Determining oil palm age from high resolution satellite imagery

Abel Chemura
March, 2012

Course Title: Geo-Information Science and Earth Observation for Environmental Modelling and Management

Level: Master of Science (MSc)

Course Duration: September 2010 – March 2012

Consortium partners: Lund University (Sweden)
University of Twente, Faculty ITC (The Netherlands)

Determining oil palm age from high resolution satellite imagery

by

Abel Chemura

Thesis submitted to the University of Twente, faculty ITC in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation, Specialisation: Environmental Modelling and Management

Thesis Assessment Board

External Examiner	Prof. P. Pilesjö
Chair	Dr. Ir. C.A.M.J. de Bie
First Supervisor	Dr Iris van Duren
Second Supervisor	Ir. L.M. van Leeuwen

UNIVERSITY OF TWENTE.

ITC

FACULTY OF GEO-INFORMATION SCIENCE AND EARTH OBSERVATION

Disclaimer

This document describes work undertaken as part of a programme of study at the University of Twente, Faculty ITC. All views and opinions expressed therein remain the sole responsibility of the author, and do not necessarily represent those of the institute.

To my mother and to the loving memory of my father,
Ferguson Chomunoda Chemura

Abstract

Expansion in area under oil palm production has been reported to cause widespread environmental impacts. The Round Table on Sustainable Palm Oil (RSPO) was then formed with a mandate to promote sustainable palm oil production and consumption. Criterion 7.3 for RSPO certification requires that all oil palm planted after 2005 must not have replaced primary forests or other high conservation value forests. The objective of this study was to therefore develop an objective and accurate remote sensing-based method that can indicate time of planting by determining age of the oil palm for application in RSPO certification. Field data on crown area and age were collected from the study site in Ghana and used to develop an empirical function predicting age from crown area. Object-based image analysis techniques were also used on a WorldView-2 image to obtain the crown area of oil palm. The crown area obtained from the object based method was then combined with the empirical function to predict age of the oil palm per field. There was a strong linear relationship between age and crown area of oil palm up to 13 years ($p<0.001$, $R^2=0.88$) beyond which no relationship was observed. The RMSE and MAE for age prediction based on crown area were around 1 year while the percentage error was 8.2%. Although the delineation accuracy depended more on stand characteristics than on age, delineation for the older oil palms (13 years) had the least accuracy (D=0.59). An overall oil palm crown delineation accuracy of 0.69 (D=0.31) was obtained. The developed approach accurately estimated oil palm ages for 27.9% of the fields, with ±1 year accuracy for 74.6% of the fields and with ±2 year accuracy for 92.4% of the fields. The prediction showed that 6 and 11 year old oil palm dominate age categories in the study area. Field characteristics such as existence of weeds and intercrops determined delineation parameters and strongly affected delineation accuracy. As these varied between stands, a field-level method was found appropriate although it is not fully-automated. Major improvement required is in the delineation of crown area. The study developed and demonstrated an approach that is useful not only for RSPO certification for Criterion 7.3 but also for spatial planning, impact assessment and precision farming in the oil palm sector.

Key words: RSPO, certification, age determination, palm oil

Acknowledgements

This study could not have been successful if it were not for the assistance, contributions and cooperation I got from very important persons. I give my sincere gratitude to my first supervisor Dr Iris van Duren whose guidance helped me to properly shape this research work. In addition, I am grateful to my second supervisor Ir Louise van Leuwen also for guiding me through this research process. The input of Dr Kies de Bie is also greatly appreciated. I am also indebted to Dr Michael Weir at ITC, Mr Ofori, Mr Kyei and Mr Fynn at Juaben Oil Palm Outgrowers Cooperative Society (JOPOCOS) and staff of the faculty of Natural Resource at KNUST(Ghana) particularly Mr. L. Addae-Wireko for making our field data collection in Ghana not only productive but enjoyable. I wish to thank my colleagues Enock Mutanga and Isaac Kwesi Nooni for the collaboration during field data collection.

I am also very grateful to the Netherlands Fellowship Programme (NUFFIC) for affording me an opportunity to pursue a dream MSc course. The facilitators, professors, lecturers and support staff of the GEM course in different countries are also thanked for impacting on me very valuable knowledge and skills and organizing the quality study. The participants of the 2010-2012 GEM course are also greatly appreciated for the collaborations and the quality time we have shared, you are truly precious "gems". The "in-laws" deserve a special mention. I also want to thank my colleague Dumisani Kutywayo, my brother Shepherd and my beloved Sitshengisiwe for the support and encouragement during my studies. This research project and the entire study also drew a lot of inspiration from Anninlla-Nyasha for whom I will always work hard for.

Table of Contents

List of figures

List of tables

Chapter 1: INTRODUCTION

1. 1Background

Palm oil is obtained from the African oil palms [*Elaeis guineensis* Jacq.]; monocotyledonous perennial plants indigenous to West Africa. Oil palms are widely grown in more than 43 countries mainly between 10^0N and 10^0S of the equator (Hardter, et al., 1997). There are two kinds of palm oil, palm kernel oil and crude palm fruit oil, and their uses as a food resource, in oleochemical industry and biofuel sectors depend on this categorization. The palm kernel oil is obtained from the seed or the kernel inside the hard-shell mesocarp yielding around 80% saturated fatty acid (oleic) and is mainly used in the manufacture of soaps, detergents and other toiletries in oleochemical industries (Basiron, 2007; Hardter, et al., 1997). Crude palm fruit oil is obtained from the soft flesh or mesocarp of the fruit. It is rich in both saturated and unsaturated (palmic) fatty acid and is used as ingredient in many foods, in leather, metal and chemical industries as well as feedstock for biofuel.

Annual global production of palm oil is over thirty-five million metric tons with Malaysia and Indonesia contributing around 80% of global production (Fitzherbert, et al., 2008; Germer & Sauerborn, 2008). The total area currently under production is over thirteen and half million hectares, the majority being under large scale plantation system operating as a nucleus of many smallholder producers (Butler, et al., 2009). Consequently, palm oil is the second most important source of vegetable oil after soybean (Fitzherbert, et al., 2008; Tan, et al., 2009). The large areas, high levels of production and wide use of palm oil have been realized in the past three decades (Figure. 1.1) due to increased demand for food, industrial and fuel products vis-à-vis the great production potential of oil palms to meet this demand.

Oil palm has the highest potential yield per hectare of all sources of vegetable oil (Corley, 2009). It can produce twice more oil than rape seed and almost four times more than soy beans, groundnut and sunflower per hectare per year (Tan, et al., 2009). Due to increasing demands for palm oil as a food resource in China, India and South America and as a biodiesel in the European Union global production is increasing at a rate of 9% annually (Koh & Wilcove, 2008; Tan, et al., 2009).

Realising this great potential, Ghana has set to increase area under oil palm by 2000ha annually under the President's Special Initiative (PSI) on oil palm plantation and exports mainly through expanding large scale plantations (Duku, 2007; Holbech, 2009). At this target, 300 thousand hectares of land are to be converted to palm oil production in the main palm oil production zone that covers the Western, Central, Brong Ahafo, Ashanti, Eastern and Volta regions(Carrere, 2010; Duku, 2007).

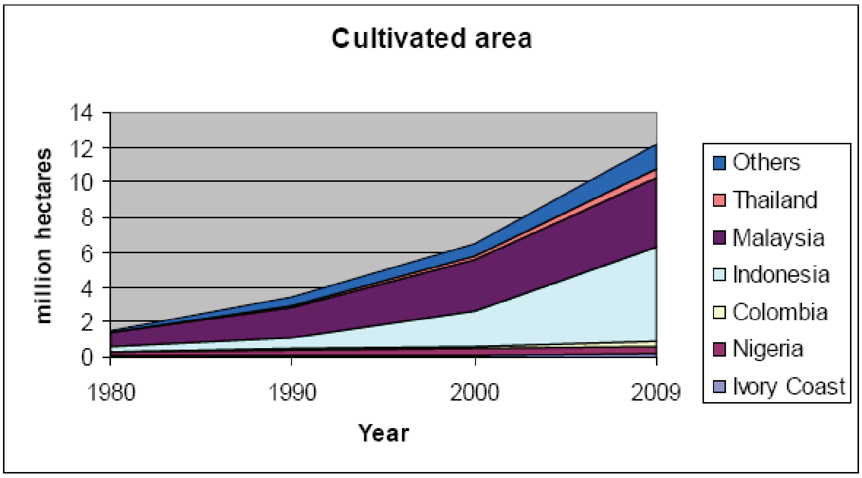


Figure 1.1:Growth in area under palm oil production:1980-2009 (Tan, et al., 2009)

Area under production in Ghana was 304 000ha by 2004 with smallholders having 88% of this land under oil palm but producing 72% of the output (Carrere, 2010; Duku, 2007). In addition, wild palm grooves covering nearly 2 million ha are an important source of palm oil and palm wine. The fact that the smallholder plantations dominate the palm oil scene in Ghana dates back to the colonial era where policies for making locals own land were promoted. However, due to the multiple failures of the government-run oil palm plantations; private companies bought them and entered the palm oil production sector in Ghana from the 1980s (Gyasi, 2003).

1.2 Problems of oil palm expansion

As market demand for palm oil products increases and societies seek profitable options for economic survival, the area under palm oil has tremendously increased in almost all major producing countries. There are concerns about the growth of palm oil production in West Africa at the expense of primary forests that provide provisioning and regulating ecosystem services at different scales (Gyasi, 2003; Norris, et al., 2010). In addition, in South-east Asia, where over 80% of global palm oil is produced (Corley, 2009) there have been widespread reports on the ecological impacts of oil palm expansion (Fitzherbert, et al., 2008; Friends of the Earth, 2007; Stone, 2007). Deforestation is among the greatest concerns about global oil palm expansion (Tan, et al., 2009; Wicke, et al., 2011).

As the oil palm plantations expand, they have resulted in significant land cover change on previously forested areas that are habitats for many endemic species (Laurance, et al., 2010; Ravindranath, et al., 2009; Tan, et al., 2009). For example, palm oil expansion has been blamed for direct and indirect contribution to species extinction (Corley, 2009; Koh & Wilcove, 2008; Norris, et al., 2010; Stone, 2007). This is worrisome because there is an overlap between palm oil production zones and biodiversity hotspots(Fischer, et al., 2009; WWF, 2007). In addition, conversion of forests, particularly in peatland ecosystems, contributes significantly to greenhouse gas emissions (Fitzherbert, et al., 2008; Laurance, et al., 2010). Furthermore, these tropical forests are important in water retention and other hydrological processes as well as for evapotranspiration that keeps the tropical areas moist (Tan, et al., 2009).

In addition to being habitats and sinks of carbon, forests provide important ecosystem services to populations living around them. The conversion of land to oil palm results in lost access to forest services that are part of livelihoods of communities living around forests (Friends of the Earth, 2007; WWF, 2007). Further, social issues related to land transfers and tenure systems that come with acquisition and/or sale of large pieces of indigenous land to oil palm companies are of concern (Achten, et al., 2010; Friends of the Earth, 2007).

Although palm oil is mainly used as a food resource and is reported to significantly improve socio-economic status of producers (Härdter, et al., 1997), when it is produced for biofuel it competes for land with food crops and this undermines food security and nutrition especially at local levels (Fischer, et al., 2009; van Dam, et al., 2008). Although the majority of these problems have been reported in Malaysia and Indonesia, where the greatest proportion of palm oil is produced, the types and scale of impacts reflect the problems faced by the global palm oil industry.

Certification of palm oil may be an option in addressing the sustainability issues facing the global palm oil sector. According to Dankers (2003) and Dries & Mancini (2006), certification is a market-driven mechanism where an independent assessment by an accredited third party provides assurance to end-users that products or services meet set standards. Standards (also referred to as code of practice) are a list of technical conditions used to define, guide and determine if products, services or processes comply with the quality, environmental, organic, labour, social or other requirements (Barjolle, et al., 2010; Dankers, 2003). Certification can therefore be viewed as a way of communicating to consumers that products have been produced in a way they approve. This communication is usually accomplished by certificates when between sellers (producers) and buyers (retailers), and through labels when between the retailers and final consumers (Dankers, 2003). A certification body was therefore formed to foster certification of palm oil.

1.3 The Roundtable for Sustainable Oil Palm Production (RSPO)

Certification may guarantee sustainability in palm oil production through ensuring social and environmental accountability. In this regard, the Roundtable on Sustainable Palm Oil was set up to develop and implement principles and criteria that promote and reward sustainable palm oil production in all producing countries through certification (Laurance, et al., 2010; Tan, et al., 2009). RSPO is a non-profit, industry led organization whose mandate is to support production and marketing of certified palm oil for the global market in a clear and transparent manner through a multi-stakeholder approach (RSPO, 2007). Its stakeholders include palm oil producers, buyers, environmental advocacy groups, governments and others involved in the palm oil production chain.

In 2005, the RSPO produced thirty-nine criteria organized into eight principles for certification of sustainable palm oil and by 2010, about ten per cent of all palm oil produced had RSPO certification (Laurance, et al., 2010; Scarlat & Dallemand, 2011). RSPO pays great attention to environmental issues as demonstrated in its criteria and twenty-five per cent of its executive board members are from environmental advocacy groups (Laurance, et al., 2010). RSPO dedicated criteria 5 and 7 to directly address environmental issues. Principle 7 deals with responsible development of new plantings, under which criterion 7.3 specifies that all new plantings must not have replaced primary forests or other important habitats (RSPO, 2007).

Although, RSPO has achieved notable success in the short time since its establishment, it faces a number of challenges. Among these challenges is the lack of efficient monitoring and enforcement of principles for RSPO certification (Laurance, et al., 2010). In addition, since palm oil is produced in 4 continents and over large areas, ensuring that members are adhering to set principles and that certified palm oil is produced in a sustainable way, is a daunting task for RSPO. Despite these challenges, RSPO has great potential to ensure that the palm oil sector is meeting increased demand for palm oil without aggravating the ecological and socio-economic conditions. Furthermore, with growing awareness and lobbying for sustainability as production and demand increases, certification will soon be a requirement for market access (van Dam, et al., 2008).

For certification of sustainable palm oil production, several criteria are defined by the RSPO. Assessment of a number of these criteria requires reliable spatio-temporal information that is expensive, time-consuming and arduous to collect using field-based methods. Therefore, a remote sensing enhanced certification approach has potential to provide sustainability assessment for palm oil production at reduced cost and subjectivity. Laurence, et al. (2010) recommended that RSPO applies remote sensing and other geospatial tools to enhance the certification process. Geospatial technologies can be used for all criteria with a spatial component, applied in real time and over vast plantations in many parts of the world (Laurance, et al., 2010; Scarlat & Dallemand, 2011).

1.4 Remote sensing for land cover change assessment

Remote sensing has provided a tool for efficient assessment of land cover and resources at local, regional and global levels (Turner, et al., 2003).

Identifying and quantifying land cover change is among the principal applications of remote sensing. Comparing images taken at two different time periods for change detection is the classical but still useful way of determining land cover/use change (Lillesand & Kiefer, 2008). Overall classification accuracies of above ninety percent have been reported with this approach (Foody, 2002; Rogan & Chen, 2004). However, this approach cannot show when exactly the change occurred because the chances of error in dealing with a series of medium resolution images increases and using high resolution images for this purpose is very expensive and also that they may not be available (Wu, 2009). The exact time of change that is missing in this multitemporal approach may be important for some applications of change detection such as those required for RSPO certification.

To obtain the information about when exactly the land cover changed, hypertemporal methods that analyse temporal NDVI profiles on low resolution imagery have been used (Rosenqvist, et al., 2003). For example, Lunetta (2006) demonstrated how hypertemporal MODIS NDVI data could be useful for identifying exactly when land cover change occurred for forest certification decisions. While this approach indicates when exactly the land cover change occurred, the spatial resolution of hypertemporal images such as MODIS and SPOT is often too course for studying localized changes (Lillesand & Kiefer, 2008). Mapping localized changes is important because ecosystem modifications due to palm oil expansion can occur at scales ranging from a few meters to many kilometers. In addition, the classical approach depends on repeat images which in tropical areas such as Ghana are not reliable because of cloud cover. Since the classical approach and the temporal analysis are not very appropriate for the intended purpose of supporting RSPO certification, an object-based image analysis (OBIA) approach could be a promising option.

1.5 Object-based image analysis

Object-based image analysis is defined by Hay & Castella (2006) as a discipline in spatial science that focuses on partitioning remote sensing imagery into meaningful objects through utilization of spatial and spectral properties. The concept of analyzing an image in object space rather than in pixel space is developed due to the inadequacies of pixel-based methods especially on high resolution images and also supported by advances in computational capacities and availability of high resolution satellite images such as IKONOS, GeoEye and WorldView (Blaschke, 2010; Navulur, 2007). OBIA is intended to mimic the human interpretation of remote sensing imagery and provide accurate and detailed spatial information that would normally take experienced people long time to process. Although the roots of OBIA are linked to medical and industrial image analysis (Blaschke, 2010), it has shown a lot of potential for applications within the remote sensing community.

Automated feature extraction and classification is the main use of OBIA in remote sensing across environmental, urban, surveying, planning, forestry and other sectors (Blaschke, 2010; Lang, 2008). Studies that compared object-based image analysis and pixel-based image processing have consistently concluded that object-based image analysis results in better classification accuracy and feature extraction compared to pixel based approaches. These studies ranged from forest inventory, urban applications , habitat identification and change detection as reviewed in detail by Gamanya (2007), Hay & Castella (2006) and Blanschke (2010). OBIA is therefore considered as the future of remote sensing because of its potential applications and widespread adoption in the remote sensing community (Hay & Castella, 2006; Navulur, 2007).

