathWorks Inc. 2012).

In order to perform the tree classification, every CHT output had to be transformed into a tree object. CHT outputs circle centre points attributed with a unique identification number, the x and y coordinates as well as the detected radius. Transforming these points into polygons based on the radius-buffer provides individual circular objects which then were used as a basis for feature extraction and tree classification.

2.3.2 Clove tree classification

For both the classification of the clove trees as well as the classification of the clove production types, we propose using a random forest classifier. Random forests (RF) have been shown to provide high class accuracies for classification problems in remote sensing and ecology (e.g. Breiman 2001, Pal 2005, Lawrence et al. 2006, Cutler et al. 2007, Watts and Lawrence 2008, Dalponte et al. 2012). We prefer RF to Support Vector Machines (SVM) because of its straightforward use with only two parameters to be set compared to SVMs where several parameters have to be defined by the user (Pal 2005, Lawrence et al. 2006, Dalponte et al. 2012). Another advantage of RF is that they are less prone to imperfect data such as unbalanced data, unscaled data or missing values (Pal 2005). Furthermore, they are robust to overfitting (Breiman 2001, Lawrence et al. 2006, Rodriguez-Galiano et al. 2012).

To apply the random forest (RF) classifier, training and validation data of all involved classes is required. While visual clove tree detection is feasible, compiling a well-balanced training set out of several tens to hundreds of species for non-clove trees is challenging. As shown by Baldeck et al. (2015), binary classification is promising. Hence, we only trained the RF classifier with two classes. One representing the clove trees, the other one representing all the other non-clove trees. For this reason we did not use the manually detected clove reference trees themselves, but all CHT detected trees whose radii contained such a reference tree. Switching this selection then results in all CHT detected trees which do not encompass a reference tree that is non-clove trees. Consequently, we obtained an almost automatically generated training and validation data set.

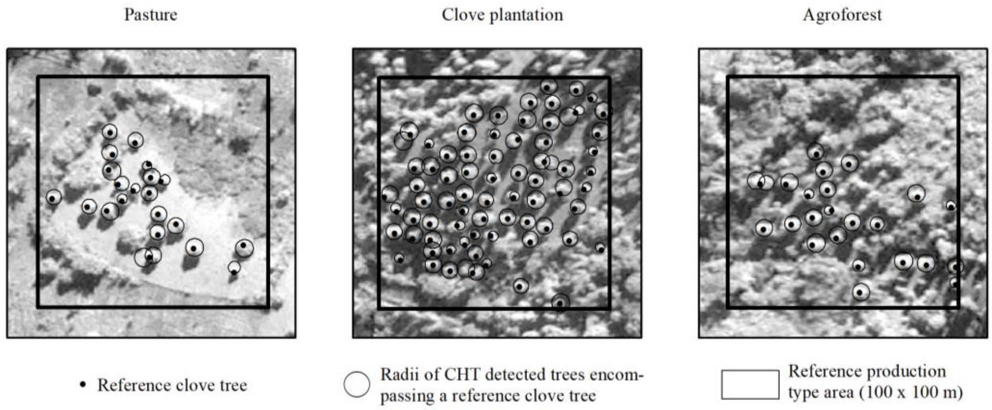

Figure 7 – An example for each production type, showing the reference clove trees (black dots) and the radii of the CHT detected trees (circles). All CHT detected trees encompassing a reference clove tree were used as training/validation data for the clove-class. All the other CHT detected circles (not displayed) were used as training/validation data representing the non-clove class.

While CHT has successfully detected most of the reference clove trees, even more false positives (non-clove trees), were detected (not displayed in Figure 7). This resulted in a highly unbalanced data set for the classification. To mitigate the drawbacks of imbalanced classification, we down sampled the majority class for training (Kubat and Matwin 1997, Chen et al. 2004). Hence 1000 samples each of clove and non-clove trees were randomly selected. After the elimination of small tree circles lying completely within a larger tree circle, a total of 992 cloves and 997 non-cloves were used for training.

For every tree object (= tree circle), we extracted several features describing the objects spectral and textural properties. Compared to hyperspectral images, which are often used for tree classification, only little spectral information is available in the used multi-spectral image. Hence we extracted various features in order to still obtain as comprehensive a description of the clove trees as possible. On the one hand, we extracted features which only rely on spectral values and on the other hand features which represent the tree's structure.

Table 3 – Features calculated for each circular object for the clove tree classification.

Feature	Property
Mean and standard deviation per channel per crown	The mean spectral reflectance in every channel per tree crown as well as how dispersed the reflectance values are within a tree crown.
Skewness and Kurtosis	The distribution of the spectral values
Average NDVI	Normalized Difference Vegetation Index (Rouse et al. 1973)
Average EVI	Enhanced Vegetation Index (Huete et al. 2002) For Pléiades, the relevant parameters are the same as they are for MODIS. G = 2.5, C1 = 6, C2 = 7.5 and L=1 (Henrich n.d.)
Average SAVI	Soil Adjusted Vegetation Index (Huete 1988)
Average VARI	Visible Atmospherically Resistant Index (Gitelson et al. 2002)
Contrast, correlation, energy and homogeneity within a tree crown	We used the pan-sharpened image's NIR channel to calculate these features from the *Gray-Level Co-Occurrence Matrix (GLCM) (*The MathWorks Inc. 2006). We found the standard deviation feature for the NIR channel most descriptive thus the NIR channel might generally contain better information to distinguish cloves from non-cloves.
'extractFeatures' function	MATLAB's 'extractFeatures' function was applied with various block sizes in order to capture the trees very central structure but also its broader structure ranging over the crown's edge (The MathWorks Inc. 2012).
'extractHOGfeatures' function	The 'extractHOGfeatures' function (HOG = histogram of oriented gradients) was applied using the HOUGH detected tree centres as centre location points (The MathWorks Inc. 2013).

All these features were calculated for the training and validation tree sets as well as for all the roughly 8 million yet unclassified trees. After all the features were calculated, a random forest classifier as proposed by Breiman (2001) was applied with 150 trees. In order to further mitigate the influence of an imbalanced data set, a cost function was applied (Kubat and Matwin 1997, Chen et al. 2004). The experimentally determined cost applied is $\begin{pmatrix} 0 & 1 \\ 5 & 0 \end{pmatrix}$. This cost matrix resulted in best results regarding both sensitivity and precision. Although higher restrictions would have further increased the values of the sensitivity parameter, precision was adversely affected and deteriorated resulting in an inferior overall result.

After all detected trees were classified, tree centres lying within an experimentally determined distance of 1.5 meters were merged. Consequently, multiple detections of one tree from asperities in the tree crown were eliminated. If all tree centres within the distance range were of the same class, the midpoint of them was calculated to locate the new centre and the average radius was assigned. In case one point was classified as clove and the other as non-clove tree, the clove centre was prioritized. This implies that the class, the location and the radius of the clove tree centre was retained in order to avoid losing too many of the clove trees as they are essential for the production type classification.

2.3.3 Production type classification

The production type classification aims to detect the three clove production types, pasture, clove plantation, and agroforest. As in the tree classification step, random forest was used, as Rodriguez-Galiano et al. (2012) have shown it to be robust and providing high classification accuracies when applying it for land-cover classifications.

As already mentioned in section 2.1, land use classification generally consists of 2 classification steps. This is also the case for our production type classification. In a first step, the main land LULC classes as defined in Table 1 are classified. In a second step, clove count information is applied in order to distinguish productive from non-productive LULC classes related to clove production (Figure 8).

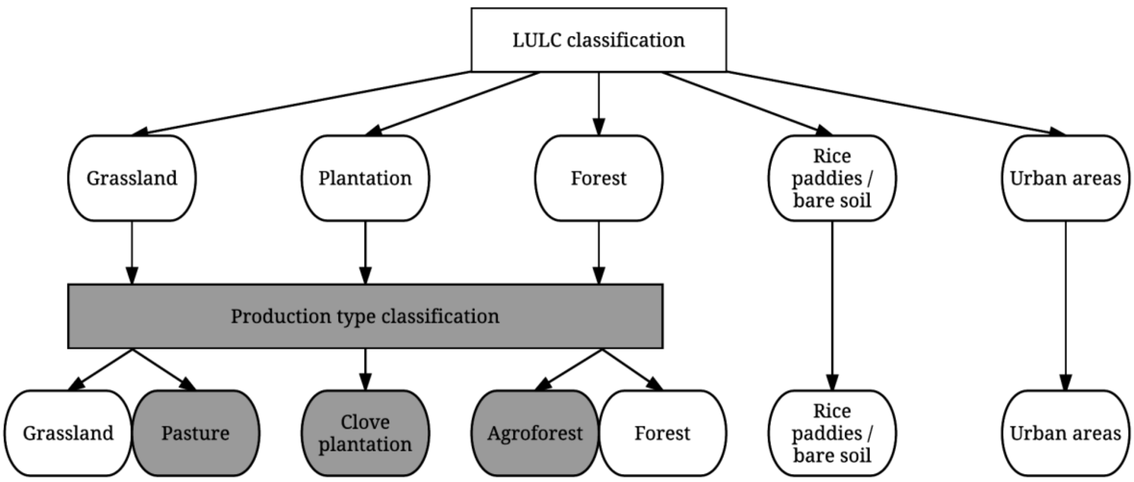

Figure 8 – 2-step classification process to obtain the three clove production systems, pasture, clove plantation and agroforest. The first step classifies LULCs with a random forest classifier. The second step classifies the clove production systems based on the presence/absence of a certain amount of CHT detected clove trees.

Although initially planned to perform the classification on production type areas of one hectare, it became apparent, that this resolution was too coarse as the farmer's plots were mostly smaller than one hectare, which caused major class mixture problems. This observation is also confirmed by Lobietti (2013) and Celio (2016) which describe plots to be around 0.2 ha in size. Thus, the grid cells used for the LULC and production type classification were reduced to 0.25 hectares.

LULC classification

In the first step, the five LULC classes grassland, plantation, forest, rice paddies/bare soil and urban areas were classified. These five classes were classified based on the extracted features described subsequently.

Based on the detected and classified trees a *Cluster and Outlier Analysis based on Moran's I* (ESRI n.d.) was performed on the entire image. Accordingly, spatial clusters of clove (e.g. potential plantation) or non-clove (e.g. very likely neither plantation nor pasture) trees were determined. Areas having only few clusters were very likely grasslands, bare soil or urban areas. For each region (grid cell), the calculated cluster specifications of each tree in the cell were stored.

Furthermore, the *distance between each tree and its nearest neighbor tree* was calculated. Subsequently, a statistical analysis of these distance measures was performed per 0.25 ha region. The statistical values calculated were *sum, mean, minimum, maximum, range and standard deviation*.

Besides the spatial object based information gathered from the detected trees also the spectral information was considered. For all pan-sharpened pixels within each 0.25 ha region, the statistics *sum, mean, median, minimum, maximum, minority, majority, range, standard deviation* and *variety* were calculated.

These features were passed on to the RF classifier which again was run with 150 trees. Due to the very balanced training set, no cost function was used this time.

Clove production type classification

In this final classification step, we aim to separate the clove production types pasture, clove plantation and agroforest from the non-productive LULC classes. As the LULC class of productive and non-productive plots regarding to clove production are almost identical in terms of spectral reflectance (Aplin 2003), the only difference is the presence or absence of clove trees. As defined in section 2.2.2, clove production types are areas where a certain amount of clove trees are present. Non-productive LULC classes on the other side are areas where no clove trees or less than a certain amount of clove trees are present. This minimum value initially was calculated based on the reference production type area of one hectare (Figure 5). As the areas on which the classification is conducted were reduced from one to 0.25 hectares, also the minimum amount of clove trees per area had to be adjusted (Table 4). The numbers have been rounded off.

Table 4 – Minimum number of clove trees per area for each production type

	Pasture	Clove plantation	Agroforest
Clove trees/hectare	9	43	9
Clove trees/0.25 hectare	2	10	2

These thresholds were applied to the production type classification (Figure 9). The LULC class grassland is classified as non-productive grassland when there are only one or no clove trees present. Grasslands having at least two clove trees are appointed as productive pastures with respect to clove production. The same threshold is applied to the forest LULC class which is divided in non-productive forest and agroforest. Due to the spectral similarity of grasslands and plantations, also this LULC class is re-evaluated with help of the additional information about the amount of present clove trees. Plantations having 9 or less clove trees are reclassified as pasture while plantations having 10 or more clove trees are classified as clove plantations.

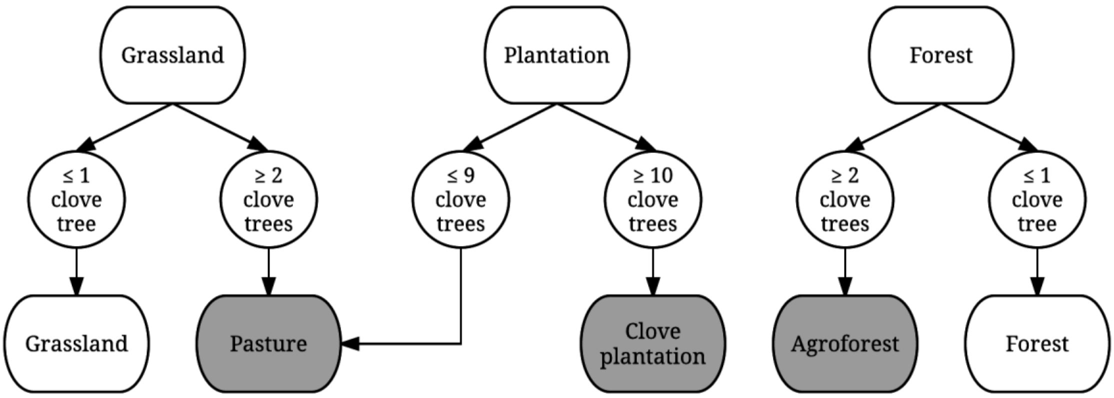

Figure 9 – Production type classification based on the number of present clove trees in the three LULC classes, grassland, plantation and forest on an area of 0.25 hectares.

By knowing which areas of the study site are used to produce cloves, together with the number of clove trees on these areas, estimates can be made of the amount of cloves produced.

2.3.4 Clove bud yield estimations

Estimating clove yields in general is difficult as they undergo high triennial fluctuations and are also dependent on the clove tree's age. Furthermore, there is no official data about clove yields in Madagascar. Some sources estimate that a clove tree yields on average 2-3 kg of dry clove buds per year when age and cycle related yield fluctuations are balanced out (Locatelli 2000, Clove Crop Cultivation Guide n.d., Horticulture Spice Crops n.d.). Other studies estimate that the yield per tree is higher, while others estimate it as lower (see Table 9). Due to these uncertainties we base our calculations on the mean value of 3 kg per tree.

For the yield calculation we multiplied the amount of detected clove trees with this averaged yield value and calculated the average yield per production type as well as the total yield of clove buds in the entire study area. Other clove products such as the leaves from the clove trees or the essential oil were not taken into account as no or only little reliable information exists about yield quantities.

2.4 Results

2.4.1 Single tree detection

The single tree detection based on the CHT algorithm resulted in a detection rate of 97.86% for the clove reference trees. 2194 clove reference trees were beforehand manually detected. Of these, 2147 were located within the radius of the CHT detected trees (see Figure 7). The exact position of the reference tree within the CHT crown radius wasn't taken into consideration.

2.4.2 Tree classification

Tree classification based on random forest resulted in an overall accuracy (OA) of 90.79%. Although the training set was artificially balanced, this value for accuracy is not representative as the validation set with the remaining trees still is extremely unbalanced. Hence, we calculated a confusion matrix with the classification results averaged from 100 iterations (Table 5).