The advantages of OBIA were summarized by Nuvulur (2007) and Blanschke (2010) and were mainly centered on its ability to incorporate spatial and contextual properties. The dimensions that OBIA can utilize to improve classifications in addition to spectral characteristics are shape, morphology, shape, temporal aspects and metadata. OBIA also integrates the best of current image processing approaches such as fuzzy logic, knowledge classification and kernel-based methods giving the user many options in solving complex classification and feature extraction problems (Navulur, 2007). Therefore, identification of individual objects on high resolution such as tree crowns opens new opportunities in mapping and monitoring forests and other resources.

1.6 Research conceptual framework

Palm oil is relatively cheaper to produce and has higher productivity than other vegetable oils. When increased demand for palm oil as a food resource is coupled with increases in fossil fuel prices and instability in many of the oil producing countries (Tan, et al., 2009), there is growing potential demand for palm oil in the global market. For instance, the EU has set a target for a minimum of twenty-per cent replacement of fossil fuel by biodiesel by 2020 in all its member countries, creating additional demand for palm oil in the energy sector. Increased palm oil production provides socio-economic opportunities at household and country scales that help reduce poverty and underdevelopment. However, land clearance to expand production comes with ecological costs that contribute to climate change and habitat loss. It is conceptualized therefore that RSPO certification is important for dealing with a multiplicity of issues at different scales while a remote sensing approach is useful for providing information about the spatial features at different levels of the oil palm system important for RSPO certification (Figure 1.2).

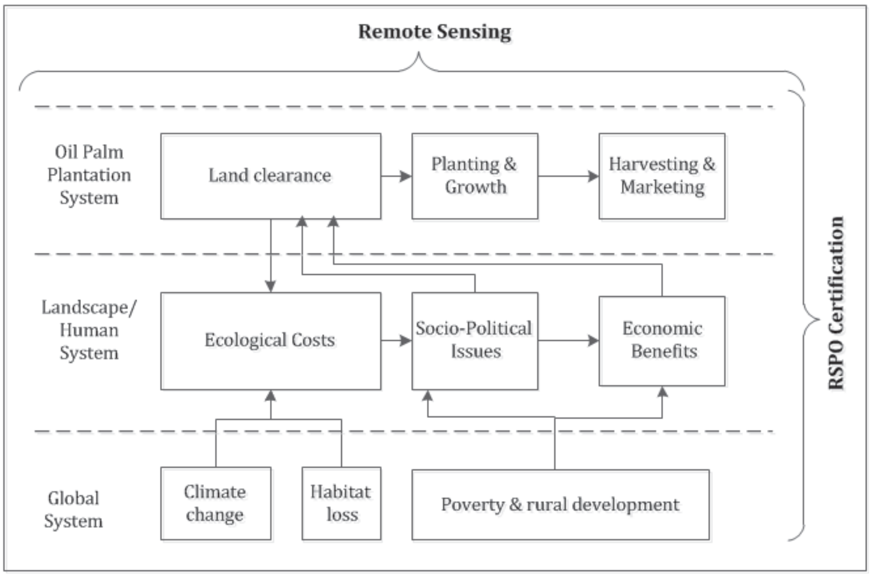


Figure 1.2: Sustainability components of an oil palm production system

The RSPO aims to harmonize increases in plantation productivity for economic development with ecological integrity, based on the concept that more can be produced at less impact to the environment (Figure 1.2). In order to achieve this goal, the RSPO needs effective monitoring mechanisms and remote sensing provides many opportunities to fill this gap.

1.7 Research problem

There is need for a novel approach that is able to accurately detect both the magnitude and time of land cover change for applications such as assessing RSPO certification Criterion 7.3 for Ghana. With Ghana planning to expand its palm oil sector, it is important that this growth is achieved in a sustainable way through following RSPO standards. In addition, information about the acreage, age and expansion of oil palm is important in precision agriculture, spatial planning and strategic impact assessments. Knowing the ages and areas can be useful in precision farming as yields and other management aspects can be easily related to the area and age of the oil palms. For expansion of oil palm with minimal environmental impact on biodiversity, spatial planners need a reliable way of assessing the current production sites in terms of age and area and use this in decision support and policy implementation. Combining OBIA and an empirical model that relate crown area to age provides the best promise to get the area under different ages of oil palm.

This research therefore sought to develop a method to map individual crowns of oil palms and when combined with empirical model; can be useful in determining the age of the oil palms. The specific characteristics for mapping oil palm in OBIA were not yet established, and while research is continuing on improving OBIA methods, this research goes further to apply it in solving environmental problems. In addition, the method was meant to enhance the RSPO certification process as it gives beforehand which areas were planted after the 2005 benchmark for certification. The ages could also be useful for determining amount of carbon stored in oil palm. The nature of oil palm crown also presents further challenges compared to the natural and other plantations for which research has been done. This approach is novel because it has never been applied before in sustainability assessments of palm oil production.

1.8 Objectives

Broad objective

The broad objective is to determine age of oil palm plantations from high resolution imagery for use as indicators of time of conversion to palm oil production required for RSPO criterion 7.3 that states that all oil palms planted after 2005 should not have resulted in deforestation of primary forests and other high value conservation areas.

Specific objectives

The specific objectives were to:

1. Determine oil palm canopy area by object-oriented analysis from high resolution satellite imagery
2. Establish the relationship between canopy area and age of the oil palm from field and satellite image collected data
3. Determine the time of land conversion to oil palm plantations using the satellite-image derived oil palm age
4. Identify where and how much land has been converted to palm oil production before and after 2005 for application of RSPO criterion 7.3

1.9 Research questions

1. To what extent can oil palm canopy area be accurately determined by object-oriented image analysis from high resolution satellite imagery?
2. What is the relationship between canopy area and age of the oil palm trees
3. How accurate is canopy area in predicting oil palm age?
4. Where and when was land converted to oil palm plantations before and after 2005?

1.10 Hypothesis

H_0: There is a positive relationship between crown area and age of oil palm

H_1: There is no significant relationship between crown area and age of oil palm

CHAPTER 2: STUDY AREA

2.1 Palm oil production in Ghana

Oil palm is indigenous to the West African rainforest belt that covers countries such as Ghana, Cameroun, Nigeria, Togo, Nigeria and Cote de Ivoire (FAO, 2003; Gyasi, 1992). Ghana, like other West African countries has therefore a long history of palm oil production, processing and use. Due to their tropical nature, oil palms require well distributed high rainfalls (at least 1600mm/year), many sunshine hours (around 2000/year) and high temperatures of between 20 and 30^{0}C (FAO, 2003; Gyasi, 1992; OPRI, 2003). These requirements have defined a palm oil production belt in the western, southern and eastern parts of Ghana where the conditions are favorable.

Gyasi (1992) categorized the oil palm belt in Ghana into 3 categories; traditional, core and active areas (Figure 2.1). The traditional zones are areas where indigenous people have been producing and harnessing oil palm (including from native grooves) before commercial production. The core areas have a lot of palm oil production in terms of percentage area under oil palm compared to other crops. The zone categorized as other active areas refer to where palm oil is produced but not very dominant on the landscapes as compared to other crops or systems. Of these zones, the core areas and the other active areas are considered as emerging zones meaning that oil palm production has expanded to replace forests and other arable land (Gyasi, 1992).

Ghana is currently the fifth largest producer of palm oil in Africa after Nigeria, Ivory Coast, Benin and Congo (FAO, 2003). The main players in the Ghana palm oil sector are large scale companies such as Benso Oil Palm Plantation Limited (Western region), Twifo Oil Palm Plantations (Central region), Ghana Oil Palm Development Corporation (Eastern region) and National Oil Palm Plantation (Ashanti region) and their shareholding spans from government, private and foreign investments (Duku, 2007). These operate large scale plantations of over 100 ha each and apply highly mechanized methods for management of the oil palms. They also operate in close unison with smallholder farmers who supply them with matter for processing in their mills (Gyasi, 2003).

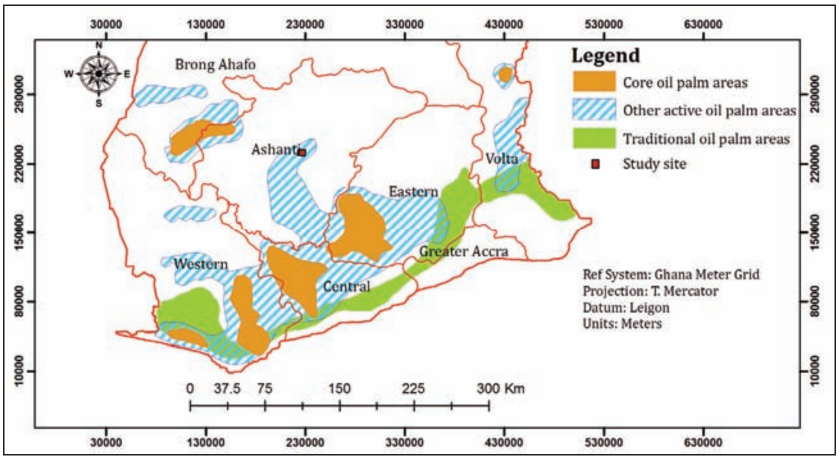


Figure 2.1:Oil palm production areas in Ghana (adapted from Gyasi 1992).

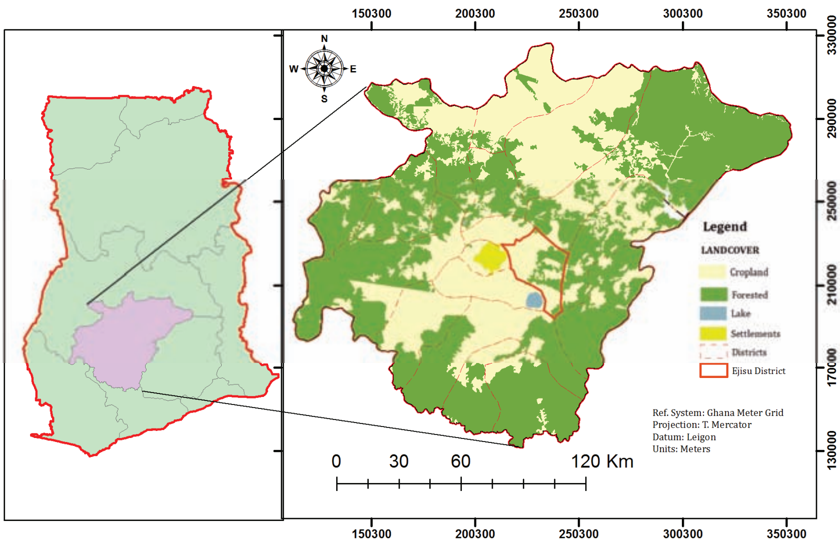


Figure 2.2: Location of Ejisu Juaben District and landcover in Ashanti region of Ghana.

Although natives have been using palm oil (mainly from wild grooves), palm oil production intensified through development of large scale and smallholder plantations for export purposes from as early as the eighteenth century (Gyasi, 1996; OPRI, 2003; WRM, 2010). A nucleus farming system where large scale producers support many smallholder farmers around them through input and technical backstopping is the most common form of oil palm production in Ghana (Carrere, 2010; Gyasi, 1996). The smallholders will in turn payback by providing throughput to the large-scale producers' mills. In terms of both area and total yield, the smallholder farmers dominate the oil palm sector in Ghana (Carrere, 2010). However, they face a number of challenges that reduce production efficiency and output per unit area (OPRI, 2003).

Interestingly, because the production system was skewed towards smallholder family farms, the impacts of Ghanaian oil palm sector on the environment has largely been viewed as minimal (Gyasi, 1996). However, the advent of the three dominant plantations (GOPDC, TOPP, and BOPP) from the late 1970s has raised serious concerns on the sustainability of the plantation system in palm oil production (Carrere, 2010; Gyasi, 1996). Combined, these three plantations account for about 20% of the total area under oil palm in Ghana and contribute around 40% of national palm oil exports (Gyasi, 1996). Increasingly, palm oil production has become important for national economic development particularly for horizontal diversification from cocoa production that dominated GDP for the country.

Several government and donor-initiatives have been implemented to promote the development of both plantation and smallholder oil palm production in Ghana. The most significant of these includes the privatization of government owned plantations in the 1980s that ushered the private sector into palm oil production (Gyasi, 2003; WRM, 2010). Multi-lateral organizations such as the World Bank have also been active promoting the growth and promotion of the oil palm sector in Ghana through funding various aspects of the supply chain starting from 1998 (Carrere, 2010; WRM, 2010). The most recent development has been the President Special Initiative on oil palm export promotion that sought to increase area under oil palm production through provision of healthy high yielding seedlings to both plantation and smallholder farmers (Carrere, 2010; Duku, 2007; WRM, 2010).

2.2 Ejisu -Juaben district

The study was carried out in Ejisu-Juaben district in Ashanti region of Ghana (Figure 2.2).The district is located within longitude 6.42 to 6.83^{0}N and latitude 1.25 to 1. 58^{0}W, covering an area of about 64 000ha (Anornu, et al., 2009). The economy of the district is based on agriculture with cocoa and palm oil production being main cash crops while other crops such as cassava, maize and cocoyam are grown for subsistence (Anornu, et al., 2009). The topography is flat to undulating, with altitude ranging between 230m and 300m and has no major landform features. Dominant soil types are derived from pre-Cambrian rock formations such as granite, Birrimian, Tarkwaian and superficial deposits. Soil fertility, agricultural productivity and cropping patterns are resultantly influenced by the distribution of these soil types (Anornu, et al., 2009).

The climate characteristics are typically equatorial with high mean total annual rainfalls of above 1000mm and high annual mean temperatures. The rainfall pattern is bimodal, the main wet season being from March to July and the minor season from September to November. Mean monthly temperatures vary between 20^{0}C in December/January and 32^{0}C in February/March and when this is combined with frequent rainfalls, results in high humidity (Anornu, et al., 2009). The agricultural calendar follows the rainfall pattern with the main cropping season being from March to July while the minor season is from September to November. There are many perennial and long-season crops produced in the area such as cocoa, plantain and oil palm, and these influence the land cover patterns for most of the year in cultivated areas while considerable area remains forested (Figure 2.2).

The study was carried out in Ghana because Ghana's interpretation of RSPO principles and criteria for certification has been approved (RSPO, 2011) and therefore the methods from this research will be timely in enhancing the certification process for Ghana. In addition, issues around oil palm expansion and land tenure, biodiversity and socioeconomic development have been reported in Ghana (Carrere, 2010; Gyasi, 2003). The specific area of the study has been identified as having a number of land cover change hotspots within the vicinity of forest reserves that are home to a wide range of floral and faunal species (Asubonteng, 2007). A high resolution image that covers large scale plantations and smallholder oil palm farms is available for the study area. In addition, permission has been granted to contact research in the large scale plantations. Studies on oil palm production and its relationship to sustainability are concentrated in South-east Asia and thus this research will provide useful research insight for the African palm oil sector and specifically for Ghana. In addition, developing empirical relationships between oil palm parameters and age may also be useful in the assessment of carbon for the REDD+ for which countries like Ghana are taking part.

CHAPTER 3: MATERIALS AND METHODS

3.1 The Research approach

The research approach for this study can be divided into three interconnected phases. The first phase is the remote sensing and image analysis part that aimed at delineating individual tree crowns through feature extraction using object-oriented image analysis of the WorldView-2 satellite image. The second phase established the relationship between crown area and age from field based measurements. It built on data collected from fieldwork and regression analysis. The third phase combined the regression models developed from field data with the individual crowns delineated from the image processing part to determine the age of the oil palms from the satellite data. This also fed into the last phase of the research where the determined ages were used for building a spatial decision support system for certification (Figure 3.1).

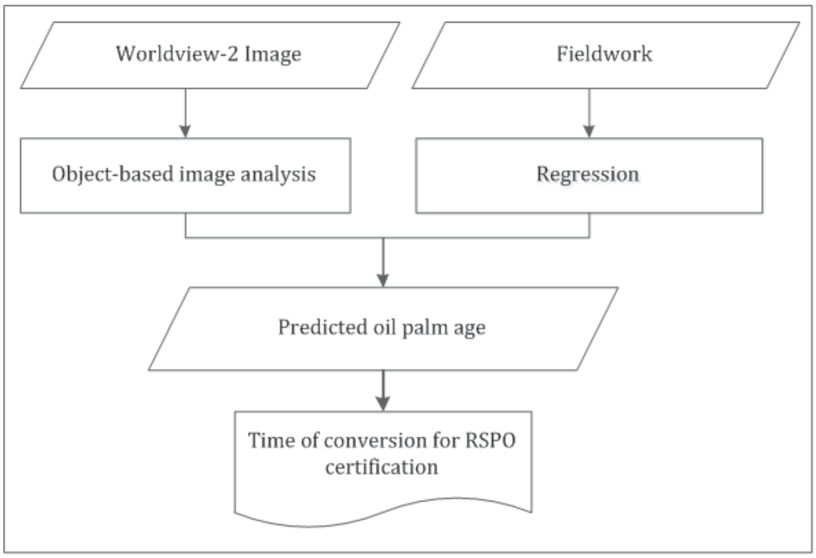


Figure 3.1: Research approach used in the study

3.2 Spatial data

Spatial data was needed in this study for planning fieldwork, data processing and for analysis of the results. The spatial data used can be categorized into three groups; WorldView-2 image, other satellite data and auxiliary spatial datasets obtained from different sources. A WorldView-2 image (Digital Globe) taken on the 4th of January 2011 was used in the study. It has 9 high resolution bands in the visible to the near-infrared range; 8 at 2m spatial resolution and 1 in the panchromatic band at 0.5m. The image has 0% cloud cover and covered an area of 52km^2. This image was chosen because it has diversity of spectral bands providing opportunities for detailed analysis. In addition, with high spatial and spectral resolution it is possible to implement individual tree extraction using object-oriented methods as intended for the study. The metadata of the WorldView 2 image is shown in Appendix 2.