Table 5 – Confusion matrix of the tree classification based on random forest.

		Reference		
		Clove	Non-Clove	**User Accuracy**
Prediction	Clove	1946	1339	**59.2%**
	Non-Clove	805	19190	**95.9%**
	Producer Accuracy	**70.7 %**	**93.5%**	

From a total of 2751 validation clove trees, on average 1946 were correctly classified as clove trees over 100 iterations. Slightly less than a third was incorrectly classified as non-clove tree. The vast majority of 20529 circular objects were used as non-clove tree validation set. Out of these, 19190 were correctly classified as being not a clove tree. 1339 were classified as clove trees although actually being a non-clove tree. These values result in 70.7% producer accuracy (PA) for clove trees and a 93.5% PA for non-clove trees averaged over 100 iterations. The user accuracy (UA) for clove trees is 59.2% and 95.9% for non-clove trees. Deduced from the confusion matrix, the classification has an average accuracy of 77.6% and a mean accuracy of 84.2%. The Kappa coefficient is 0.59.

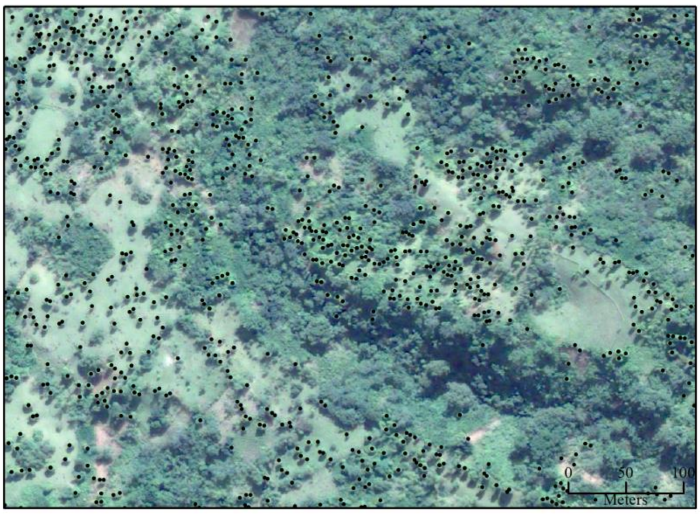

Figure 10 – Excerpt of the study site showing all automatically detected clove trees.

2.4.3 Production type classification

To evaluate the production type classification, a two-step validation system corresponding to the two classification steps has been applied.

LULC classification

To validate the first classification step, the LULC classification, the reference LULC classes were split into a training and validation set. Each set contained 40 training/validation plots for each LULC class. The confusion matrices from the random forest classification based on this validation set can be seen in Table 6. In order to find out by how much the inclusion of tree related information (cluster analysis and distance) has improved the classification result compared to the prevalent LULC classification solely based on spectral reflectance, the classification was performed twice. The left side of Table 6 shows the results of the classification solely based on the spectral reflectance values. The right side shows the confusion matrix of the classification combining both, tree related information and spectral information. For both confusion matrices, the results again were averaged over 100 random forest classification iterations.

Table 6 – Confusion matrices of the LULC classification. The left confusion matrix shows the classification result using spectral features only, the right matrix the classification results when both, spectral features and tree related information features, were combined. The results are averaged from 100 iterations.

	Spectral features only						Spectral features & clove related features					
Reference/ Prediction	Grassland	Plantation	Forest	Rice / bare soil	Urban	User Accuracy	Grassland	Plantation	Forest	Rice / bare soil	Urban	User Accuracy
Grassland	27	9	0	4	0	**67.5%**	30	8	0	2	0	**75.0%**
Plantation	19	14	6	1	0	**35.0%**	3	31	6	0	0	**77.5%**
Forest	0	5	35	0	0	**87.5%**	0	4	36	0	0	**90.0%**
Rice / bare soil	2	1	0	35	2	**87.5%**	0	1	0	38	1	**95.0%**
Urban	0	0	0	0	40	**100.0%**	0	0	0	0	40	**100.0%**
Producer Accuracy	**56.3%**	**48.3%**	**85.4%**	**87.5%**	**95.2%**		**90.9%**	**70.5%**	**85.7%**	**95.0%**	**97.6%**	

Using only spectral information for LULC classification resulted in an OA of 75.5%. This is 12% less than the OA of the combined classification (87.5%). As all classes here are perfectly balanced, OA is in this case a suitable measure for the reliability of the classification. It also becomes apparent that all UAs and PAs (except for the UA of urban areas) are inferior compared to the combined classification. While the rather clearly distinctive classes, forest, rice paddies/bare soil and urban areas perform well, the spectrally very similar classes, grassland and plantation pose a problem to the algorithm. For

grassland, the UA is 67.5% and the PA 56.3%. Plantation's UA is even lower with only 35.0% and also the PA is lower with 48.3%.
For the combined approach, the best user accuracies are achieved for the classes rice paddies/bare soil and urban as both of them are very well distinguishable even solely based on spectral inputs. Rice paddies/bare soil achieved an UA of 95% and for the urban class even all samples were correctly classified resulting in a 100% UA. The PA for the two classes are very high with values of 95% again for rice paddies/bare soil and 97.6% for urban areas. Forest was classified with a UA of 90% and a PA of 85.7%. The classification algorithm was slightly more challenged by the spectrally very similar classes grassland and plantation. The classification of the plantation samples resulted in a UA of 77.5% and a PA of 70.5%. The UA for grassland was even slightly worse with a value of 75%. However, the PA of 90.9% is once more a very good classification result. Still, this is a much better result than the one achieved by using solely spectral information to classify the LULC classes. The average and mean accuracy is 87.5% for the combined approach, the Kappa coefficient is 0.67.

While the classification result of the spectral approach will not be used any further due to its inferiority to the combined classification result, it still is a good indicator of the importance of tree related information obtained from CHT and tree classification. It also indicates the importance of applying this additional information in a second classification step to further refine the classification output and be able to distinguish productive and non-productive LULC classes.

Production type classification

To validate the second classification step, the production type classification, equalized stratified random sampling was applied on the entire study area to get 20 samples per production type. These samples were then classified by the expert. Subsequently, the expert based classification was compared with the classification outputs of the production type classification. The outputs from this validation are displayed in Table 7.

Table 7 – Confusion matrix of the production type classification

Reference Prediction	Pasture	Clove plantation	Agroforest	Grassland	Forest	Rice / bare soil	Urban	User Accuracy
Pasture	17	1	1	0	0	1	0	85.0%
Clove Plantation	4	13	3	0	0	0	0	65.0%
Agroforest	0	0	13	0	7	0	0	65.0%
Grassland	0	0	0	17	1	2	0	85.0%
Forest	2	0	2	0	16	0	0	80.0%
Rice / bare soil	0	0	0	1	0	19	0	95.0%
Urban	2	0	0	0	1	3	14	70.0%
Producer Accuracy	68.0%	92.9%	68.4%	94.4%	64.0%	76.0%	100.0%	

The OA of the production type classification is 77.9%. The averaged UA over all classes is as well 77.9%, the averaged OA over all classes is 80.5%. The Kappa coefficient is 0.74. As Table 7 shows, the class accuracies are more heterogeneous than in the LULC classification. Both, pasture and grassland have a UA of 85% while grassland shows a much higher PA (94.4%) compared to pasture's PA of 68%. Also, plantation and agroforest have the same UAs of 65% each, while their PAs again vary. Plantation has a PA of 92.9% while the PA of agroforest is 68.4%. Also forest itself has a higher UA (80%) than PA (64%). Rice paddies/bare soil again were well classified regarding the UA of 95% and the PA of 76%. Urban areas were classified inferior to the LULC classification regarding UA (70%), while the PA increased to 100%.

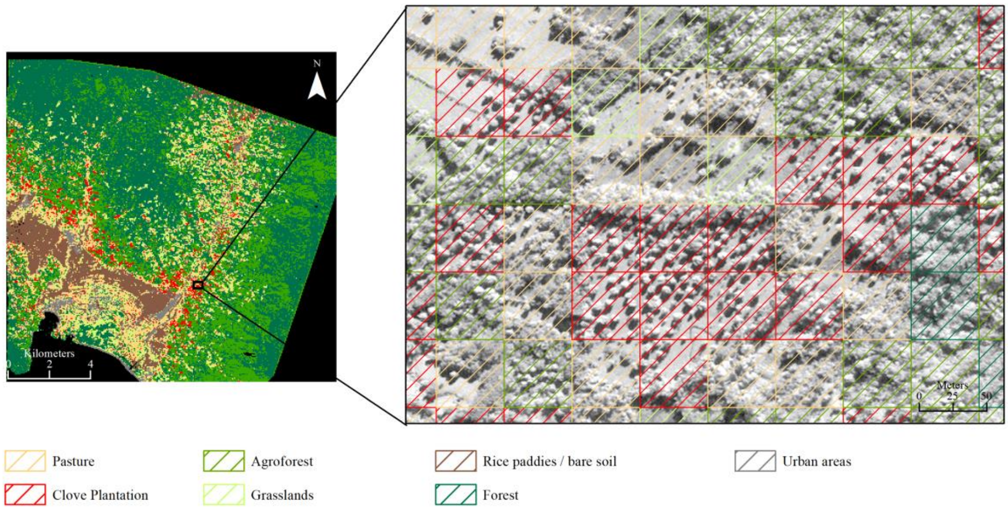

Figure 11 – Shows the result of the production type classification for the whole study area (left) and an excerpt (right).

2.4.4 Clove bud yield per production type and further production type statistics

Our calculations have shown that with an estimated per-tree yield of 3 kg, a total yield of about 575 tons of cloves is produced in the entire study area. In addition to calculating total yield, we have also calculated the average yield per type of production. Furthermore, we have calculated the average clove density and the average distance between clove trees per production type (Table 8).

Table 8 – Average clove tree density and average distance between clove trees per 1 hectare production type plot.

	Pasture	Plantation	Agroforest
Average densitiy [trees/ha]	17.5	70.9	21.0
Average distance [m]	10.8	6.5	10.2
Average yield [kg/ha]	53	213	63

According to our calculations, pastures produce an average yield of approximately 53 kg/ha. A similar amount is achieved in agroforests. Here, the yield per hectare is 63 kg. Clove plantations, on the other hand, produce considerably more dry clove buds due to the higher number of trees. Here, the yield is about 213 kg/ha. The average clove tree density and distance for both pastures and agroforest are in the same range of about 20 trees/ha and 10 m respectively. The average distance of about 6.5 m between clove trees on plantations is also confirmed by Maistre (1964) and Danthu et al. (2014).

One of the main objectives of calculating the average clove bud yield, as well as the clove density and the distance between clove trees per production type, was to be able to complement data from the literature with our data. We consider this to be important, as there is little information on cloves and their production in Madagascar so far, and therefore each additional study contributes to a better understanding of this crop and its local cultivation.

Table 9 – Summary of data found in literature about clove production systems in Madagascar supplemented by the information obtained in the present study.

	Pasture				Clove plantation				Agroforest			
	Density [trees/ha]	Distance [m]	Yield dry [kg/tree]	Yield dry [kg/ha]	Density [trees/ha]	Distance [m]	Yield dry [kg/tree]	Yield dry [kg/ha]	Density [trees/ha]	Distance [m]	Yield dry [kg/tree]	Yield dry [kg/ha]
Celio 2016	-	7-10 5.7-7.4	4	-	-	5-7 6.4	-	-	-	7.1	5	-
Levasseur et al. 2012*	354 50 Mean: 202	-	0.47** 0.048** Mean: 0.26**	167 2.4 Mean: 84.7	96	-	2.4**	230	337 156 Mean: 246.5	-	1.5** 0.72** Mean: 1.11**	509 113 Mean: 311
Lobietti 2013	180	-	-	-	239	-	-	-	195	-	-	-
Locatelli 2000	-	-	-	-	150 Range: 30-300	8	3 Range: 3-25	-	-	-	-	-
Ministère des Affaires étrangères 2012	-	-	-	-	-	4-5	2-5	450	-	-	-	-
Present study	18	11	3***	53	71	6.5	3***	213	21	10	3***	63

* Values from Levasseur et al. 201 are sampled at two different sites; mean was calculated for this study
** Values calculated by us by dividing the reported yields/ha by the amount of trees per hectare
*** Estimate based on literature survey

Our calculations are based on the assumption that a clove tree produces an average of 3 kg of dry clove buds over the years. Assuming an average yield of only 2 kg instead, the total amount of dry clove buds produced would be (linearly) reduced to 383 tons for the entire study area. Assuming 5 kg/tree, however, the yield would increase to 959 tons. Since not only the choice of yield per tree but also other factors such as the farmers' decision to harvest cloves or leaves influence the final yield, we have additionally calculated the number of productive trees. This is the number of CHT detected clove trees located in an area classified as a clove production type (Table 10).

Table 10 – Number of clove trees on clove production areas in the entire study area

	Pasture	Plantation	Agroforest	Total
Number of trees	4‘236	40‘833	108‘545	191‘743

2.5 Discussion

2.5.1 Single tree detection

From the results obtained by applying CHT to detect clove trees we infer that CHT is a promising algorithm for automated single tree detection. The detection is of similar quality for the different production types as well as in different topography resulting in varying illumination (Figure 7). This approach also excelled in regard to its easy applicability. While other approaches require several steps to detect tree crown centres and crown boundaries, CHT automatically provides these outputs in one go. CHT is especially well suited when the tree position is of major interest in order to count trees or deduce tree densities. Approximations about tree sizes and hence potential tree ages are also feasible. However, reducing tree crowns to circular shapes will not be suitable for all tree species and will not give exact tree crown delineations as they might be required for some applications.

Although the CHT detection rate and crown delineation outputs are promising, CHT as it was applied in this study also revealed some weaknesses. Due to the algorithm’s nature to initially search for gradients in the image, not only circles representing trees are found but also various other circular objects. It showed that the algorithm is especially affected in urban areas as well as in areas of bare soil or grasslands with bright reflection spots.

The potential solution of applying a NDVI mask to mitigate this challenge (at least in the urban areas) was discarded due to the extensive shadow areas in the tropical forest which would have been masked out as well. Another solution to mitigate the hypersensitivity to circular objects is to decrease the algorithm’s sensitivity parameter and increase the edge threshold parameter. Both adjustments will result in less detected circles. We haven’t applied these adjustments as it was our primary goal to detect as many reference clove trees as possible. Another potential solution to reduce the number of detected circles might be to apply a filter in advance of CHT in order to eliminate weak gradients as they might occur on pastures.

In the present study, CHT detected too many circles due to the site specific presence of various land covers instead of just forest. We suppose that scenes containing exclusively trees and especially scenes from homogenous forest patches (as for example found in coniferous forests) would perform better. Still the general challenge which CHT poses is the detection of all kind of circular objects and not only the desired ones.

Hence, one has to be aware that CHT for single tree detection can almost only be used in combination with a subsequent classification if the study area consists of different land cover types. This is necessary in order to end up with circles indicating trees or a specific tree species only. We show that tree species classification based on CHT outputs is possible for the clove tree classification in this study.

2.5.2 Tree species classification

Random forest based clove tree classification resulted in outcomes with a producer accuracy of almost 71% and a user accuracy of almost 60%. Compared to the values of Baldeck et al. (2015), the classification results in this present study are lower. Considering the different preconditions of the studies, these values are evaluated as acceptable.

In our case, the classification was complicated by various factors. Precious information about tree height was not available. Also, it was not possible to take advantage of any blossoms that would have clearly distinguished the tree species from others. Furthermore, only visually acquired references were available as fieldwork in such a vast and remote area was not practical. Although generated by an expert, errors might exist in the reference data. As the principle for the reference collection was to only mark trees as references of which we were certain of it being a clove tree, omissions are very likely. This might explain a small part of the rather high error of commission concerning clove trees.