An ASTER image (VNIR, 15m spatial resolution) taken in February 2010, was used to assess the landcover and locations of features in the study area in preparation of field work. Together with the Google Earth (Google®, 2011), the ASTER image was used for navigation to sampling sites as well as for stratifying the age classes in the plantation. Topographic and historical digital maps, digital elevation models and satellite images were used in the study. These were obtained from the ITC database and from Ghana at a Glance database developed by World Bank (2004). These datasets were used for planning fieldwork, navigation and for preliminary studies of the area. These included a 1:250000 topomap, 1:50000 topomap, SRTM DEM, thematic layers (landcover, hydrology, soil type, geology, population, conservation areas and transport network) Landsat Thematic Mapper images (2002-2003).

3.3 Pre-fieldwork

A sampling strategy was developed before going for fieldwork. This involved analysis of landcover in the study area by using the ASTER image and available spatial data and assessment of identification of oil palm plantations from the Google Earth that formed the sampling frame. Field maps were developed for sampling and loaded into the IPAQ for navigation and sample location as well as printed.

3.4 Data collection

Data was collected from fieldwork carried out between 12 September and 14 October 2011 in Ashanti region of Ghana (Chapter 2).

3.4.1. Sampling design

Data was collected from a large scale corporate plantation and smallholder farmers in Ejisu-Juaben district. The objective was to obtain measurements from different age-classes. The exact age classes on the ground could not be established before visiting the study area, but on the 2003 Google Earth image and the 2010 ASTER image, age categories in the corporate plantation were discernable based on canopy cover and the oil palm fields were therefore stratified into young, medium and old stands on the ASTER image. Stratified sampling was used for selecting samples for data collection from stands inside the large corporate plantation. For determining the specific trees to be measured in the plantation and on the smallholder farms, random numbers were generated between 1 and 30 (30 was the minimum number of trees in a smallholder farm for it to be considered for sampling).

3.4.2. Oil palm measurements

Using a field map and IPAQ ArcPad GPS, the location of selected sample sites was determined and this formed a starting point for selecting the stands for sampling. Not all age classes were present in corporate plantation and therefore other samples were collected from smallholder farms, taking into cognisance the different management system between smallholder and corporate plantations. Information obtained from Juaben Oil Palm Outgrowers Society (JOPOCOS) showed that the farm sizes for smallholders ranged between 0.3ha and 17ha and distributed in 25 communities. Communities that fell within the WorldView image boundaries were selected for sampling (Figure 3.2).

Stands sampled were even-aged and measurements were made from north to south orientation of planting rows (Figure 3.3). From the north-eastern corner of the field, the individual trees were counted in rows to the west until the tree with the random number was identified. Once this tree was identified, measurements were taken from the northern and southern tree from the randomly identified tree which formed the centre of the stand (Figure 3.3) 3 trees were measured per stand. This was done so that the exact field measured trees will be identified on the image for comparison between field measurements and remotely sensed crown area.

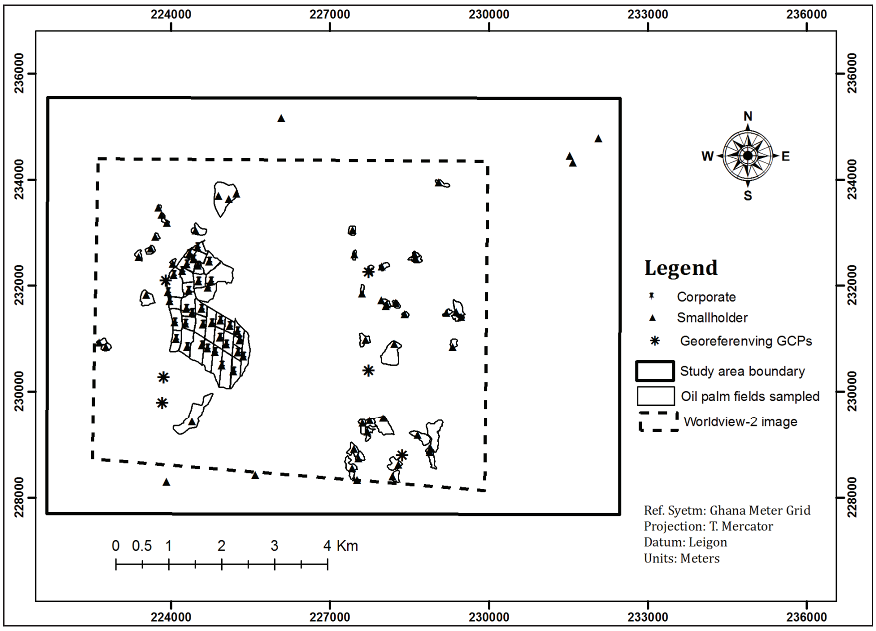


Figure 3.2: Data points on WorldView-2 and ASTER images showing sampling sites

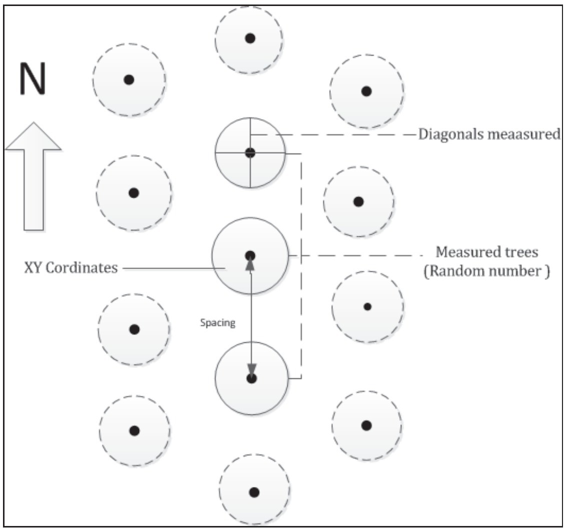


Figure 3.3: Selection of trees to be measured and measured parameters

Crown diameter was measured by recording the ground distance between the drip points of the tree in perpendicular directions for each of the 3 trees using a tape measure. This was done to capture the variation in shape of the tree in different directions and the two measurements were done to intersect at a right angle. Plant spacing was measured at each stand using a tape measure and remarks on the general condition of the field were also recorded. Plant spacing was measured because plant density was shown to have effect on leaf area in oil palms as crowns quickly interlock when spacing is small.

3.4.3. Determining age of oil palm stands

The information on ages of each oil palm stand was obtained through on-site interviews with farmers and extension workers. They were asked to provide the year of planting for that field and all stands where the farmers were not available or the extension worker did not precisely know the year of planting were not sampled. For the corporate plantation, the management that assisted in locating sampling plots were asked to state the year of planting. In addition, confirmation of the provided ages was obtained from records of planting, area and location each section of the plantation. The precision of the obtained ages was therefore in years. It was assumed that field planting of oil palm was done in the main rain season and therefore no significant in-year differences were expected in the years. The year of planting was converted directly to years. The details of each of the data collected and the instrument used are shown in Table 3.1.

Table 3.1: Summary of parameter recorded and reasons for including them

Parameter	Units	Instrument	Purpose for recording
Age	Years	Counts	Building model of age and CPA
Crown Diameter	Metres	Tape	Explanatory variable for the model
Management	Scale(1-2)	Score	Assessing model sensitivity

3.5 Relationship between oil palm crown area and age

To convert the crown diameter to crown area, analysis of the relationship between measured diagonals showed that the basic shape that best represents crown shape is a circle and this was used for calculation of crown area. Data was collected from 88 stands (Research Question 2). A scatter plot of age and crown area (CPA) was made to find the general relationship between the two parameters. After finding the relationship, the best function that described the relationship was fitted to the data to come up with a function that can predict age from CPA. The field data was randomly portioned into 60:40 for model building and validation respectively (Appendix 3). Residuals of the model were checked for normality using Lillilifor's test.

To determine the performance of the regression model in predicting age, statistical analysis was done on the validation dataset (n=29). The coefficient of determination (R^2), significance of the regression (α=0.05) , root mean square error (RMSE, Equation 3.1), mean relative error (MRE, Equation 3.2) and mean absolute error (MAE, Equation 3.3) were used to determine the strength of the model in predicting age from crown area.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum (y_i - \hat{y})^2} \qquad [3.1]$$

$$\mathrm{MRE} = \left(\frac{1}{n}\sum \left| \frac{y_i - \hat{y}_i}{\hat{y}_i} \right| \right) * 100 \qquad [3.2]$$

$$\mathrm{MAE} = \left(\frac{1}{n}\sum | y_i - \hat{y}_i | \right) \qquad [3.3]$$

where for both cases n is the number of data points, y_i is the actual age from field data at that data point and $\hat{y}_i$ is the model predicted age at that data point (Ozdemir, 2008; Suratman, et al., 2004).

3.6 Object-based tree crown delineation

In order to obtain individual crown area from the WorldView image a number of steps were followed (Figure 3.4). After obtaining the individual tree crown area, the results were processed in a GIS environment and combined with the field developed models for prediction of oil palm age from the OBIA-obtained crown area.

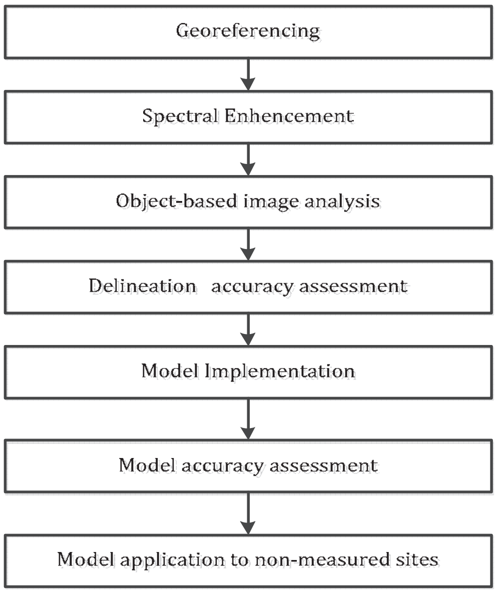


Figure 3.4:Steps in image processing and modelling for age of oil palm from OBIA

Georeferencing and spectral enhancement

Positional accuracy is important for feature extraction from high resolution images. To achieve this, six ground control points collected at road intersections were used for geometric correction. The RMSE for the georeferencing was 0.21m. The WorldView-2 image had 8 multispectral bands (2m spatial resolution) and 1 panchromatic band (0.5m spatial resolution). For determining the individual tree crowns the multispectral bands need to have a higher resolution. To achieve this, pan-sharpening using image fusion was done. Image fusion is merging multispectral images with panchromatic images to achieve high radiometric and geometric resolution. Pan-sharpening is an image fusion approach where lower resolution multispectral pixels are combined with the high resolution panchromatic band pixels to get a high resolution multispectral image (Padwick, et al., 2010).

The hyper spherical colour space (HCS) resolution merge pan sharpening method was used to fuse the panchromatic and the MS bands in Erdas Imagine 2011. HCS is a component substitution sharpening method that was recommended for pan-sharpening WorldView-2 images. This is because it improves contrasts in the image and facilitates recognition of edges and shapes. It is also able to handle a large number of multispectral bands without much distortion (Padwick, et al., 2010). The final result was a 0.5m resolution 8 band MSS image. In order to improve discerning features on the image, a histogram equalisation was done after pan-sharpening.

A 3x3 low pass filter was then used to smooth the image after pan-sharpening. Smoothening through filtering was required to normalise the reflectance between high (bright) and low (dark) frequency features in the images (Lillesand & Kiefer, 2008). This is very important for removing noise and other spatial variations in the image while exposing feature edges and this is known to facilitate the extraction process (Darwish, et al., 2003). This resulted in clear features on the image and after this the image was ready for segmentation.

Since three trees were measured on each stand, the location of each stand was recorded by taking geographic coordinates (xy data) of the centre trees using a GPS (Figure 3.5). In order make sure that the three field measured trees are compared with the segmented crowns, a 17.5m buffer was created around the stand centres and the trees extracted by masking with the buffer. 17.5m was determined to be ideal because the plant spacing was 9m with measurements taken from 3 trees giving a length of 27m and a 17.5m buffer will give circular stand diameter of 35m covering the 3 oil palms actually measured in the field (Figure 3.5). The procedure was repeated on fields where no field measurements were taken in order to harmonize and combine the data. On these fields, the centre of the stand was selected as where there are uniform-looking trees.

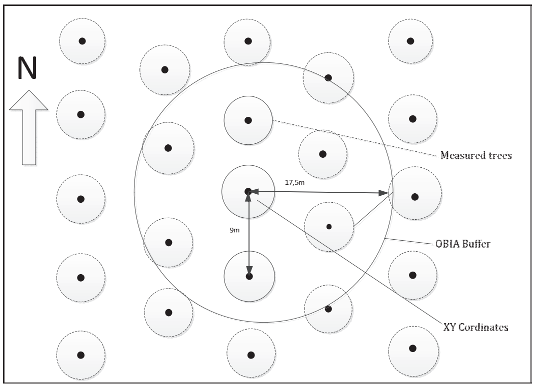


Figure 3.5:Measured trees on each stand in relation to buffers for extraction

Individual crown area delineation

Individual oil palm crowns were obtained through image segmentation in eCognition software. The basis of OBIA is image segmentation which is the grouping of pixels based on their characteristics (Xiaoxia, et al., 2005). Image segmentation algorithms divide the image into semantically significant objects based on their spectral, morphological and other characteristics(Arbiol, et al., 2006). These can be further processed and improved until meaningful objects are derived from the image. Several segmentation approaches have therefore been developed and they vary in terms of both application and simplicity (or complexity).

Image segmentation approaches can be categorized into bottom-up or top-down algorithms. In the bottom-up approach, adjacent pixels are merged to form bigger objects while in the top-down approach bigger objects are cut into smaller objects (Trimble, 2010). These processes are based on homogeneity in spectral, geometric and other statistical relationships (Navulur, 2007; Xiaoxia, et al., 2005). In this study, the bottom up approach (multiresolution segmentation) was used. This was then combined with the ability of OBIA to incorporate other features particularly in the spatial domain, such as relationships, topologies and processes to delineate individual crowns. (Blaschke, 2010; Gamanya, et al., 2007)

Definiens eCognition (Trimble Gmbh®) was used as it has emerged as a leading platform for implementation of OBIA and is closely linked to the development and adoption of cognition network language for remote sensing applications (Blaschke, 2010; Blaschke, et al., 2011). It has a user-friendly interface that hides many libraries and databases for segmentation and classification enabling users to go through the process without much programming requirements. Figure 3.6 shows the stages that were followed in order to delineate the individual oil palm crowns from the satellite image in eCognition Developer.

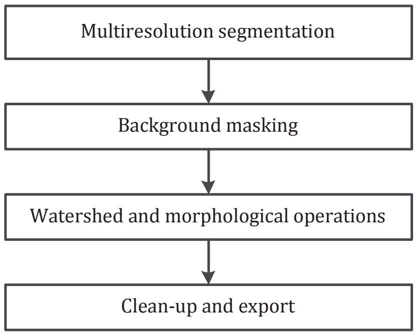


Figure 3.6: Steps used for individual tree crown delineation in eCognition

The Near-Infrared -1 (770–895nm), Red Edge (705-745nm), Red (630-690nm), Green (510-580nm), and Blue (450-510nm) bands were used for tree crown delineation. Of the 8 WorldView-2 bands, these were found most relevant for vegetation and background analysis based on the descriptions by Marshall (2011) and Digital Globe (2009) on the potential uses of the WorldView-2 bands. These were stacked and saved in Erdas Imagine format for processing in eCognition Developer.

Multiresolution segmentation

Multiresolution segmentation was used to cut the image into smaller objects based on band reflectance, shape and colour characteristics. Multiresolution segmentation in eCognition is a region-based algorithm that applies bottom-up approach to segmentation where each pixel is considered an individual object first and then merged to form pairs of similar objects and onwards (Darwish, et al., 2003). Four main settings were used to influence the segmentation. These were the scale parameter, band weights, shape influence and compactness values. In OBIA 'object candidates' depends very much on scale as different scales produce different objects. It is therefore very important to set a scale parameter that suits the size and characteristics of the objects of interest. The ESP tool for estimation of scale parameter developed by Dragut et al (2010) was used to estimate the most appropriate scale parameter. The ESP tool estimates the most appropriate scale parameter by generating sample objects at different scales and then calculating the local variance at each scale. The basis of this approach is that local variance increases with increase in scale parameter (red line in the Figure 3.7). Therefore, the most appropriate scale parameter at which segmentation of the image is best is at the smallest scale with the highest rate of change in variance (first pick in the blue line in Figure 3.7).