The major challenge that reduced the classification quality was most likely the approximated tree crown delineation. Although CHT circles do represent the tree crown approximately, the delineation is difficult and thus an impureness of the spectral signatures might occur.

There are two kinds of imprecise delineations. One is that the detected circle is too small. This occurred mainly for very large non-clove trees, such as for example Mango trees, as they exceed the predefined radius of the CHT. This leads to only the rather bright upper part of the tree crown being captured. Hence, the reflection of this tree object was brighter and of lighter green causing the algorithm to misclassify it as a clove tree. This partly explains the rather high number of false positives.

The other challenge is that the detected circle is too large. This is mainly occurring with small trees with shadowing effects. As the detected circle is larger than the actual tree, the shadow is figured into the calculation of the spectral signature as well. Hence, the spectral signature appears darker and the tree is classified as non-clove. This explains part of the false negative classification results.

Another challenge is the above mentioned detection of circular objects not being trees. As the training and validation sets were located in vegetation-only areas, mainly the detected circles on bright pastures are problematic. The bright spots on the pastures feature a very similar spectral signature as the top of clove trees. Therefore, circles located on pastures often were misclassified as clove trees resulting in additional false positives.

The feature importance for the tree classification showed a rather low importance of approximately 0.3 for most features. We suppose this low feature importance to result from the high similarity of cloves and the surrounding vegetation, resulting in similar, for the differentiation not particularly meaningful features. The features with the highest importance are standard deviation of the spectral reflections in the bands blue, green and NIR as well as the skewness of the NIR channel per tree crown. Furthermore, some of the features calculated by the 'extractFeatures' function (The MathWorks Inc. 2012) showed a rather high importance. The most important feature of all, with a feature importance of 0.65, was the standard deviation of the crowns spectral reflectance in the NIR channel. The importance of the NIR channel is also apparent when looking at the false-color image where the clove trees have a slightly different hue compared to the surrounding vegetation (see Figure 3).

It turns out that clove tree classification correctly eliminated most of the circular objects which were not trees (e.g. bright spots on pastures/bare soil) and also provided a reliable overall classification of the separation of clove trees from other trees. Considering the varying terrain and illumination effects, the classification output is promising to use it as input for the clove production type classification.

2.5.3 Production type classification

LULC classification

The LULC classification performed very well and produced a high overall accuracy. The combination of spectral information with specific single tree related information such as tree class (clove/non-clove) or tree location resulted in a 12% better classification result compared to utilizing spectral information only.

When looking at the feature importance, spectral data naturally shows very high importance with an average feature importance of 0.7 on a scale from 0 to 1. The improvement of the combined classification very likely results from the maximum distance between trees per plot feature and the information about HL-outliers (an outlier featuring a high (H) value which is surrounded by features having a low (L) value). Their feature importance is 0.7 and 0.71 respectively. This confirms that the main land cover classes such as urban areas, bare soil or forest are well classifiable with the common and well known spectral approach. However, as soon as classes are more alike, further information is required for a high quality of the classification. Even more information is required to distinguish the specific land use classes, pasture, clove plantation and agroforest from the non-productive LULC classes.

Production type classification

The production type classification based on clove thresholds is of high quality as can be seen in Table 7. The decrease in OA accuracy compared to the LULC classification results from the training and validation being no longer based on our homogeneous and ideally class representing references, but on the very heterogeneous grid cells laid over the entire study area. Introducing a grid over the entire study site resulted in many grid cells containing a mixture of classes as for example a plantation surrounded by agroforest. While this is induced by the local circumstances of heterogeneous small scale farming, applying a different approach such as using irregular objects (e.g. Hay et al. 2005, Mallinis et al. 2008) might have mitigated this effect. We still propose the grid approach for our purpose being very suitable. Reasons are on the one hand the training of the random forest classifier and on the other hand the outputs required to be referring to one hectare as measuring unit. Successfully applying a random forest classifier requires the features of the data to be classified to be equal in scale to the features of the training data. By using a regular grid where the cells to classify have the same size as the references, this requirement was fulfilled. Furthermore, our thresholds were calculated in relation to a certain area which is why the objects to be classified must have the exact same area. In addition, the calculations of the clove tree densities and the amount of clove yield per hectare were facilitated.

Going more into detail of the production type classification output, we observe some class accuracies improve while others decrease. Most noticeable is the decrease in UA in urban areas. The main source of error regarding this class was the misclassification of sand (along the beach) and highly reflective bare soils as urban areas. This misclassification, however, already occurred in the first classification step. When the LULC classes were classified, none of the references encompassed such a region (e.g. sand) as only ideal representations of a class were chosen as references. Therefore, this misclassification was not noticed in the beginning as the validation of the LULC classification was based on the ideal references and not randomly sampled grid cells.

Regarding the production types, all of them were reliably classified. The main reason why clove plantation and agroforest achieved only an UA of 65% is caused by the setting of the threshold. Setting thresholds to separate classes to a certain degree is always problematic as the model is strict. This was observed in clove plantations. Some plots were classified as plantations although they would have been pastures. Two different reasons were identified critical. On the one hand, more plantations would have been (correctly) classified as pastures by setting a lower threshold for the plantation to pasture reclassification. On the other hand, also setting a threshold for the reverse reclassification pasture to plantation might have been required.

In the Agroforest class, the threshold challenge is similar. The main problem here is that clove trees also occur naturally in the tropical forest without being used commercially. The rather low threshold of two trees is thus also reached by forest regions which, due to their location, are actually not suitable as agroforests. In order to counteract this problem, a further information parameter would have been necessary. If an additional parameter such as the distance from settlements would have been included as well, plots being far away from settlements would not have been reclassified.

Another reason for the rather low values of PA and UA for the agroforest class could also have originated from the agroforest class as such. Agroforest is not specifically defined. Rather, it is a plot where various plants are cultivated based on the farmer’s personal needs and depending on the plots location. Hence, agroforest plots cannot be standardized and thus are more difficult to classify than other classes.

2.5.4 Clove bud yield per production type and further production type statistics

The calculated yields are also influenced by the determination of values and the application of thresholds. The yield value of 3 kg/tree, based on a majority found in the literature, is a choice that has far-reaching consequences. Although this value can be regarded as relatively reliable, yields for the study area vary by several hundred tonnes, depending on the value used for the calculation.

The thresholds set in the production type classification also lead to further uncertainties in the yield estimate. As one can see in Figure 11, a large forest area is classified as agroforest due to the low thresholds. However, the actual number of agroforest systems is likely to be lower in reality. Consequently, the yield generated in agroforest systems will probably be lower than calculated in this study. The average yield generated in a single agroforest system, on the other hand, is likely to be slightly higher than calculated. This is because the majority of agroforest parcels in our case have only 2-3 clove trees, whereas agroforest parcels close to villages often include 4-7 clove trees resulting in a higher yield. On the other hand, some trees in the vicinity of villages, which according to our classification grow on non-producing areas, have not been taken into account in the yield calculation. Although this is likely to provide a slight compensation for the overestimation of the yield generated by agroforest systems, it might not be able to cancel it out.

Due to the absence of validation possibilities of the calculated yields, it is difficult to estimate the accuracy of our calculations. If one compares our values with those of other studies (Table 9), one can see that our yield values per production type are considerably lower. However, this is probably due to the fact that the clove tree density in most of the other studies was many times higher than in our study area.

A contrasting picture emerges when comparing our yield with the official FAO figures. According to FAOSTAT (n.d.), Madagascar exported 11687 tonnes of cloves in 2013. For 2014, when the used satellite images were taken, no official trade data exists yet but the clove production is estimated to be 10851 tonnes (FAOSTAT n.d.). According to our calculations, 575 tonnes of this total of dried clove buds would be produced in our study area. This would be about 5.3% of the total clove production in Madagascar. This value is very high, especially considering how small the study area is compared to the area of Madagascar. We therefore assume that our calculated yields tend to be rather too high.