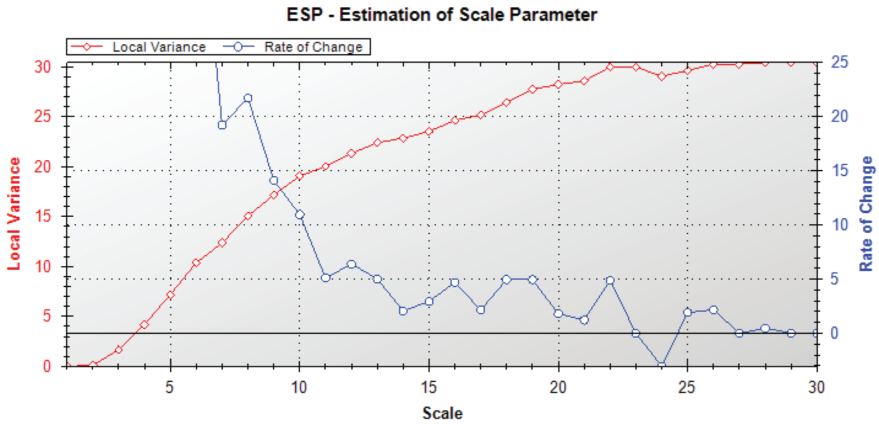


Figure 3.7: Determining the scale parameter using ESP Tool

The NIR band was given a weight of 3 while the other bands were given a weight of 1. The NIR received higher weight in oil palm tree identification done by Shafri et al (2011) because tree crowns reflect more in the NIR band than in the other bands (Glenn, et al., 2008; Ray, 1994; Sims & Gamon, 2002). The shape influence was set at 0.5 in order to balance the shape with the influence of colour, both of which are important for segmentation of tree crowns. A compactness value of 0.9 (the highest) was used for segmentation based on the understanding that tree crowns are not smooth as they have within-crown variations and not so abrupt edges as compared with building roofs for example. Thus, setting a compactness value at 0.9 ensured that the smoothness influence was minimal in the segmentation (Trimble, 2010).

The oil palm crowns were star-shaped on the image with the centres having the highest reflectance in the NIR compared to the edge of the rachis and to the background (Figure 3.8). Based on the visual and statistical properties (such as mean band reflectance) of the segments, three categories of objects were distinguished at each stand. These were the crown cores (local maximas) where reflectance in the Near Infra-Red, RE, and Green, vegetation indices such as NDVI were high (shown in red in Figure 3.8b). The second was the edges of the rachis where leaf density is lower (shown in light blue colour in Figure 3.8b). Unlike in the crown cores and the rachis edges, some segments showed strong absorption of the vegetation bands (dark blue to black objects in Figure 3.8b) and these were considered background features.

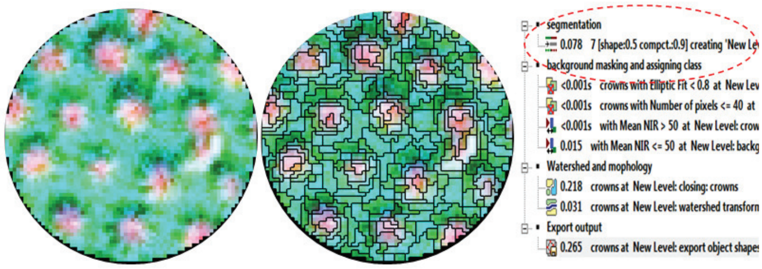


Figure 3.8:False colour composite of the image before and after segmentation

Background masking

The objects obtained from segmentation were then assigned into different classes based on their mean NIR reflectance and NDVI values. Based on the probable existence (or non-existence) of weeds/intercrops, the soil moisture in the background and the thick leathery structure of the leaves of the oil palms as seen in the false colour composite (NIR, Red and Blue), the mean NIR value and NDVI of each segment was used to classify it as potential crown or as background (background included such features as roads, bare ground, shadows, weeds, other vegetation, constructions and water). The NIR thresholds used for this classification depended on the factors above and were as such varied per field scene (Figure 3.9). The most common were 50 (for old trees and stands with relatively moist soil background), 100 for mature trees and 150 (for young stands and or intercropped/weeds). In a few circumstances where the NIR and NDVI was not able to distinguish oil palm crowns, the Blue band was used to identify the background based on the influence of soil reflectance and then subsequently used for assigning the objects into the different classes.

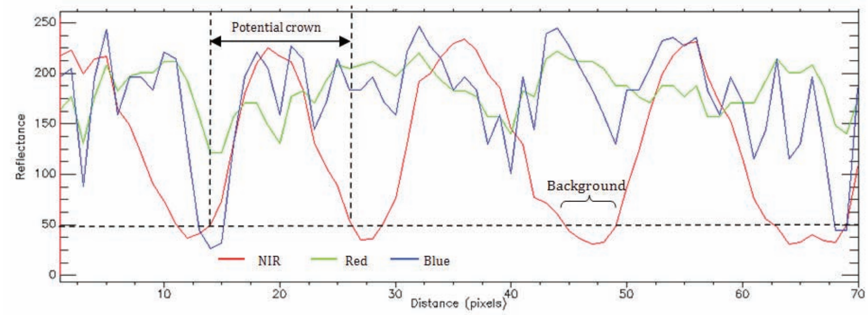


Figure 3.9:Selecting thresholds and bands for background masking for one stand

After assigning the objects to classes, the objects were combined based on the number of pixels allowable for each potential crown. It was determined from field work that the minimum possible size of an oil palm crown was about 8m^2 (equivalent to 32 pixels). In order to restrict the potential crowns above the minimum, a threshold of 40 was used to combine potential crown objects into candidate crowns. Only candidate crowns with an elliptic fit (given the standard spacing and uniformity of plants the crowns were assumed to be elliptic to circular) above 0.8 were retained. This was done to remove irregular segments created within canopies (Figure 3.10b).

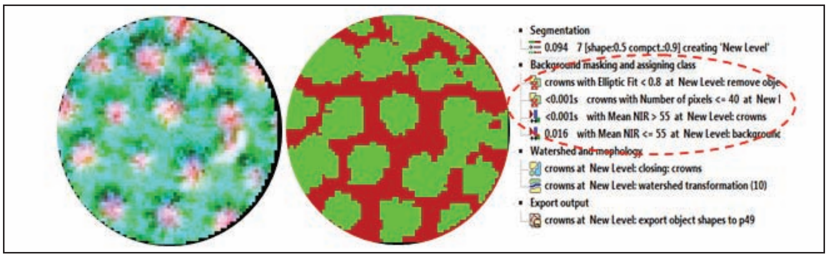


Figure 3.10::(a) Original image and (b)masking background by characteristics

Watershed transformation and morphological operations

Assigning class based on mean band reflectance, NDVI and elliptic fit resulted in joined objects some of which had a size far beyond what is possible for an oil palm crown and these were probably groups of intermingled crowns or overgrown weeds. In order to bring these to possible crown sizes, watershed transformations and morphological operations were used. The watershed transformation algorithm considers the image objects as a topographic surface. According to Trimble (2010), it calculates "an inverted distance map based on the inverted distances for each pixel to the image object border". It uses the local maxima (hills in a catchment) and local minima (valleys in an actual catchment). However these will be inverted as the hills will be inverted (Figure 3.11) to form valleys and the valleys to form hills (Wolf & Heipke, 2007).

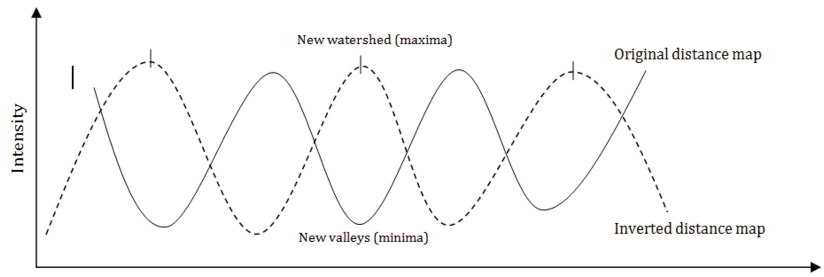


Figure 3.11:The watershed implementation sued for shaping the tree crowns

The individual oil palm crowns (brightness peaks) will form valleys and the background and shadows will form hills. The valleys are gradually "flooded' and where the waters meet a boundary is created, the image objects are split, thus separating intermingled tree crowns (at marked points in Figure 3.7) and this is applied to already segmented objects (Trimble, 2010; Wolf & Heipke, 2007). The watershed transformation was used to separate joined objects using the minimum possible crown diameter obtained from field work (5m giving 10 pixels) as the length factor (Figure 3.12a).

After watershed transformation, the morphology algorithm was then applied on the result to create closed circular objects that represent individual oil palm crowns. The procedure is based on image-processing mathematical morphological operations that compare each pixel in the image with neighbouring pixels and based on desired shapes (circular for oil palm crowns), size and general structure add to or remove it from a class (Trimble, 2010). This therefore made the segments assume a circular to elliptic shape that approximates the actual shape of the oil palm crown (Figure 3.12b). The resulting objects were cleaned up to remove non-representative objects (too small to be an oil palm crown) and exported as vector layer to a GIS environment with number of pixels as attributes. This was considered the final oil palm crown and exported in shapefile (Figure 3.12b).

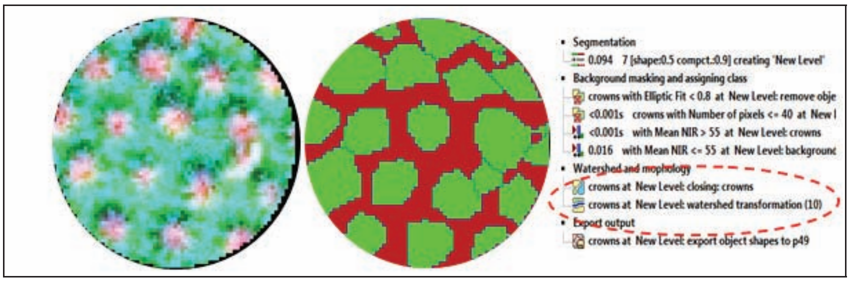


Figure 3.12:(a)Original image (b)crowns after watershed and morphological operations

3.7 Accuracy assessment of tree crown delineation

After completing the object based analysis, the segments were evaluated for accuracy. Accuracy assessment is an important part of OBIA as it gives an indication of the quality of the segmentation. Accuracy assessment in remote sensing is a statistical measure of how much the derived feature classes agree with reality (Foody, 2002). The error matrix is a typical measure of the accuracy of pixel based classifiers but this method was considered not to be appropriate for the OBIA approach used in this study (Clinton, et al., 2010).

Accuracy assessment of OBIA segmentation compares the segmented objects with reference objects and these were crown areas measured from the field and on-screen digitized crowns (Blaschke, et al., 2011; Clinton, et al., 2010). The accuracy assessment was done by comparing the segments with on-screen digitized crowns and field measured crown areas. The stands that were randomly subset for accuracy assessment of the field model were also used for accuracy assessment of the segmentation (2 of the stands in this dataset were outside the image and thus n=27).

Two methods of accuracy assessment were applied. In the first method, the degree of over and under segmentation of OBIA segments relative to manually digitized reference crowns was determined (Clinton, et al., 2010; Erikson, 2004). Clinton (2010) explained that the values for over and under segmentation are 0 when the OBIA objects match the reference objects perfectly and will be near 1 if there is a great geometrical mismatch. In addition, a combined measure that utilizes the weighted values of over and under segmentation to produce a comparison statistic for segmentation accuracy suggested by Clinton (2010) was also used. This combined measure is referred to as segmentation goodness of fit (D) and is calculated as below (Equation 3.4). As with over and under segmentation, the best segmentation gives D-values close to zero and poor segmentation give values close to 1. The quality of segmentation was evaluated per age class of the validation data.

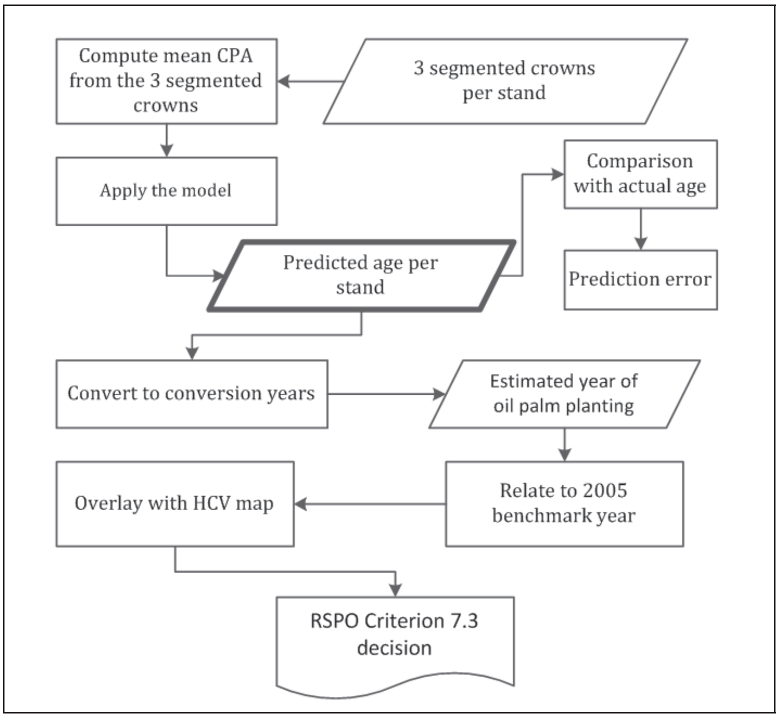
$$D_i = \sqrt{\frac{\text{Oversegmentation}_i^{\,2} + \text{Undersegmentation}_i^{\,2}}{2}} \qquad [3.4]$$

In the second accuracy assessment method, the correlation between segmented and field measured crown area was calculated (Wang, 2010). This approach was adopted in addition to the D-statistics because some factors such as the spatial and spectral resolution may affect the reliability of manual digitizing for accuracy assessment. Furthermore, different analysts can come up with different segment shapes and sizes as the boundary depends on the analysts' judgement and quality of sight. Therefore, using both the on-screen digitized and field measurements for accuracy assessment was found necessary. The r and the significance of the correlation were used as a measure of the strength of the correlation between the segmented and field measured crown area, indicating the quality of the segmentation.

3.8 Determining oil palm age from OBIA delineated crown area

The OBIA delineated crowns were used to determine the age of oil palm at each stand through application of the field developed regression model. In each stand, three delineated full crowns were selected and averaged to give the mean crown area for that stand (the plot represented by the 17.5m radius buffer). Three trees were selected to correspond with the method used in field work where only 3 trees were measured. In addition the buffer size developed based on spacing also ensured that for each stand, a minimum of three (and a maximum of 6) full oil palms were incorporated for delineation (Figure 3.13). The stand represented the oil palm field (the rest of the oil palms per site beyond the stand) that was mapped according to visual variations or boundaries such as forests and roads.

To get the location and the site for each prediction, the spreadsheet used to compute the mean delineated crown area and for implementation of the regression model was coded with point IDs similar to those used for recording the XY coordinates for each site. For each stand, the field was demarcated based on uniformity and existence of other noticeable boundaries such as roads, forests edges and other land uses. The same process was done for both field measured and non-measured stands. The crown area for each of the delineated crown was entered into a spreadsheet and the mean crown area calculated and used for age prediction. The spreadsheet with the predicted ages was opened in ArcGIS and joined using the IDs to the field maps, giving the prediction per stand and the error in the prediction. Comparing the model predicted and the actual age at that stand gave the error of the prediction per field. The area for each age category was also determined in the same way.



3.13: Age prediction from delineated crowns and prediction accuracy assessment

Using other auxiliary spatial datasets on land use in Ghana, the different age categories were overlaid over the protected areas map and the potential high conservation value map. This was done to develop the map as a decision support tool for certification assessment for RSPO criterion 7.2. The locations and area planted with each age category were therefore determined and converted to percentages.

CHAPTER 4: RESULTS

4.1 Oil palm crown area delineation

4.1.1 Comparison of digitized and segmented crown area

A high segmentation accuracy of 0.89 and 0.86 were obtained for 6 and 7 year old palm oil stands respectively (Figure 4.1, Table 4.1). In both cases the over segmentation error was small as the segmented crowns were bigger than the digitized crowns.

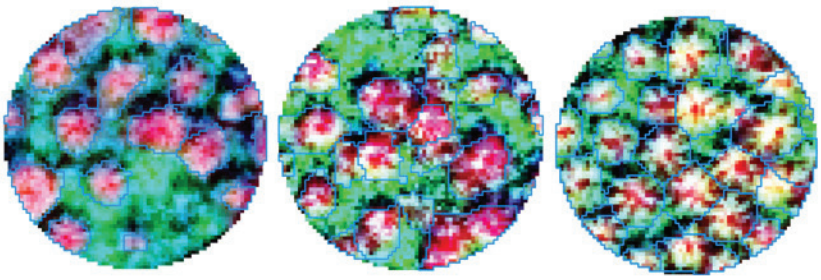


Figure 4.1:The segmented crowns compared to a false colour of oil palms

The highest delineation error was obtained for the 13 year old stands (0.59) followed by the 4 year old stands (Table 4.1). For the 13 year old stand the errors were mostly due to over segmentation error while for the 4 year old stands it was from both over-segmentation and under-segmentation errors (Table 4.1, Figure 4.2).

Table 4.1: Segmentation goodness of fit for validation data (n=27)

Age	D	Accuracy
2	0.25	0.75
3	0.34	0.66
4	0.40	0.60
5	0.38	0.62
6	0.11	0.89
7	0.14	0.86
8	0.25	0.75
12	0.36	0.64
13	0.59	0.41
All	0.31	0.69

In some age classes such as 5 and 8 years both the over and under segmentation errors contributed to the final error while in some age classes either over or under segmentation were important source of error (such as 2, 7 and 13 years) in contributing to the error. Nonetheless, there was no relationship between age and over segmentation error (Figure 4.2a), under-segmentation error (Figure 4.2b) and overall accuracy (Figure 4.2c) suggesting that other factors apart from age explain the delineation accuracy. Despite the lack of relationship between age and segmentation error, the over-segmentation error was notably high for the 13 year old stands which therefore contributed to this age class having the least overall accuracy (Figure 4.2a and Figure 4.2c). There was also no relationship between the number of stands in the validation data set per age class and the accuracy achieved (Figure 4.2d).