This can also be explained as it was possible to decide whether a tree was used for the production of cloves or for the production of leaves to produce essential oil. Since the latter is incompatible with clove bud harvesting, it must be assumed that only a certain fraction of the detected clove trees in the production systems are actually used for the production of clove buds. In situ or statistical data would be required to define this fraction.

2.6 Conclusion

In this study we used state of the art remote sensing data and methods to detect and classify clove trees into the three prevalent clove production systems in Madagascar. We have shown that Circular Hough Transform (CHT) is a promising and comparatively simple to use method for automated single clove tree detection in a tropical forest. This method is especially effective when the location of a tree and only an approximate delineation of the tree crown are required. A high detection rate of 97.9% of clove reference trees was achieved.

The outputs from CHT were used to produce a clove tree classification based on a random forest classifier. Especially information from the NIR band was important for the distinction of clove trees from other trees. The tree classification result in turn was used to successfully classify the three clove production types: pasture, clove plantation, and agroforest. Combining spectral with tree related properties for the production type classification resulted in an overall accuracy of 77.9%.

Based on the classified production types, we estimated the clove bud yield in the study site to range from approximately 53 kg/ha in pastures to 213 kg/ha in plantations (63 kg/ha in agroforests). Our analyses, however, have shown that more in situ or statistically reliable yield data is required to address the large uncertainties in these calculations. We thus strongly encourage further research, especially in the in situ data acquisition of crop yields and the fraction of trees used for the clove bud production.

For the first time, we show that clove trees and clove production systems were classifiable on a large scale based on remote sensing data. Still, we encourage applying and further improving the insights gained in this study about the procedure from object-based single-crop detection to yield estimation to other regions or even for other crops.

3 Discussion

The initial aim of this master thesis was to inform the r4d project "Managing Telecoupled Landscapes" about methodological possibilities of remote sensing to classify clove production systems in north-eastern Madagascar. The common idea was to automatically identify the clove trees in the study site as it has been done in other scientific papers about tree detection. The information about the clove tree's positions could then be used to identify all areas belonging to one of the three clove production types. As soon as it is known where these production types are located, they can be spectrally analysed and a classification of clove production types can be performed on a larger scale. In the course of this thesis, however, it soon crystallized that there are some major obstacles impeding quick and straight forward implementation of the original idea.

In this discussion, the research questions presented at the beginning of this thesis will be answered, and the difficulties that prevented the initially planned implementation will be explained.

3.1 How can single tree crowns in tropical forests be detected and delineated in an automated way using multi-spectral satellite data?

3.1.1 The challenge

In 2015 Baldeck et al. (2015) wrote: *"[…], the preferred model was based on crown-mean spectra, and thus operational species mapping would require automatic delineation of tree crowns throughout the image prior to applying the classification model to predict species identity. At the time of the study [2005], the ability to accurately, automatically delineate individual tree crowns in a closed-canopy tropical forest did not exist, and nearly a decade later it still does not."* Also Baldeck et al. (2015) were forced to delineate all their training crowns by hand as no solution to automatically do so existed. It was thus part of this Master's thesis to first find a solution to this nontrivial challenge to later classify the clove production systems.

In the beginning of the thesis, the most common approaches such as finding local maxima and minima were tested to find single trees in the study area. While local maxima detection worked out rather well also in this tropical setting, finding local minima to create the 'valleys' around the tree crowns caused problems. The main challenge was the inhomogeneous land cover and the dense canopies composed of trees very diverse in shape and size. This inhomogeneity had two effects. On the one hand, it resulted in a very discontinuous network of minima with lots of gaps, dead ends and entire accumulations of local minima pixels. Especially gaps were very problematic as unclosed networks will not allow correct region-segmentation originating from the local maxima seeds. On the other hand, the canopy of the tropical rainforest sometimes was too dense to find any local minima or only a few single pixels indicating local minima. Consequently, it was difficult to create a (closed) network to perform region-segmentation.

Different solution from the literature did not improve the outcome in this complex setting. Pre-processing the image by masking out areas which are not forest/vegetation (Gougeon and Leckie 2006) was not feasible due to vast shadow areas within the forest itself. Masking them out led to a great loss of necessary information. Also, the application of filters (Culvenor 2002) was not as successful as expected. Information content was lost and most of the gaps still could not be closed. Performing edge-detection only on the most suitable single-band found by using Principal Component Analysis (PCA) (Wang et al. 2004) was as well was not as successful as hoped for. In addition, varying the scale at which local minima were searched (Wang et al. 2004) resulted in no considerable improvement for a consistent local minima detection to perform successfully.

3.1.2 The solution

In order to overcome these challenges, an approach was sought where the single trees are not dependent on each other, that is, no continuous network is required to detect single trees. Therefore, an algorithm was required which can detect individual objects in an image. Benefitting from the circular shape of the clove trees (i.e., circular objects) the Circular Hough Transform (CHT) algorithm (Duda and Hart 1972, Atherton and Kerbyson 1999, Rizon et al. 2005) was investigated (see section 2.3.1 for a description of this algorithm). CHT is a combination of a bottom-up tree detection algorithm and a flexible template matching algorithm. It outputs circle centers and circle radii for all the circles detected in the image. The CHT is said to be robust to the presence of noise, varying illumination conditions as well as to occlusion (The MathWorks Inc. 2012). By applying this algorithm, 97.86% of all reference clove trees in the image were detected.

3.1.3 Advantages and disadvantages

CHT has various advantages which are especially valuable in the context of the r4d program. CHT is very simple to apply if there is a readily implemented function available. Only very few initial parameters (e.g. radius, edge threshold) have to be set by the user. Hence, CHT can be viewed as an automatic single tree detection algorithm. Furthermore, CHT can be applied to various scales. Due to the individually adjustable radius size for which the algorithm has to search the image, this parameter can be freely adjusted depending on the image and its resolution used for the tree detection.

CHT is able to detect and approximately delineate single trees in a VHR multi-spectral satellite image. This is especially valuable in the context of the r4d project, as multi-spectral satellite images meet all user requirements of the project. This data is rather inexpensive and globally available. Consequently, CHT to detect single clove trees as shown in this thesis can be applied for the other study sites in Laos and Myanmar as well by even using the same sensor with the same properties allowing global comparison. Additionally, CHT not only outputs the tree crown center but an entire ‘tree object’ as it also gives an approximate delineation of the tree crown. As already mentioned earlier, image objects allow gaining a multiple amount of information compared to single pixels, what in return is very favorable for the tree classification later on (Chubey et al. 2006).

The downside of this algorithm is that not only clove trees or trees in general are detected but all circular objects present in the scene. Hence, in our case this algorithm found millions of other circular objects besides the desired clove trees. It thus is indispensable to further process this output in order to filter out the undesired objects.

Another disadvantage is that vast amounts of data are generated as every single tree is saved as an own entity. This requires a suitable data storage infrastructure. Furthermore, one has to be aware that to accomplish this task, individual trees have to be recognizable in the image, so that the CHT algorithm can find them reliably. This implies that only VHR data is suitable for this purpose, which means that the large, long-time data archives of Landsat or more recently Sentinel-2 cannot be used with this method because of the too low spatial resolution.

3.1.4 Recommendations for the r4d project

With regard to the r4d project, there is a high potential of the CHT algorithm to detect clove trees in Madagascar (see section 3.1.3). However, as will be shown in the next step of the tree species classification, the amount of data generated by this approach could be a major challenge. An alternative to this approach, which is based directly on tree species classification, is therefore presented in section 3.2.4. Additional considerations, which have to be made with regard to the whole project, are explained in section 3.3.4.