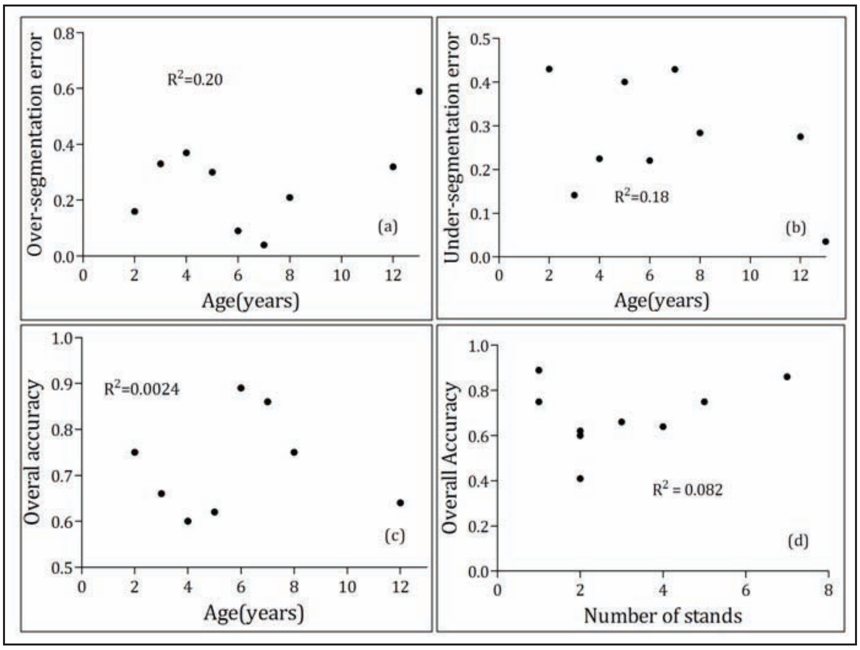


Figure 4.2: Relationship between age and over-segmentation, under-segmentation, and over-segmentation, and number of stands and delineation accuracy.

4.1.2 Comparison of OBIA and field measured crown area

Comparing the delineated and field measured crown areas showed that There was a strong relationship between field measured crown area and OBIA segmented crown area indicating that the segmentation crown area closely approximated the field measured crown area (R^2=0.81, r=0.9, p<0.0001). There was least variability in the prediction for younger oil palms (up to 6 years) while large variability in OBIA crown area was observed in the 13 and 7 year old age class (Figure 4.3a). For the 13 year old stands, the spread between the actual and predicted crown area is apparent where the actual crown area was over 80m² (Figure 4.3b).

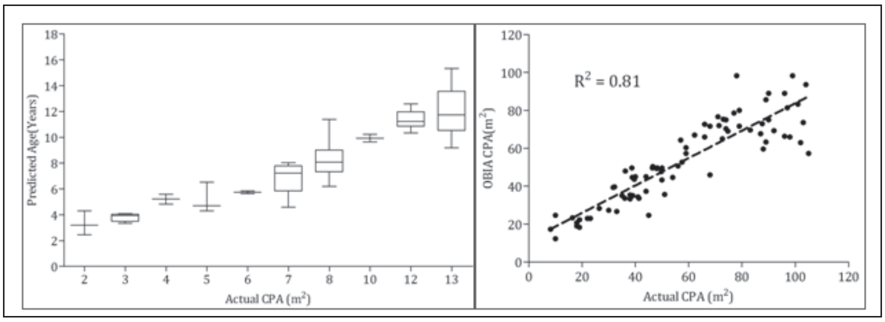


Figure 4.3: Relationship between OBIA and field measured CPA (n=80)

4.2 Relationship between oil palm crown area and age

4.2.1 Field data

Data on age and crown diameter were collected from a total of 88 stands of 3 trees (a total of 264 oil palm trees) during field work (Table 4.2). Of these, 36 were in the large scale corporate plantation and 52 from smallholder farmers. The dominant planting system was triangular plots with a spacing of 9m (143 plants per ha) except for exceptional cases where spacing was reduced up to 6m (214 plants per ha) and in one case the spacing was 11m (117 trees per ha). Measurements were recorded for 14 age classes between 2 and 21 years. The dominant ages were 7, 8 and 12 years which together contribute 41 stands. Crown projection area (CPA) calculated from crown diameter ranged between 8.2m² to 104.6 m².

Table 4.2: Descriptive statistics of the field data collected on age and CPA

Variable	N	Mean	Standard deviation	Min	Max
Age	88	9.5	4.9	2	21
CPA	88	58.0	26.5	8.2	104.6

4.2.2 Fitting models to the data

A positive linear relationship was observed between age and crown area up to an age of 13 years (Figure 4.3). No apparent relationship was evident between age and crown area from 13 years onwards as crown did not respond to age anymore. The crown area saturated around 100m² and this was reached at around 13 years (Figure 4.4). Since the older oil palms have overlapping rachis and shadows, they are difficult to differentiate using remote sensing. However, the older oil palms are also not necessary for the certification requirements as they were definitely established before 2005.

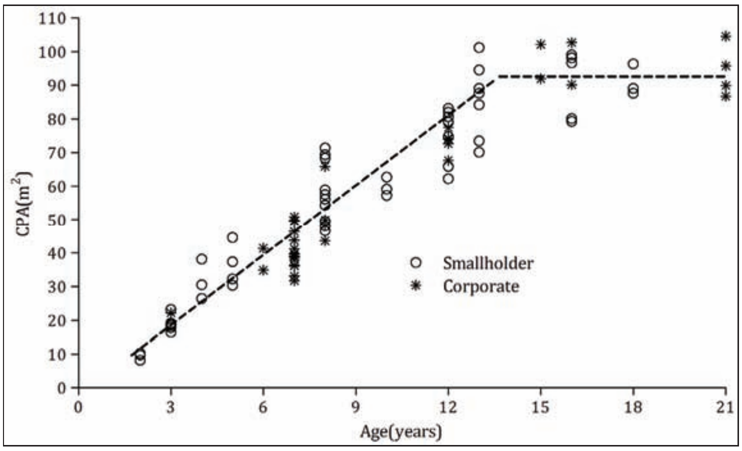


Figure 4.4:Relationship between age and CPA on corporate and smallholder (n=88)

It was therefore decided to fit a linear model between age and crown area up to 13 years and all the age classes above that were discarded. A significant relationship was obtained between age and area (R^2=0.88, p<0.001). The estimated standard error of the model was 1.2 years. The slope of the model was highly significant while the intercept was not significantly different from the origin (Figure 4.5).

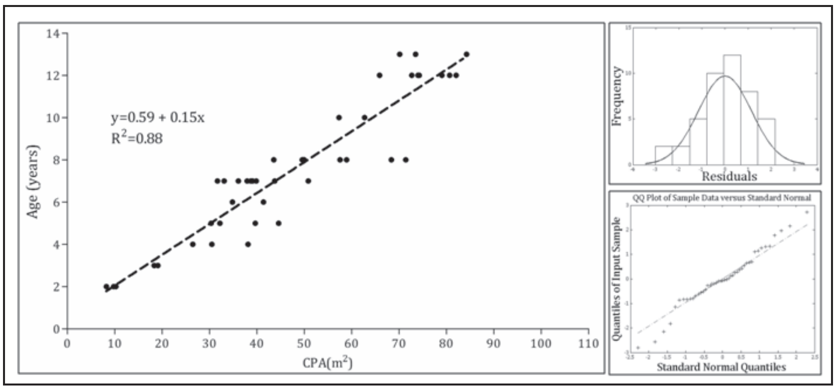


Figure 4.5:Fitting model to the training data with the residual and QQ plot(n=43)

Therefore, the following function was obtained for predicting oil palm age from CPA (Equation 4.1);

$$\text{Age (years)} = 0.59 + 0.15 * \text{CPA } (m^2) \qquad [4.1]$$

4.2.3 Accuracy assessment of the model

The ability of the field developed function to predict the age of oil palm was tested on the training and the on an independent data set. Model errors were lower for calibration data as compared to independent data (Table 4.3). RMSE was 1.2 years for the calibration data but increased to 1.3 for the validation data. MAE was less than 1 year for both the calibration and validation data. Although the percentage error was less than 10% for both datasets, it was much higher in the validation data (8.2%) that in the model calibration data. Basing on the performance of the model on the independent data, it can was considered within acceptable predictive performance.

Table 4.3: Model performance on calibration and validation data

Measure	Calibration (n=44)	Validation (n=29)
RMSE (years)	1.2	1.3
MRE (%)	3.2	8.2
MAE (years)	0.8	0.9

Residuals were highest between 60m^2 and 70m^2 when the model was applied to an independent data set (the remaining 40% of the field data not used in model building) where actual ages varied between 7 years and 12 years. The correlation between predicted and actual ages was very strong (R^2=0.91) although the model overestimated oil palm age in most cases (Figure 4.6).

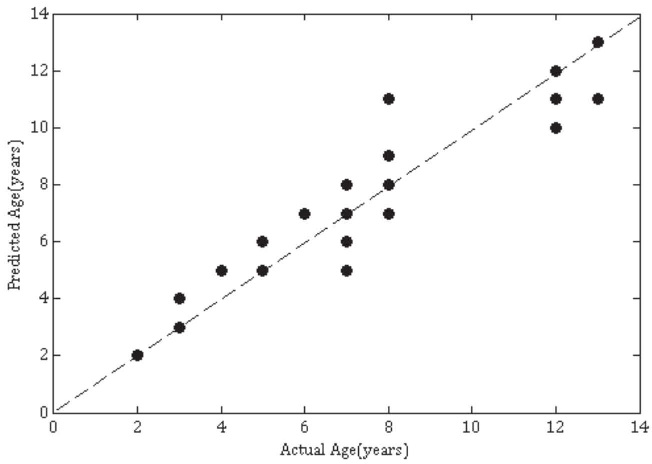


Figure 4.6: Relationship between model predicted and actual ages (n=29)

4.3 Predicting oil palm age from OBIA delineated crown area

The OBIA delineated crown areas were used as explanatory variables in the field developed model to predict the ages of oil palm per stand.

4.3.1 Predicted oil palm age

The prediction showed that 6 and 11 year old oil palm plantations dominate the area under oil palm with 16.7%(116.7ha) and 14.6% (101.5ha) respectively (Figure 4.7). The results therefore indicate that there were more new oil palm plantings in 2000 and in 2005. Based on the age distribution map (Figure 4.8), the least common age classes were 2 and 3 years with 4.8ha (0.7%) and 24.2ha (3.5%) of area which were estimated to have been planted in 2009 and 2008 respectively. For the study area, 48% of the area (334.6ha) was estimated to be between 6 and 9 years old while 66% of the total area under palm oil is under 10 years old (Figure 4.7). From these predicted ages, it was also obtained that there was over 1000% growth in area under oil palm in the study area between 1998 and 2009. The greatest annual growth rate in area under oil palm was between 1999 and 2000 where area under oil palm doubled. Significant annual growth rates in area under oil palm of between 20 and 25% were also observed between 2002 and 2005.

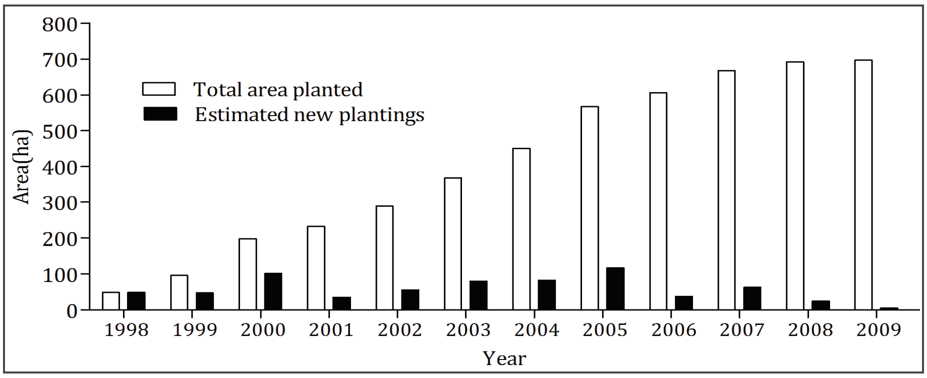


Figure 4.7: Area under each predicted age class

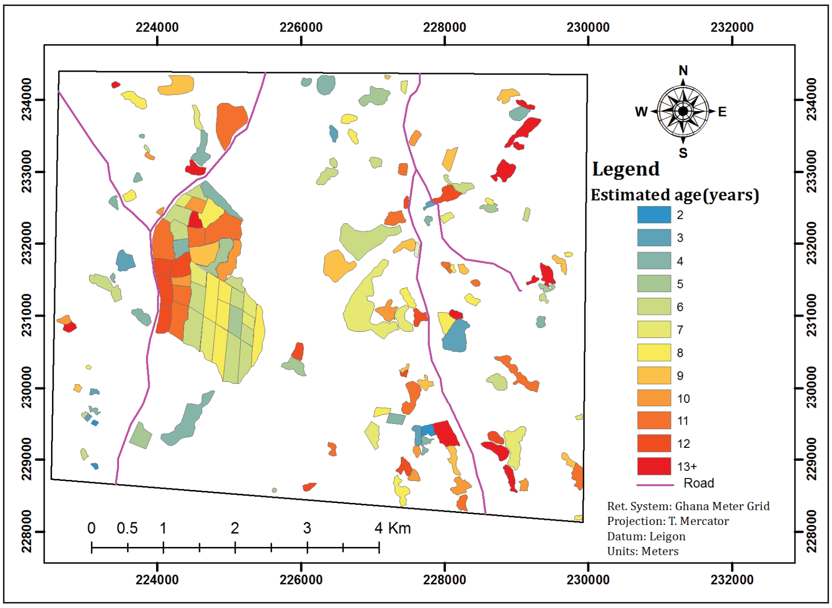


Figure 4.8: The estimated distribution of oil palm ages

4.3.2 Age estimation errors

Comparing the actual ages and the estimated oil palm ages showed that that the error ranged between an under estimation of 4 years to an over estimation of 3 years in oil palm age (Figure 4.9). Although the majority of the predictions were accurate, it is observable that in two cases with large errors (an underestimation of 4 years and an overestimation of 3 years), the areas covered are large.

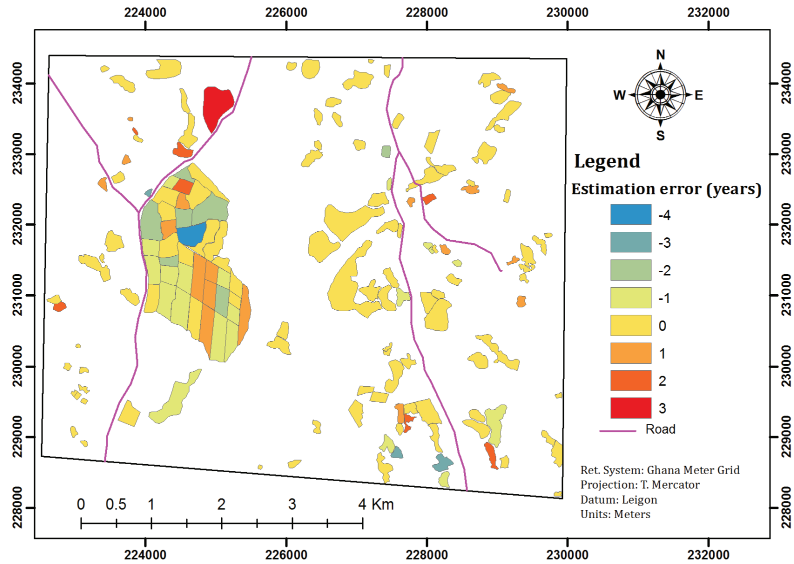


Figure 4.9:The distribution of oil palm age estimation errors

Although the prediction gave a large error range (7 years), the prediction was accurate for 27.9% of the stands, within ±1 year error for 74.6% of the stands and within ±2 year error for 92.4% of the stands. The largest errors of more than 2 years were either for the youngest (less than 4 years) and oldest (more than 12 years) oil palms (Figure 4.10).

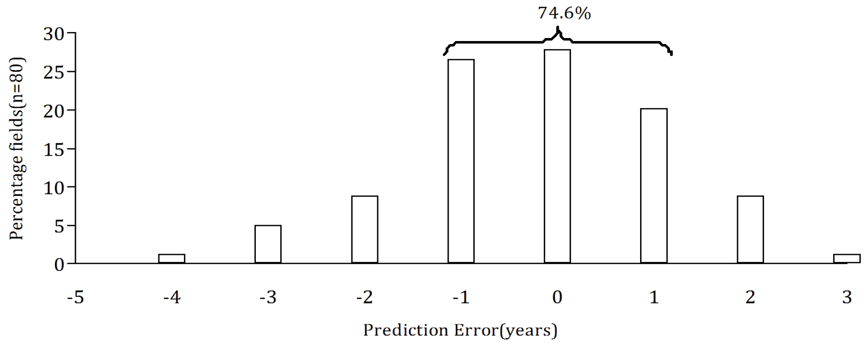


Figure 4.10: Prediction errors in field measure stands (n=80)

4.3.3 Planting time and time of conversion

The predicted ages were put into 3 categories in order to determine the approximate time of conversion which is required for assessment of RSPO criterion 7.3. The categories were oil palm fields definitely planted after 2005 (less than 4 years old at the time of image acquisition), planted around 2005 (5 to 7 years old) and planted before 2005 (more than 7 years). This categorization was based on the required benchmark for implementation of the RSPO criterion 7.3. In addition, there was also an added uncertainty of the time of land preparation before actual planting as this could not be confirmed and was estimated to also be around 1 year maximum. The distribution of the oil palm according to the estimated time of conversion is as shown in Figure 4.11.