3.2 How can clove trees be detected/classified in an automated way using the spectral properties of the canopy?

3.2.1 The challenge

While single tree detection in tropical forests as such already is a demanding task, also the subsequent tree species classification is a challenge in the tropics. Again, Baldeck et al. (2015) describe the problem at hand precisely:

*"In a foundational study, Clark et al. [7] [*Clark et al. 2005*] attempted to classify seven canopy tree species from a diverse Costa Rican rainforest based on their remotely-sensed hyperspectral signatures collected with the airborne sensor HYDICE. Their most successful model classified the crowns of their study species with 92% accuracy. Despite these encouraging results, this classification model could not be used to map any of the seven study species across the study site. The primary reason for this was that the classification model differentiated the seven study species from one another, but not from the hundreds of other tree and liana species present at the site."*

The incredible density of different tree species and thus finding suitable features that enable clove trees to be distinguished from the surrounding vegetation are therefore a great challenge when it comes to classifying individual tree species in the tropics.

3.2.2 The solution

To overcome the 'mapping' challenge, Baldeck et al. (2015) propose a one-against-all classification method based on binary Support Vector Machine (SVM) and biased SVM. This approach was adopted in this thesis by reducing the clove tree species classification to a binary problem. This was done by training the random forest classification algorithm on two classes only. One class contained the clove trees and the other class all the other detected circular objects regardless of what these circular objects represented (e.g. other trees, grasslands, bright circular spots in urban areas etc.). Instead of the SVM classifier a random forest (RF) classifier was used. This is because RF have been shown to provide high class accuracies for classification problems in remote sensing and ecology (e.g. Breiman 2001, Pal 2005, Lawrence et al. 2006, Cutler et al. 2007, Watts and Lawrence 2008, Dalponte et al. 2012). Furthermore, fewer parameters have to be set compared to SVMs where several parameters have to be defined by the user (Pal 2005, Lawrence et al. 2006, Dalponte et al. 2012). Another advantage of RF is that this method is less prone to imperfect data such as unbalanced data, unscaled data or missing values (Pal 2005).

To perform the classification, features describing the objects' properties had to be calculated for all the detected circular objects. Various compositions of different feature sets were investigated to optimize the classification result. Classification attempts with only spectral features as input were not accurate enough. For this reason, structural features ('extractFeatures' function (The MathWorks Inc. 2012) and 'HOG features' (The MathWorks Inc. 2013)) were taken into account as well. The finally extracted features are described in Table 3.

Although it was possible to classify the clove trees on the basis of these calculated features, looking at the feature's importance shows that many features were only moderately important for recognizing the cloves. This fact indicates the general difficulty of recognizing a certain plant species among many other plants. The most distinctive spectral features were the standard deviation of the spectral reflection in the blue, green and NIR bands as well as the skewness of the NIR channel per tree crown. It also showed that some of the features calculated by the 'extractFeatures' function (The MathWorks Inc. 2012) had a rather high importance as well. This indicates that no only spectral but also structural features were important for the classification. The final classification resulted in a producer accuracy of 70.7% and a user accuracy of 59.2% for cloves trees.

These accuracies are lower than the ones Baldeck et al. (2015) achieved in their tree classification. A closer look, however, reveals that the point of departure for the two studies cannot be compared directly. While it was a prerequisite of this thesis to be able to automatically detect and delineate single trees (see section 2.3.1), Baldeck et al. (2015) had manually delineated the tree crowns of all their training trees. Having perfect tree delineations allowed them to classify the trees on a pixel basis. Thus, they could search their scene for matching pixels which in the end were then aggregated to individual crowns. In our case, the automatically produced tree crown delineations were satisfactory but not accurate enough to simply feed all the pixels within a delineated crown to the classifier as training data. Hence, we could not classify pixels but rather had to classify the entire objects. Furthermore, it showed that the model of Baldeck et al. (2015) did not successfully classify tree crowns with diameters of 5 meters or smaller. The clove trees in our study are rarely exceeding diameters of 8 meters; most had a diameter of less than 6 meters. Another advantage of Baldeck et al. (2015) was that their entire study area was completely covered with very dense tropical rainforest. Hence, there were no other (natural) land covers having very similar spectral properties such as for example grasslands.

3.2.3 Advantages and disadvantages

When talking about the approach here, we mean the combination of the single tree detection on object level and the classification of these single tree objects. Because if the output of the single tree detection had been different (i.e. no tree objects), a different classification method would have had to be chosen.

An advantage of this approach was that information about both, clove trees and non-clove trees were gathered at the same time. Knowing the location of all the objects in both classes provided information about the forest composition. With this information, for example, the cluster analysis (ESRI n.d.) for the LULC classification (see section 2.3.3) could have been carried out. When a certain tree class is classified on the pixel level, however, no information is gathered about the location or species of the surrounding or not classified trees.

The disadvantages of object-based tree species classification are all related to the incredible amount of objects generated by CHT detection. Calculating features for almost 8 million objects is computationally demanding. Hence, a powerful computer as well as enough processing time is required to perform such calculations. Furthermore, vast amounts of data are generated what makes data organization demanding and cumbersome. Finding solutions to these two challenges took months, with the automated calculations themselves ultimately taking another month on a high performance desktop computer.

Hence, the time it takes to calculate the features for all objects and the enormous amount of data generated present challenges regarding the scalability of this method to the three entire research areas of the r4d project.

3.2.4 Recommendations for the r4d project

One of the prerequisites given by the project was that the clove trees could be detected and delineated automatically. Based on this premise, the approach to detect individual trees with the help of CHT was developed. With this approach, it was also automatically determined that tree species classification must be carried out at the object level. As mentioned above, there are some advantages (see Chubey et al. 2006), however, it was at the same time demanding in terms of time and computational power.

It is thus questionable if the automatic detection and delineation of clove trees in the long term of this project is feasible. Thus, it is highly recommended to investigate the manual delineation of clove trees for training and then perform a classification on the pixel level.

Classification on the pixel level was performed by Baldeck et al. (2015) and resulted in high classification accuracies (see however the different starting points of the two studies in section 3.2.2). Their approach was as follows: first of all, representative specimens of the tree species to be classified were searched for in the imagery data and manually delineated. Next, all pixels within these crown borders could be used as training pixels for this species. Afterwards, all pixels in the image were classified using the trained classification algorithm. Collections of such classified pixels of this species were then grouped into 'crown blobs'. Detailed information about the pixel-level approach can be found in Baldeck et al. (2015).

Although not tested in this thesis, the approach of classification at the pixel level might be faster and computationally less expensive. Classifying clove trees on a pixel and not on the object level might also enable tree classification based on images with a slightly lower spatial resolution than the imagery used in this thesis. One or two pixels per tree might be enough to capture the essential information of a clove tree if the training data is pure due to the perfect manual delineation, while several pixels were required to classify a crown object in the approach of this thesis.

Still, some challenges might arise in the step of the LULC classification as cluster analysis, as it was performed in this thesis, is not possible anymore. This is because pixel-level classification would only provide the location of the clove trees but no information about the other non-clove trees in the area is provided. However, in a pinch, maybe also the LULC classification solely based on spectral information could be used as basis for the subsequent production type classification. As only the amount of trees is required for the final production type classification, this step would not be influenced if reasonable 'crown-blobs' were found.

Of course, these are all assumptions and it is not clear whether the approach of Baldeck et al. (2015) can actually be transferred to our research area because of the different local conditions. In addition, it is likely that many unexpected hurdles will also arise with the pixel-level approach. Nevertheless, from the point of view of the r4d project, it would certainly be worth to test this option.

Another way to avoid the challenge of handling the large amount of data with only the limited computing capacity of desktop computers would be to consider cloud computing infrastructures. Depending on which service is used, however, additional costs might occur. An interesting possibility would be to use a cloud infrastructure like the Google Earth Engine. This platform could offer a suitable solution to adhere to the object-oriented approach of this thesis. However, the methodologic and parallel-computing restrictions were not investigated in-depth during this thesis.

3.3 How can clove production types be classified and what are the respective production rates quantified on a regional level?