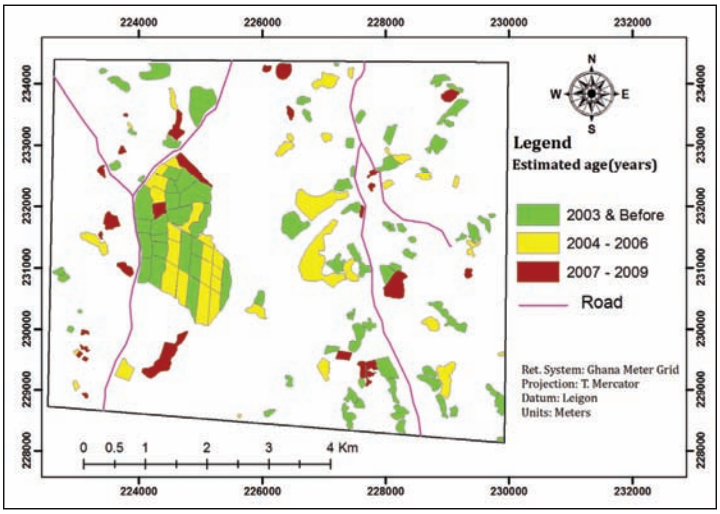


Figure 4.11: Estimated time of conversion to oil palms farming

The largest area under oil palm in the study area was estimated to have been planted before 2005 accounting for 52.8% (368.2ha) of the total area under oil palm farming (Table 4.4). Of this area, the largest proportion was under the smallholder farmers (59.3%). Considerable land was estimated to have been planted with oil palm between 2004 and 2006 accounting for 34% of the area under oil palm (237.2ha). The majority of this conversion occurred in the smallholder farmers where an estimated 139.9ha (58.9%) of area planted between 2004 and 2006 was in the smallholder sector compared to about 97.3ha (41.1%) in the corporate sector. According to the estimated ages, there has been less new planting between 2007 and 2009 in the corporate plantation (4.6ha) as compared to the smallholder sector where 94.9% of the estimated planting in this period (86.8ha) were planted (Table 4.4). These areas have therefore been planted after the RSPO benchmark year of 2005 and criterion 7.3 is applicable.

Table 4.4: Estimated period and area converted to oil palm farms

Planting time	Corporate	%	Smallholder	%	Total	Total %
2007 - 2009	4.6	5.1	86.8	94.9	91.4	100
2004 - 2006	97.3	41.1	139.9	58.9	237.2	100
2003 & Before	149.9	40.7	218.4	59.3	368.2	100
Total	251.7	36.1	445.1	63.9	696.8	100

4.3.4 Protected areas and high conservation value areas

Criterion 7.3 states that none of the plantings after 2005 should have been planted on protected areas, replaced primary forests or any area required to maintain or enhance one or more high conservation value areas. According to RSPO(2011), this requirement applies to both smallholder and corporate producers.

Protected areas

None of the fields were planted on protected areas as nearest forest reserve (Bobiri forest) is over 6km from the image boundary while the nearest wildlife reserve (Bomfobiri Wildlife Sanctuary) is 26.5km away (Figure 4.11). The study area is also considerably surrounded by protected areas forests and wildlife sanctuaries especially in the eastern part where there is Asonari, Anum Su North , and Kumawu forest reserves (Figure 4.12).

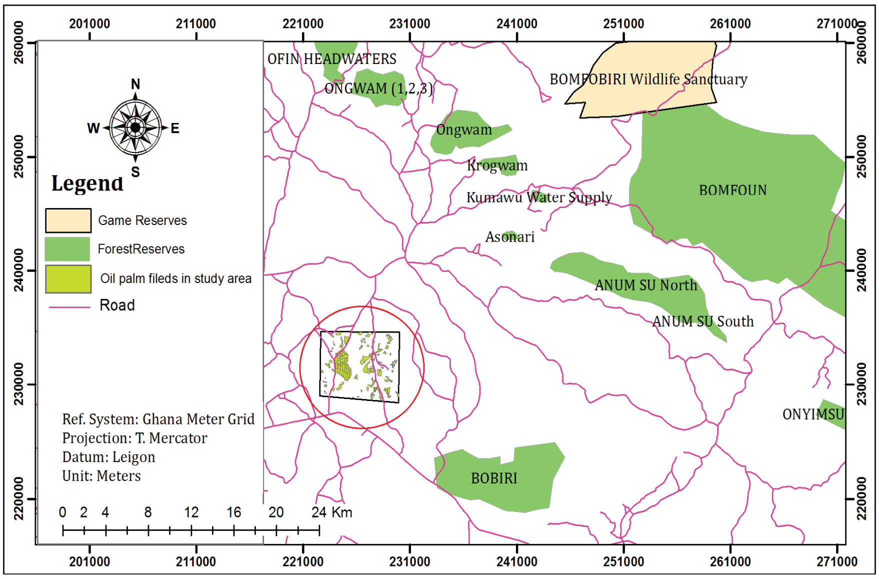


Figure 4.12: Location of the study area in relation to conservation areas

Potential high conservation value areas

RSPO (2011)defines a high conservation value (HCV) area as "forest areas containing globally, regionally or nationally significant large landscape level forests, contained within, or containing the management unit, where viable populations of most if not all naturally occurring species exists in natural patterns of distribution and abundance". This also includes forest areas providing essential services to communities. Based on this definition, the land cover map obtained from Ghana-at-a-Glance Project (2004) identified part of the study area as a riverine ecosystem (Figure 4.13) which could be considered part of a HCV (although this is not a confirmed HCV).

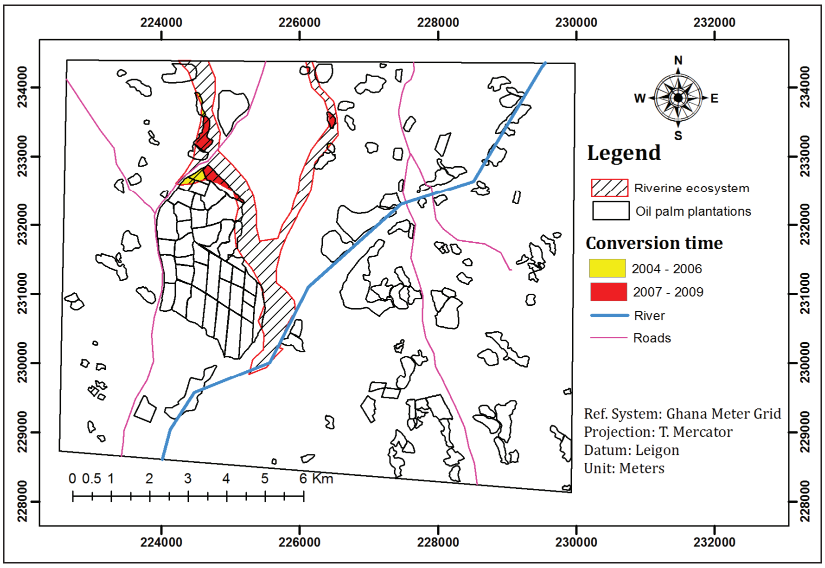


Figure 4.13: New planting planted in riverine ecosystem between 2004 and 2009

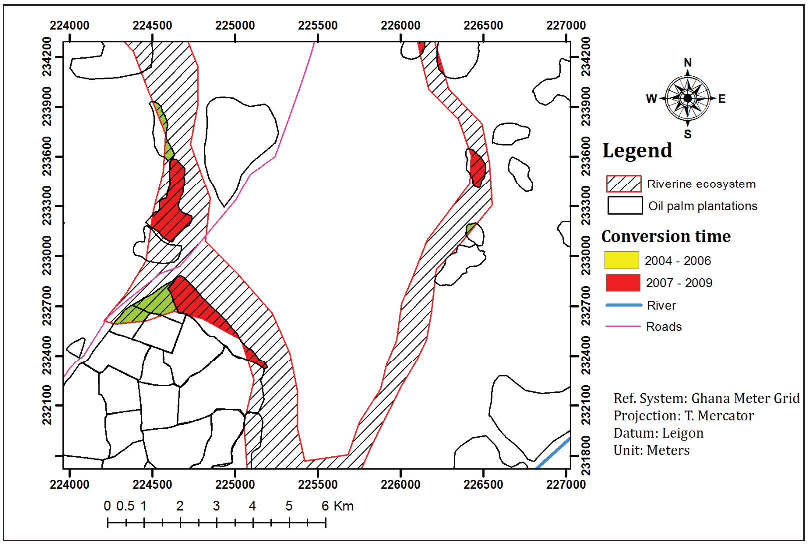


Figure 4.14: Determining sites for RSPO Criterion 7.3 using predicted age

Overlaying the HCV map on the age-map clearly showed the area that was planted inside the HCV for making a decision on certification. However, since the prediction was done at field level, the overlay did not consider the field but the exact in-field boundaries. This resulted in some parts of the field having been planted after the required time while the other part was outside (Figure 4.14). About 31ha of new oil palm plantings in the study area between 2004 and 2009 were planted on the riverine ecosystem. Of this, only 32% were in the corporate plantation while the majority (20.76ha) were in the smallholder sector (Table 4.5). Slightly over half (56%) of the total area planted in the potentially RSPO criterion 7.3 applicable time period was found to have been planted recently (2007 to 2009). The estimation showed that was three times as much new planting in the smallholder sector compared to the corporate sector between 2007 and 2009.

Table 4.5: Land conversion on riverine ecosystem between 2004 and 2009

Conversion time	Smallholder(ha)	Corporate(ha)	Total(ha)
2004 - 2006	7.93	5.7	13.63
2007 - 2009	12.83	4.15	16.98
Total	20.76	9.85	30.61

CHAPTER 5: DISCUSSION

This study demonstrated the feasibility of applying a remote sensing-based approach for estimation of oil palm age to support RSPO certification. In this process, some insight was obtained about the applicability of such an approach in terms of the value of the outcomes and the strength and weaknesses of the methodological framework developed. The most significant issues are discussed here in detail.

5.1 Applicability of the approach for RSPO certification

It was shown that using crown area delineated by OBIA from high resolution satellite imagery and an empirical regression model can give an age map that, when overlaid with a HCV map, is useful as a decision support tool for RSPO certification for criterion 7.3. Nonetheless, the true value of such an approach depends on the tolerable error, as there are many sources of uncertainty. It was established that oil palm age can be predicted in discrete years using this approach. The discrete years can be directly used for determining the time conversion required for RSPO certification. The applicability of this approach was demonstrated as it can be recommended that palm oil produced from both the corporate and the smallholder farmers in the study area do not qualify for RSPO certification as they would breach criterion 7.3 basing only on the plantings from 2007 to 2009 which were definitely planted after the benchmark period of 2005 (that is if the riverine was a confirmed HCV).

An age prediction error of around one year realised in this approach may be acceptable for supporting RSPO certification. This is because the predicted ages can be categorized based on this error as planted after 2005, around 2005 and before 2005 as was demonstrated. Those classified as planted after 2005 will need to be checked if they have not been planted on protected areas or other high conservation areas. Those planted around 2005 (2004 -2006) will require field verification to determine the correct time of planting. This reduces the time, effort and cost of palm oil sustainability certification while making the decision more objective and scientific.

In addition to the methodologically inherent 1 year error in the approach, it may also be necessary to factor in the time between land clearance and actual planting. In some cases, farmers may clear the land a year (or season) before planting. This approach could also be very important for determining the planting time in smallholder plantations where records on plantings may not be properly kept and therefore planting time difficult or uncertain when obtained even from field-based on-site verification. Although an independent determination of the time of planting may be better than collecting information from producers, most large scale plantations apply efficient management systems including proper record keeping from which information on size, sites and time planted can be obtained. The risk of error from applying this approach may also be higher in smallholdings as they apply different management systems and are most likely to have intercrops.

The fact that the delineation and hence prediction accuracy was more accurate for the younger age classes may indicate the possibility of introducing a repeat cycle for the application of the method for age determination. The method gave more accurate age predictions up to 5 years and near-accurate prediction up to 10 years and did not work well for ages above 10 years. This may mean that a 5 year repeat cycle will always give more accurate oil palm age estimations and depending on the accuracy required even a 10 year repeat cycle will be reliable. This is especially important when considering the costs of acquiring high resolution imagery required for accurate delineation. Thus, if the high resolution image has to be acquired once every 5 or 10 years, the relative cost-saving of this approach is attractive.

Although this approach is promising in determining age of palm oil for RSPO certification, it is dependent on high spatial resolution imagery that is expensive to obtain compared to other methods that were based on free Landsat and other imagery (Ibrahim, et al., 2000; McMorrow, 2001). An upscaling mechanism to medium resolution may thus be required to reduce the costs. The cost-benefit ratio of adopting this approach could be positive comparing the costs of flights and personnel for field verification with those of acquiring a high resolution image. It may also be useful as an initial assessment for RSPO certification of oil palm oil producers that will give important baseline information about the area to be certified.

Although this research focused on assessing applicability of the approach on criterion 7.3, it can also be speculated that the results could be useful for assessing other RSPO certification criteria such as 5.1, 5.2, 6.1 and 7.1 on social and environmental impact assessment of management and replanting.

The results obtained from applying this approach are potentially very useful beyond RSPO certification. For example, the estimation of the area with each age class could be useful for precision farming especially by multinationals in terms of planning inputs and projecting harvests (and related factors such as labour, machine hours and revenues). Therefore, the method developed in this study could be combined with other remote sensing methods for oil palm plantation management such as automatic tree counting (H. Z. M. Shafri, et al., 2011) and disease detection (Shafri & Anuar, 2008; H. Z. M. Shafri, et al., 2011) into a plantation management system serving different purposes.

In addition, age of oil palm may be useful for carbon modelling and mapping required for understanding the carbon footprint of the oil palm sector as was shown in other studies (Dewi, et al., 2009; Thenkabail, et al., 2004). Also and maybe importantly, a method that gives a reliable estimate of progression in area under oil palm could be useful for assessing the relationship between oil palm oil expansion and deforestation, biodiversity and landscape quality which have been widely discussed in the context of questioning the sustainability of the oil palm sector (Nellemann, et al., 2007; Partzsch, 2011; Phalan, et al., 2009; Stone, 2007; Struebig, 2010; Tan, et al., 2009). For example, relationships between the growth in area under oil palm and faunal biodiversity (populations, health and behaviour) over time could provide key insights on the cause-and-effect relationships that are useful for conservation planning.

Having seen the potential of this approach, it is worth noting that it would be more convenient to have a method that can automatically determine ages of all oil palm plantations over a large area at once and also not limited to 13 years. Such an approach may be more useful for studies on policy impacts, impacts of oil palm expansion on biodiversity over longer time periods and for land cover change studies. Given this reality, the approach demonstrated in this study may be very applicable for certification of individual plantations but still has an uncertainty that is relatively large for a precise assessment of land conversion. This approach does not replace on-site assessments for compliance with other non-spatial criteria and therefore field assessment may be inevitable, which can be used for a more accurate age determination too. Even so, to create an overview of where potentially sustainable oil palm can be found and for cumulative impact assessments and spatial planning purposes it seems a very useful approach. Over and above that, it may reduce the time and effort by focusing on areas with age uncertainties in the on-site checking process thereby making the certification process more efficient in terms of outputs, areas covered, costs and time.

5.2 Oil palm crown area delineation

The segmentation good of fit (0.69) and the correlation between segmented and field measured crown area (0.81) on a scale of [0,1] indicates the successful delineation of individual tree crowns using OBIA. These results may give an impression that the performance of the delineation was good, but as Wolf & Heipke, (2007) rightly observed, the results on individual tree crown delineation are difficult to standardize and compare between researchers. This is because of different study sites with different scene characteristics, different data sets (spatial and spectral resolutions) and different tree types. Different evaluation criteria have also been used and the D-statistics used in this study is relatively new to the field, having been developed by Clinton, et al (2010) and still to be widely applied for comparison. Although different algorithms and platforms are used, the general process of individual tree delineation is relatively the same as that adopted in this study starting with segmentation, followed by membership functions and then refinement(Larsen, et al., 2011; Niccolai, et al., 2010; Wolf & Heipke, 2007).

The results have shown no direct relationship between the age of the oil palm and the accuracy of the delineation. This result was somewhat unexpected as it was considered that younger oil palms could be easily delineated as there are no problems of overlapping branches and shadows cast upon other palms. The lack of a direct relationship may suggest that the accuracy of the delineation is more site-characteristic dependent than age dependent. The site characteristics such as intercropping and weeds introduce radiometric and geometric confusion to the segmentation and classification algorithms (Figure 5.1) especially where vegetation-based bands (NIR, Green and Red) and indices (such as NDVI) are primarily used for delineation (Pouliot, et al., 2002). Other research on determining age of oil palm using remote sensing approaches reported accuracy for younger age classes (Ibrahim, et al., 2000; McMorrow, 2001; Thenkabail, et al., 2004). The spectral and spatial characteristics of the oil palms differ with age but the changes in spectral response with age may not be enough for discrete age modelling (Thenkabail, et al., 2004) while the changes in spatial characteristics may be significant enough between years for discrete modelling.

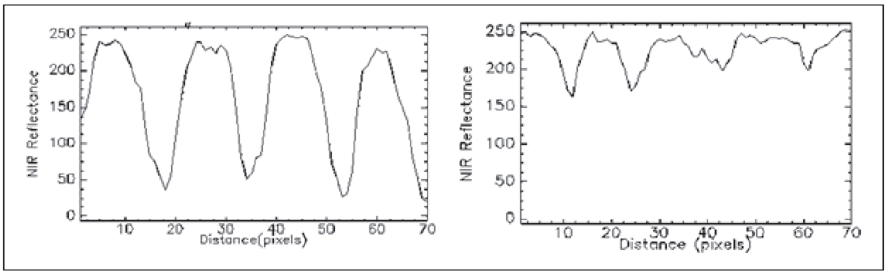


Figure 5.1:NIR profile of same age stands (a) without weeds/intercrop (b) with weeds/intercrop

The NIR was most consistently able to be useful for separating oil palm crowns with background. The red edge band which was considered potentially very useful could not perform better that the NIR. This was not surprising given that the Landsat MIR bands were the most significant in classification and age class determination of oil palm (Ibrahim, et al., 2000; McMorrow, 1995, 2001). Therefore, of the WorldView-2 bands, the NIR2 (860–1040nm) might have been more useful for age discrimination but as Thenkabail, et al (2004) observed with IKONOS data, spectral richness may be more important that spatial resolution in oil palm land cover classification, biomass estimation and discrete age determination. Although the WorldView-2 provides more opportunities both spatially and spectrally, the spectral diversity in hyperspectral data could therefore provide added abilities for oil palm crown delineation. Due to the fuzziness of leaf density gradient from the crown centre, on many occasions it was difficult to figure out exactly where the crown ends. This is made even more complicated where there is undergrowth (Appendix 1f-h). Although this may be the general spatial reflectance profile for trees (Hirschmugl, et al., 2007; Pouliot, et al., 2002; Wolf & Heipke, 2007), it could be more problematic in delineation of oil palms given its star-shaped form compared to conoid and hemispherical forms common in other trees.

The problems of weeds and intercrops can be linked to the date of image acquisition as the photosynthesising annual crops and weeds are more prominent in the wet seasons compared to the dry season. It is therefore recommended that imagery be acquired in the dry season for tree crown delineation for perennials like oil palms in order to improve the accuracy. Despite the lack of a direct relationship between age and accuracy, the results show that it is more difficult to obtain accurate delineation for older oil palms. This indicates that the problems of shadows and overlapping branches may be particular for this age class while site characteristics are more important for young age categories less than 13 years. The shadows in young oil palm plantations were correctly masked out while in older oil palms the shadows were cast upon other oil palm crowns and were therefore erroneously masked out (Figure 5.2). This partly explains the segmentation error reported for older oil palms. The effect of shadow has been found to be dependent on the sun azimuth angle in relation to the satellite position at the time of imaging (Leckie, et al., 2005). When shadow is cast upon vegetation, the reflectance in the vegetation bands is grossly distorted.

Figure 5.2:Effect of shadows on the delineation accuracy for young and older oil palms

It may be expected that automatic crown delineation would be feasible given the relative uniform characteristics of oil palm plantations as compared to natural forests for example. However, it was realized that there are many factors that are different at each stand, and thus a method for delineation that considers each field's characteristics could be better than a blanket approach. A stand-based method, may not be very easy for delineation of large oil palm plantations (with many age stands) and for delineation of numerous smallholder farms because of the human and computational requirements. To solve this problem, other researchers applied preliminary stratification (such as based on tree density by Whiteside, et al. (2011)) before delineation in order to adjust segmentation and delineation parameters accordingly. Advanced image pre-processing such as implemented by Shafri (2011) may also be useful in improving the performance of the delineation of individual crowns. Different levels of automation in individual tree crown delineation have been developed and applied for pine plantations (Hirschmugl, et al., 2007; Larsen, et al., 2011; Pouliot, et al., 2002), eucalyptus (Whiteside, et al., 2011) and other forest types (Niccolai, et al., 2010). While the method adopted in this study requires considerable work adjusting parameters per stand, it could be useful for a sampling-based delineation where mean crown sizes are representative such as in plantations.

5.3 Relationship between CPA and age

It is a common biological phenomenon that at a certain age, growth of some parameters ceases as was shown by oil palm tree crowns in this study. Therefore the application of a method that depends on a saturating parameter is only applicable to the point of saturation which in this study limits the applicability of the function up to 13 years. Applications of methods that can provide an opportunity for estimating additional characteristics such as height and thickness such as Lidar and radar may be more useful for age prediction especially for older oil palms (assuming that there is a stronger non-saturating relationship between age and height). However, the prediction problems of the function are apparent for older oil palms which were not of primary interest for this study. The form of the relationship match almost exactly the form presented by McMorrow (2001) with field measurements done in Malaysia (Figure 5.3). From this, it can be speculated that the function developed in this study may be useful for other countries and regions as it is dependent more on the physiology of the oil palms than on geographical characteristics.

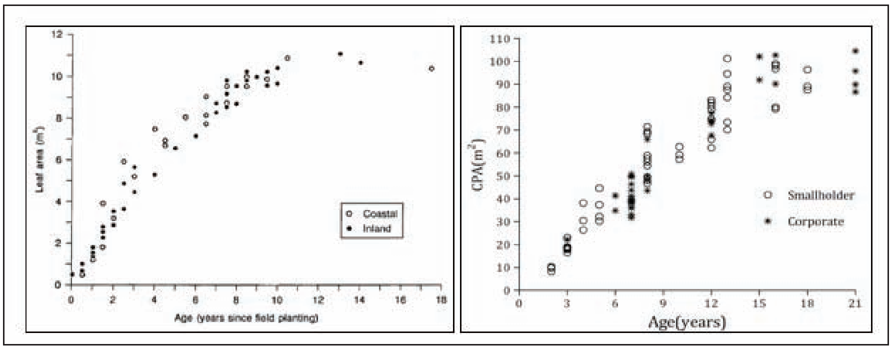


Figure 5.3: Relationship between oil palm age and (a)leaf area(McMorrow, 2001) & (b) crown area in this study

The ability of a crown area based function to estimate ages in the precision of years makes it more attractive than reflectance based methods although it can only be applicable up to saturation age. It is however difficult to compare the accuracies with reflectance regression classification approaches which give results in binned age classes. In addition, oil palm crowns have different shapes and spectral characteristics than the trees evaluated in other studies. Even in cases where the studies were on oil palm (Ibrahim, et al., 2000; McMorrow, 1995, 2001), the approaches and sites were completely different from the one applied in this study and therefore very difficult to compare. Kalliovirta & Tokola (2005) concluded that in predicting the age of birch forests, crown diameter had the least errors and recommended that only crown diameter should be used for age prediction of birch stands. Contrary, the unreliability of crown area as the only independent variable has been cited in other studies (Pouliot, et al., 2002).

The function developed for estimating oil palm age from crown area proved to be robust in estimating oil palm age in the study area and perhaps could also be useful for estimating oil palm ages in the study region, in Ghana and in other regions with similar management and climatic conditions. Since there were no significant differences ($p>0.05$) in the slopes of the model between smallholder and corporate plantations (Figure 5.4), the developed model (Equation 4.1) can be used for modelling oil palm age in the study area. There is therefore no need for separate models for smallholder and corporate oil palm sectors. It may therefore be inferred that the aspects of management such as weeding circles, density fertilization and use of agrochemicals that differ between smallholder and corporate plantations have no significant effect on the relationship between crown area and age. The observation that there were no difference in the slopes of the model is contrary to the fact that field experiments relating fertilization, density and genotype have reported significant impact on crown expansion (Breure, 1985). Nonetheless, the functionality and applicability of the developed model may be affected by factors such as differences in soil types and fertility, diseases and pest damage, plant spacing, irrigation, oil palm varieties and other management practices such and pruning especially when applied over larger areas (Breure, 1985). The error slightly less than 1 year of the model in predicting oil palm age could therefore be explained by the variability in these factors at each measured stand.

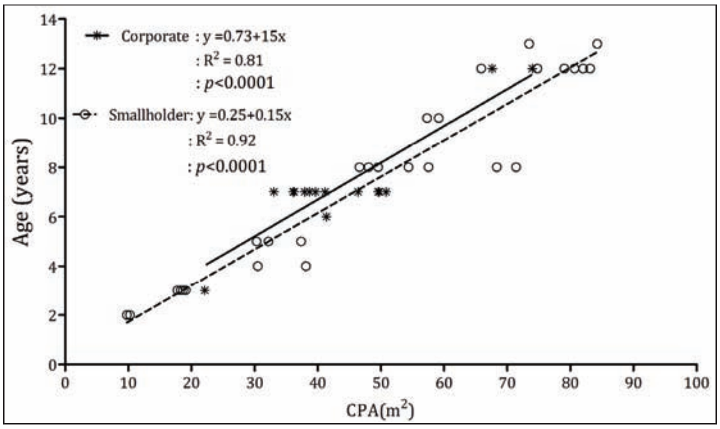


Figure 5.4: Sensitivity of the model to management system

A second order polynomial that follows the saturation could have produced a model able to predict oil palm age beyond 13 years. However, this could have produced more errors in the prediction through error propagation as a linear function is more parsimonious. In addition, it is not useful to have a model able to predict beyond 13 years when the delineation is only reliably accurate up to that age. Linear functions have been widely and reliably used as functions for predicting other plant parameter from crown area or crown diameter (Table 5.1).

Table 5.1: Application of linear functions in predicting stand parameters

Parameters	Study	Country	Species
Crown area and age	Kalliovirta & Tokola (2005)	Finland,	Pine, Spruce birch
Crown diameter and DBH	Avsar (2004), Hemery, et al. (2005), Peper, et al. (2001), Mugo, et al. (2011)	Britain, California, Kenya	Pine, many, many, many
Leaf area and age	Gerritsma & Soebagyo, (1999)		Oil palm
Crown area and height	Avsar, (2004), Peper, et al. (2001), Kalliovirta & Tokola (2005)	Turkey, California, Finland	Pine, many, pine

Other studies have applied other functional forms such as 'flexible' models, second-degree polynomials, power functions and others (Avsar, 2004; Chase & Henson, 2010; Peper, et al., 2001; Suratman, et al., 2004). These functions are reported to have good modelling performance but are difficult to generalize beyond the conditions, species and study sites in which they have been developed. A linear model therefore remains the most applicable model for relating the oil palm age and crown area.

5.4 Predicted conversion time

The estimations showed that the dominant age classes in the study area were 6 and 11 years old (planted in 2005 and 2000). As a result of the President Special Initiative, many new oil palm plantations were established in the period shortly after 2003 and are thus dominating the age classes (Duku, 2007). The 11 years old plantations correspond with the World Bank funding of oil palm development in Ghana (Carrere, 2010; Gyasi, 2003). These initiatives brought cheap to free seedlings, heightened extension technical support and provided policy framework for oil palm expansion and thus could have contributed large areas being converted to oil palm production. This indicates that the conversion and expansion of oil palm production areas in the study area due to national or international development programs has been correctly shown by this approach.

Mapping the age of oil palm showed the spatial and temporal oil palm developments. The knowledge of how oil palm expanded over space and time can therefore be useful for analyzing the effect of policies such as the

PSI (from 2003) or the multilateral development funding by the World Bank (from 1998) on the sector. Therefore, in addition to advocating for inclusion of RSPO criterion (such as Criterion 7.3) in the design and implementation of such oil palm development agendas, this approach could also be useful for analyzing the impacts of these initiatives on the environment across space and time. For example, the results of this approach may form part of a strategic impact assessment on impact of oil palm development on biodiversity or on food crop production.

5.5 Protected areas and high conservation values areas

For a country such as Ghana, it is may be highly unlikely for large scale expansion of oil palm plantation into protected areas such as forest reserves and wildlife sanctuaries to occur. However, islands of inversion could be possible especially by smallholder farmers and therefore a remote sensing based method will not only be useful for determining the ages but for identifying such activities. Nonetheless, as was observed from Figure 4.11, a nature friendly system of oil palm production is very important as the plantation could be established in wildlife corridors. For example, the plantations in the study area are between Bobiri, Anum Su North, Asonari and other reserves and it could be that these form habitats for wildlife that migrate between them for prey or herbivory. Certification in this area therefore provides opportunities for biodiversity conservation.

It was also clearly demonstrated that areas planted in HCVs after the benchmark year can be easily and objectively determined by overlaying the age maps with the HCV map. This is a more localized application of the approach that was shown by Fitzherbert et al (2008) on the relationship between oil palm areas and biodiversity hotspots at global level. This showed the sites, area and when the land was potentially converted to oil palm production. It will be easy then to know which areas automatically are not eligible for RSPO certification based on Criterion 7.3 and therefore no need for field visits or verification of other criteria. This may be important for saving costs of travelling to sites that are obviously not going to receive certification and therefore even on-site assessments are not necessary. However, caution should be taken that not all new plantings after 2005 maybe on HCVs or protected areas as land could be converted from another agricultural use or a replanting of oil palm. This verification can be again done by a remote sensing approach, but this does not require delineation approaches and very high resolution imagery as needed in determining the age.

5.6 Sensitivity and error analysis

Comparing the estimated and the actual ages showed that age prediction errors ranged from an underestimation of 4 years to an over estimation of 3 years. These errors could originate from the delineation, the prediction function or both. Although the results have shown that the most significant error sources were in predictions of older oil palm (13+ years), in terms of numbers this age was not dominating. Therefore, in addition to the problems with the older palms, there were also numerous errors in the younger age classes. As was explained in other remote sensing-based age estimations, canopy closure and associated leaf area index affect the spectral response and saturates at certain ages (McMorrow, 1995, 2001). As this may affect the accuracy in older age classes, it shows that the cause of errors could be different between different age classes and therefore the sensitivity varies depending on ages.

In addition, the problem of error propagation may be severe when combining 2 models; in this case remote sensing and a regression function both of which have their individual inaccuracies and the problem may be severe when they are combined. To demonstrate the effect of the combined errors, Figure 5.5a shows the effect of changing the model slope from the lower confidence limit to the upper confidence limit on the RMSE. The RMSE increases when the slope changes within limits to a maximum of about 1.6 years for the upper and the lower limit. On the other hand, changing the obtained OBIA CPA by ±10% demonstrates that increasing the values of the obtained OBIA by a range from 1 to 10 % increases the RMSE (Figure 5.5). However, when the values are decreased by the same range, the accuracy actually improves (lower RMSE) until up to a decrease of 6% of the obtained values. This shows that the crown area values obtained for the dominating younger age classes (2-10 years) were an over estimation of the crowns area and adjusting parameters to lessen the crown area may improve the accuracy but only up to a limited level. Therefore, while the applied model slope coefficient had optimized in terms of error (giving least RMSE), there is need for improving the delineation. This suggests that greater attention in application of this approach is required for crown area delineation in order to achieve reliable age estimates.

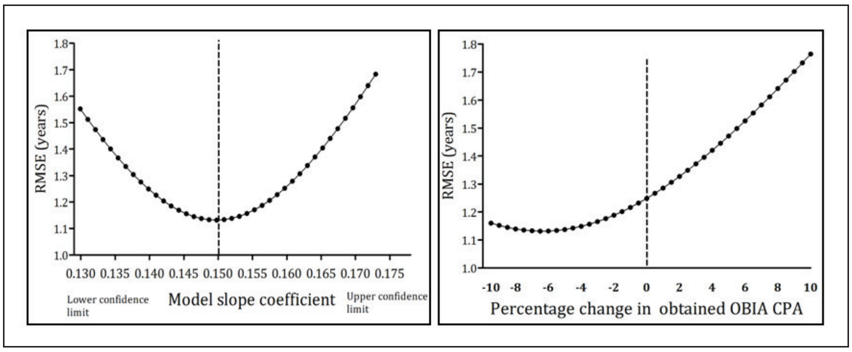


Figure 5.5: Analysis of error from (a)model and (b) OBIA delineation

The error propagation in the proposed approach could also explain the relative accuracies reported. For example the effect of the under segmentation in crown delineation could be reduced by over estimation of the model when these are combined for age prediction. As the most significant errors were actually for the older oil palms (over 10 years), which are not of direct interest for certification, the method can be considered scalable for assessing compliance with Criterion 7.3 for the oil palm sector. This is despite the fact that error at individual stand levels could be discouraging while the overall accuracy is very impressive.

CHAPTER 6: CONCLUSIONS & RECOMMENDATIONS

6.1 Conclusion

Individual crown area of oil palms can be determined using object based image analysis and the obtained crown can be used for predicting age of oil palms at field level. Many factors however affect the delineation accuracy and the most significant found in this study are stand characteristic particularly undergrowth (weeds and intercrops). The density of undergrowth differs in each field and a stand-level approach was found more suitable than delineation of the whole image. A significant positive linear relationship was observed between crown area and age of oil palm up to 13 years, beyond which no relationship is apparent. It was therefore c that a linear model would best for predicting the age of oil palm from crown area. It was concluded that the linear function was useful to predict the age of oil palm per field with accuracy of ±1 year up to 13 years. This happens to coincide with the age where delineation accuracy is also possible. It was demonstrated that no land was converted from protected areas to oil palm after 2005 and that it is possible to overlay a HCV map on the developed age map for RSPO criterion 7.3 certification.

6.2 Recommendations

Based on the methodology and findings of this study, the following recommendations are made:

- The approach demonstrated here depends on delineation of oil palm crowns on representative areas of a field and therefore needs to be more automated to make it more efficient for wider coverage such as national or regional oil palm age mapping. This will make the adoption of the approach more efficient for application in oil palm certification. Possible areas of improvement include investigation of hyper-spectral datasets for crown delineation. Upscaling to medium resolution imagery is also recommended given that high resolution images are expensive and not always available.