3.3.1 The challenge

In the beginning of this thesis, the single tree detection and classification approach was performed with the intention to gain information to distinguish the three production types (pasture, clove plantation and agroforest) from each other. It was assumed that this was possible solely based on the information about the clove tree density, the distance among the clove trees and the spectral information for each production type. In the course of this thesis, however, it crystallized that not the distinction among the production types was the main problem but the distinction of the production types from their surrounding environments.

This is a well-known challenge when it comes to classifying land uses (e.g. Barnsley and Barr 1996, Cihlar and Jansen 2001, Zhang and Wang 2003, Lackner and Conway 2008). While land cover in remote sensing data can usually be classified on the basis of spectral information, this is not possible in most cases with land use. Land use classes are in general spectrally barely different from the land cover classes they belong to (Aplin 2003, Lackner and Conway 2008). For this reason, the challenge in land use classification is to find further parameters that allow a more detailed, spectrally independent differentiation.

With regard to the calculation of the clove yield in the study area, the biggest challenge is that there is hardly any reliable information on the basis of which the exact yields could be calculated.

3.3.2 The solution

It was found that the only parameter allowing a distinction between the productive land uses, pasture, clove plantation and agroforest and the other non-productive LULC classes is the number of clove trees. While non-productive areas have none to only few clove trees, the clove production types feature more clove trees per area.

For this reason, we have calculated the minimum number of clove trees in each production type based on our clove and production type reference areas. If this minimum number is reached in the areas to be classified, they are classified as clove production type. If the minimum number is surpassed, the area is classified as productive LULC area (Figure 9).

Based on this knowledge, a 2-step classification procedure was applied (Figure 8). First, the five LULC classes, grassland, plantation, forest, rice paddies/bare soil, and urban areas were classified.

Subsequently, the calculated minimum-thresholds were applied to distinguish the clove production types from the non-productive LULC classes.

The overall accuracy of the LULC classification was 87.5%. It could also be shown that performing this classification on spectral information only, resulted in a 12% lower overall classification accuracy when spectral and tree related information were combined. Tree related information was implemented by performing a cluster analysis and calculating distances among the detected trees. In the cluster analysis, the information from the tree species classification was utilized. The cluster analysis showed for example where there are significant clusters of cloves or non-cloves and in which areas no significant clusters were found.

As with the tree species classification, different combinations of features have been tested to achieve the best possible classification. When trying to use only the features with a feature importance of more than 0.6, extreme overfitting of the classifier occurred. This resulted in all the grid cells being assigned to 3 classes only. Thus, all features, regardless of their importance, were used to finally train the classifier (see section 2.3.3).

The second classification step, in which the calculated thresholds were used, was validated by applying an equalized stratified random sampling method. The overall accuracy of this final production type classification was 77.9%. The three clove production types were classified with a user and producer accuracy (UA/PA) of 85%/68%, 65%/92% and 65%/68% for pasture, clove plantation and agroforest, respectively.

The clove yield estimates were calculated by combining the gained knowledge about where the areas used for clove production are and how many clove trees there are on these areas. An attempt was made to mitigate the weak point in this calculation, namely the lack of reliable yield data, by collecting and comparing different data from other studies on cloves and clove production systems. The value of 3 kg/tree was the most frequently mentioned, which is why this value was used in the present study to calculate the yields.

3.3.3 Advantages and disadvantages

It is questionable to what extent one can talk about advantages and disadvantages of both solutions described here. The solutions applied are much more the consequence of the previous decisions and methods used, leaving little room to consider other possibly better solutions.

The LULC classification showed the advantage of object-based tree detection and tree species classification. Due to the output produced there, it was possible to perform a cluster analysis and thus visibly improve a classification that was otherwise often based on spectral values only.

A considerable advantage of the application of thresholds in the final production type classification is its fast and efficient application. The thresholds themselves are relatively simple to calculate and the (re-)classification can also be done based on a few mathematical operations. Consequently, there is no need to train a classifier again.

However, at the same time the biggest disadvantage of the final production type classification is the use of thresholds. This makes the (re-)classification strict, which does not correspond to the natural, flowing transitions between the different classes. Furthermore, only one parameter, namely the number of cloves, has been taken into account. Additional parameters, such as the distance to the settlements, could at best have further improved the final result and mitigated the strictness of the thresholds. The way in which the thresholds were calculated can also be viewed critically, although no official data was available here either, so that the thresholds had to be based on some kind of own calculations anyways.

As far as yield calculations are concerned, the simple applicability must be emphasised as an advantage. There are no major disadvantages as such, but there is a weak data basis, causing the overall results to be not really representative and reliable. While the yield per tree of 3kg seems relatively realistic and is supported by multiple references in the literature, no parameters influencing the yield could be taken into account due to missing reference data. Particularly noteworthy in this context is the parameter providing information on how many of the trees are used on average for clove production and how many are used for the production of the essential oils. Trees that are used to produce the oil cannot be used to produce clove buds. Thus, the final yield would be reduced depending on the fraction of the detected trees used for the production of clove buds.

3.3.4 Recommendations for the r4d project

It should be investigated whether it is possible to classify clove production types and, above all, whether these findings can be up-scaled to the whole of Madagascar.

As it turned out, it is basically possible to classify clove production types with a high accuracy. However, it was only possible to detect production types by the number of present clove trees. This means that information at the single tree level is required to classify the production types.

Hence, while it was time-consuming and technically complex to calculate all features for the 8 million detected objects in the study area (see section 2.3.2 and 3.2.3) it will be difficult if not impossible to calculate the features for all the trees on Madagascar with the currently available means. Even if data handling should be somehow feasible by using cloud computing infrastructures, it has to be considered that cloud-free VHR multi-spectral data has to be obtained for the whole of Madagascar. This is difficult due to the high fractional cloud cover in Madagascar. In addition, this would also be correspondingly expensive.

However, the urgently needed acquisition of additional information on clove trees and especially clove yields seems to be much more realistic. This thesis has shown that an estimation of clove yields can be achieved by remote sensing methods, but the values available for the final calculation still contain too little information and therefore lead to a high uncertainty. This means that if sound knowledge about locally generated clove yields should be obtained with the help of remote sensing, the data basis must first be improved. It is thus paramount to invest more time to systematically collect reliable reference data on the ground.

4 Conclusion

This master thesis contains a scientific paper chapter demonstrating the successful classification of clove production systems in Madagascar on the basis of remote sensing data.

Despite the challenges in tropical rainforests, individual trees could be reliably detected and classified. It was shown that CHT is a very promising method for automated single clove tree detection in tropical forests, resulting in the high detection rate of 97.9% for the clove reference trees. This method is especially suitable when the location of a tree and only an approximate delineation of the tree crown are required. The object-oriented approach linked to the Circular Hough Transform also enabled a reliable classification of the clove trees. While this approach was computationally demanding, it was also possible to extract structural information about the trees thanks to this approach. Based on this information, the classification was considerably improved. The tree classification result was used to successfully classify the three clove production types pasture, clove plantation, and agroforest. Combining spectral with tree related properties for the production type classification resulted in an overall accuracy of 77.9%.

For the first time, single clove trees and entire clove production systems could be reliably classified and mapped for a large study area. On the basis of this information, it was not only possible to calculate further information such as clove yields, but also tracking future changes in clove production will now be possible. However, due to the limited in situ reference data basis on clove yields, our yield estimates have to be assessed carefully before further usage. Hence, this thesis has shown that a reasonable estimate of clove yields in north-eastern Madagascar can be achieved by remote sensing methods, but more reliable data on the production of cloves have to be collected on site before a reliable statement about locally generated clove yields can be made.

It would be exciting to apply the approach developed in this master thesis to other regions or for other crops. If more reliable yield data can be collected and the performance of this approach be further improved, the insights gained in this way offer an excellent alternative to the little official crop production data available.

Declaration of Authorship

Personal declaration: I hereby declare that the submitted thesis is the result of my own, independent work. All external sources are explicitly acknowledged in the thesis.

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Place, Date	Signature

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