- Predicting oil palm age from remote sensed crown area was shown to only be possible up to 13 years and an approach that can expend the applicability of the model beyond the 13 years may be required. Other functional forms between age and CPA should therefore be tried. This is necessary for improving the accuracy in determining ages of older trees and for making the methods more applicable outside certification. It may be necessary to develop oil palm specific growth models or to borrow potentially applicable age-crown functions from other studies for achieving this.

- RSPO should adopt this approach as a certification decision support tool not specifically for Criterion 7.3 but for other criteria that require spatial data. In addition, other conservations agencies and support group could also use the same or an adapted approach for assessing age-based oil palm attributes and other characteristics. This is because of the cost effectiveness, time upturn and objectivity obtained from using it.

- There is need for an up-to-date HCV map for Ghana. This HCV map will be useful not only for assisting sustainability certification of palm oil production but for as part of biodiversity inventory. In addition, all palm oil producing countries should develop their HCV maps for application of remote sensing and other methods for RSPO certification.

APPENDICES

Appendix 1: Field Data collection

a)Crown diameter measurement b)Locating sample points with IPAQ c) Identifying sample plots on map d) Weed free young oil palm field e) Measuring oil palm diameter f)Measuring oil palm height g)Undergrowth in a oil palm field h) Weeds in oil palm field

Appendix 2: WorldView-2 image and metadata

GENERATIONTIME>2011-09-21T08:28:18.000000Z</GENERATIONTIME>
PRODUCTORDERID>052583754010_01_P001</PRODUCTORDERID>
PRODUCTCATALOGID>2030010089D26B00</PRODUCTCATALOGID>
IMAGEDESCRIPTOR>ORStandard2A</IMAGEDESCRIPTOR>
BANDID>P</BANDID>
PANSHARPENALGORITHM>None</PANSHARPENALGORITHM>
NUMROWS>12336</NUMROWS>
NUMCOLUMNS>14716</NUMCOLUMNS>
PRODUCTLEVEL>LV2A</PRODUCTLEVEL>
PRODUCTTYPE>Standard</PRODUCTTYPE>
NUMBEROFLOOKS>1</NUMBEROFLOOKS>
RADIOMETRICLEVEL>Corrected</RADIOMETRICLEVEL>
RADIOMETRICENHANCEMENT>Off</RADIOMETRICENHANCEMENT>
BITSPERPIXEL>16</BITSPERPIXEL>
COMPRESSIONTYPE>None</COMPRESSIONTYPE>
OUTPUTFORMAT>GeoTIFF</OUTPUTFORMAT>
<ULLON>-1.467776570000000e+00</ULLON>
<ULLAT>6.789094040000000e+00</ULLAT>
<ULHAE>3.127400000000000e+02</ULHAE>
<URLON>-1.401217810000000e+00</URLON>
<URLAT>6.788879090000000e+00</URLAT>
<URHAE>3.127400000000000e+02</URHAE>
<LRLON>-1.401401120000000e+00</LRLON>
<LRLAT>6.733109410000000e+00</LRLAT>

<LRHAE>3.127400000000000e+02</LRHAE>
<LLLON>-1.467952250000000e+00</LLLON>
<LLLAT>6.733322570000000e+00</LLLAT>
<LLHAE>3.127400000000000e+02</LLHAE>
<ABSCALFACTOR>5.678345000000000e-02</ABSCALFACTOR>
EFFECTIVEBANDWIDTH>2.846000000000000e-01</EFFECTIVEBANDWIDTH>
SATID>WV02</SATID>
MODE>FullSwath</MODE>
SCANDIRECTION>Forward</SCANDIRECTION>
CATID>1030010008862F00</CATID>
FIRSTLINETIME>2011-01-04T10:47:12.385874Z</FIRSTLINETIME>
AVGLINERATE>2.000003000000000e+04</AVGLINERATE>
EXPOSUREDURATION>1.600000000000000e-03</EXPOSUREDURATION>
MINCOLLECTEDROWGSD>4.820000000000000e-01</MINCOLLECTEDROWGSD>
MAXCOLLECTEDROWGSD>4.830000000000000e-01</MAXCOLLECTEDROWGSD>
MEANCOLLECTEDROWGSD>4.820000000000000e-01</MEANCOLLECTEDROWGSD>
MINCOLLECTEDCOLGSD>4.880000000000000e-01</MINCOLLECTEDCOLGSD>
MAXCOLLECTEDCOLGSD>4.880000000000000e-01</MAXCOLLECTEDCOLGSD>
MEANCOLLECTEDCOLGSD>4.880000000000000e-01</MEANCOLLECTEDCOLGSD>
MEANCOLLECTEDGSD>4.850000000000000e-01</MEANCOLLECTEDGSD>
ROWUNCERTAINTY>2.881000000000000e+01</ROWUNCERTAINTY>
COLUNCERTAINTY>4.186000000000000e+01</COLUNCERTAINTY>
MINSUNAZ>1.460000000000000e+02</MINSUNAZ>
MAXSUNAZ>1.460000000000000e+02</MAXSUNAZ>
MEANSUNAZ>1.460000000000000e+02</MEANSUNAZ>
MINSUNEL>5.420000000000000e+01</MINSUNEL>
MAXSUNEL>5.420000000000000e+01</MAXSUNEL>
MEANSUNEL>5.420000000000000e+01</MEANSUNEL>
MINSATAZ>1.252000000000000e+02</MINSATAZ>
MAXSATAZ>1.265000000000000e+02</MAXSATAZ>
MEANSATAZ>1.260000000000000e+02</MEANSATAZ>
MINSATEL>7.520000000000000e+01</MINSATEL>
MAXSATEL>7.530000000000000e+01</MAXSATEL>
MEANSATEL>7.530000000000000e+01</MEANSATEL>
MININTRACKVIEWANGLE>-6.000000000000000e+00</MININTRACKVIEWANGLE>
MAXINTRACKVIEWANGLE>-5.900000000000000e+00</MAXINTRACKVIEWANGLE>
MEANINTRACKVIEWANGLE>-
5.900000000000000e+00</MEANINTRACKVIEWANGLE>
MINCROSSTRACKVIEWANGLE>1.160000000000000e+01</MINCROSSTRACKVIEWAN
GLE>
MAXCROSSTRACKVIEWANGLE>1.170000000000000e+01</MAXCROSSTRACKVIEWAN
GLE>
MEANCROSSTRACKVIEWANGLE>1.170000000000000e+01</MEANCROSSTRACKVIEW
ANGLE
MINOFFNADIRVIEWANGLE>1.310000000000000e+01</MINOFFNADIRVIEWANGLE>
MAXOFFNADIRVIEWANGLE>1.310000000000000e+01</MAXOFFNADIRVIEWANGLE>
MEANOFFNADIRVIEWANGLE>1.310000000000000e+01</MEANOFFNADIRVIEWANGL
E>
PNIIRS>5.000000000000000e+00</PNIIRS>
CLOUDCOVER>0.000000000000000e+00</CLOUDCOVER>
RESAMPLINGKERNEL>CC</RESAMPLINGKERNEL>
POSITIONKNOWLEDGESRC>R</POSITIONKNOWLEDGESRC>
ATTITUDEKNOWLEDGESRC>R</ATTITUDEKNOWLEDGESRC>
REVNUMBER>6501</REVNUMBER></IMAGE>

Appendix 3: Field data processing in Matlab

Random partitioning data into 60:40

```
x=randsample(72,72); %random number generation
t=x(1:43);    % 60% of the data
v=x(44:72);   %40% of the data
 %% writing output to csv
% training data
train=all_data(t,:); %model training data
csvwrite('train2.csv',train);
header=['age,cpa,height,mgt,ID'];
outid = fopen('train2.csv', 'w+');
fprintf(outid, '%s', header);
fclose(outid);
dlmwrite ('train.csv',train,'roffset',1,'-append')
 % Validation data
valid=all_data(v,:); %model validation data
csvwrite('valid2.csv',valid);
header=['age,cpa,height,mgt,ID'];
outid = fopen('valid2.csv', 'w+');
fprintf(outid, '%s', header);
fclose(outid);
dlmwrite ('valid2.csv',valid,'roffset',1,'-append')
% aa=45;
```

Fitting a models to the training data

```
%% Building a  regression model
p=polyfit(cpa,age,1)  % model
R=corrcoef(age,cpa);  %R
R(1,2)
 yresid = age - yfit;
  %r-squared
 SSresid = sum(yresid.^2);
 SStotal = (length(age)-1) * var(age);
 rsq = 1 - SSresid/SStotal
 %adjusted rsquare
 R2adjusted = 1 - (SSresid / SStotal)*((43-1)/(43-1-1))

  %% plotting residuals for checking normality
figure
histfit( yresid)
% title('Histogram of residuals:
h = get(gca,'Children');
set(h(2),'FaceColor',[1 1 1])
ylim([0 25]);
xlabel('Residuals', 'fontsize',11,'fontweight','b')
ylabel('Frequency','fontsize',11,'fontweight','b')

% lillilifor test for normality
fprintf('Testing normality: ');
  if lillietest( yresid) == 1
     fprintf(' likely to be non-normal\n');
  else
     fprintf('There is no evidence of non-normality\n');
  end;

 figure
 qqplot(yresid);

%% Error statistics of calibration data
ageModAct1=0.59+cpa.*0.15;
ageModAct=round(ageModAct1);

R12 = corrcoef([ageModAct age]);
r12 = R12(1,2); % Correlation coefficient
r12sq = r12^2; % Coefficient of determination

RMSE=sqrt(sum((ageModAct-age).^2)/length(age));
MRE=sqrt(((sum((ageModAct-age)./age)./length(age))*100).^2);
MAE=mean(sqrt((ageModAct-age).^2));
 % aa=45;
```

Testing model on independent data set and error statistics

```
%% implementing the model to get modeled age
ageModAct1=0.59+cpa.*0.15;
ageModAct=round(ageModAct1);

%% error statistics
R12 = corrcoef([ageModAct ageObs]);
r12 = R12(1,2); % Correlation coefficient
r12sq = r12^2; % Coefficient of determination
 RMSE=sqrt(sum((ageModAct-ageObs).^2)/length(ageObs));
MRE=sqrt(((sum((ageModAct-ageObs)./ageObs)./length(ageObs))*100).^2);
 MAE=mean(sqrt((ageModAct-ageObs).^2));

%% 1:1 plot of actual and predicted
 plot(ageObs,ageModAct,'ok','LineWidth',2);
ylim([0 14])
xlim([0 14])
xlabel('Actual Age(years)', 'fontsize',12)
ylabel('Predicted Age(years)', 'fontsize',13)

%% Correlation between modeled and actual age
R12 = corrcoef([ageModAct ageObs]);
r12 = R12(1,2); % Correlation coefficient
r12sq = r12^2; % Coefficient of determination
aa=45;
```

REFERENCES

Achten, W. M. J., Vandenbempt, P., Almeida, J., Mathijs, E., & Muys, B. (2010). Life cycle assessment of a palm oil system with simultaneous production of biodiesel and cooking oil in Cameroon. *Environmental Science and Technology, 44*(12), 4809-4815.

Anornu, G. K., Kortatsi, B. K., & Saeed, Z. M. (2009). Evaluation of groundwater resources potential in the Ejisu-Juaben district of Ghana. *African Journal of Environmental Science and Technology, 3*(10), 332-340.

Arbiol, R., Zhang, J., & Pala, Y. (2006). *Advanced classification techniques: A review*. Paper presented at the ISPRS Commission Mid-term Symbosium 'From Pixels to Processes'.

Asubonteng, K. O. (2007). *Identification of land use/cover transfer hotspots in Ejisu-Juabeng District, Ghana.* Univeristy of Twente, Enschede.

Avsar, M. D. (2004). The relationship between diameter at breast height, tree height and crown dameter in Calabrian pines (Pinus brutia Ten.) of Baskonus Mountain, Kahramanamaras, Turkey. *Journal of Biological Sciences 4*(4), 437-440.

Barjolle, D., Damary, M., & Schaer, B. (2010). *Certification schemes and sustainable rural development: Analytical framework for assessment of impacts.* Paper presented at the International EAAE-SYAL Seminar - Spatial Dynamics in Agri-food Systems: Implications for sustainability and consumer welfare, 27-30 October, Parma.

Basiron, Y. (2007). Palm oil production through sustainable plantations. *European Journal of Lipid Sciences and Technology, 109*, 289-295.

Blaschke, T. (2010). Object based image analysis for remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing, 65*, 2-16.

Blaschke, T., Johansen, K., & Tiede, D. (2011). Object-based image analysis for vegetation mapping anf monitoring. In Q. Weng (Ed.), *Advances in environmental remote sensing: Sensors, algorithms and application* (pp. 610): CRC Press.

Breure, C. J. (1985). Relevant factors associated with crown expansion in oil palm (Elaeis guineensisJacq.). *Euphytica, 34*(1), 161-175.

Butler, R., Koh, L. P., & Ghazoul, J. (2009). REDD in the red: palm oil could undermine carbon payment schemes. *Conservation Letters, 2*, 67-83.

Carrere, R. (2010). Oil palm in Africa: Past present and future scenarios, WRM series on tree plantations (Vol. 15,

Chase, L. D. C., & Henson, I. E. (2010). A detailed greenhouse gas budget for palm oil production. *International Journal of Agricultural Sustainability, 8*(3), 199-214.

Clinton, N., Holt, A., Scarborough, J., Yan, L., & Gong, P. (2010). Accuracy assessment measures for object-based image segmentation goodness. *Photogrammetric Engineering & Remote Sensing, Vol. 76*(3), 289–299.

Corley, R. H. V. (2009). How much palm oil do we need? *Environmental Science & Policy, 12*(2), 134-139.

Dankers, C. (2003). *Environmental and Social Standards, Certification and Labelling for Cash Crops*. Rome: FAO Commodities and Trade.

Darwish, A., Leukert, K., & Reinhardt, W. (2003, 21-25 July 2003). *Image segmentation for the purpose of object-based classification.* Paper presented at the Geoscience and Remote Sensing Symposium, 2003. IGARSS '03. Proceedings. 2003 IEEE International.

Dewi, S., Khasanah, N., Rahayu, S., Ekadinata, A., & Noordwijk, M. (2009). Carbon Footprint of Indonesian palm oil production: A pilot study. *World Agroforestry Centre (ICRAF) SEA Regional Office*.

Digital Globe (2009). The Benefits of the 8 Spectral Bands of WorldView-2: Whitepaper Retrieved 28 November 2011, from http://worldview2.digitalglobe.com/docs/WorldView-2_8-Band_Applications_Whitepaper.pdf

Dragut, L., Tiede, D., & Levick, S. R. (2010). ESP: a tool to estimate scale parameter for multiresolution image segmentation of remotely sensed data. *International Journal of Geographical Information Science, 24*(6), 859-871.

Dries, L., & Mancini, M. C. (2006). Food quality assurance and certification schemes. *European Commision Stakeholder Hearing, 11/12 May 2006*, 48.

Duku, M. H. (2007, 4 July 2007). *Status of biofuel development in Ghana.* Paper presented at the Biofuels from Palm Oil: Emerging Technologies and their Assessments, Kualur Lumpur, Malaysia.

Erikson, M. (2004). *Segmentation and classification of individual tree crowns in high spatial resolution aerial images.* Unpublished Doctoral Thesis, Swedish University of Agricultural Sciences, Uppsala.

FAO (2003). Small-scale palm oil processing in Africa. *FAO Agricultural Services Bulettin, 148*.

Fischer, G., Hizsnyik, E., Prieler, S., Shah, M., & van Velthuizen, H. (2009). *Biofuels and food security: Implications of an accelerated biofuels production*. Vienna, Austria: International Institute for Applied Systems Analysis (IIASA),.

Fitzherbert, E. B., Struebig, M. J., Morel, A., Danielsen, F., Brühl, C. A., Donald, P. F., & Phalan, B. (2008). How will oil palm expansion affect biodiversity? *Trends in Ecology & Evolution, 23*(10), 538-545.

Foody, G. M. (2002). Status of land cover classification accuracy assessment. *Remote Sensing of Environment, 80*(1), 185-201.

Friends of the Earth (2007). *Policy, practice and predijuce: A review of legal, environmental and social practices of oil palm plantation companies of the Wilmar Group in Sambas District, West Kalimantan (Indonesia)*. Amsterdam: Friends of the Earth/Lambaga Gemawan/ KONTAK Rakyat Borneo.

Gamanya, R., De Maeyer, P., & De Dapper, M. (2007). An automated satellite image classification design using object-oriented segmentation algorithms: A move towards standardization. *Expert Systems with Applications, 32*(2), 616-624.

Germer, J., & Sauerborn, J. (2008). Estimation of the impact of oil palm plantation establishment on greenhouse gas balance. *Environment, Development and Sustainability, 10*(6), 697-716.

Gerritsma, W., & Soebagyo, X. F. (1999). An nalysis of the growth of the leaf area of oil palms in Indonesia. *Experimental Agriculture, 35*, 293-308.

Glenn, E. P., Huete, A. R., Nagler, P. L., & Nelson, S. G. (2008). Relationship between remotely-sensed vegetation indices, canopy attributes and plant physiological processes: What vegetation indices can and cannot tell us about the landscape. *Sensors, 8*(4), 2136-2160.

Gyasi, E. A. (1992). Emergence of a new oil palm belt in Ghana. *Tijdschrift voor economische en sociale geografie, 83*(1), 39-49.

Gyasi, E. A. (1996). The environmental impact and sustainability of plantations in Sub-Saharan Africa: Ghana's experiences with oil-palm plantations. In G. Benneh, W. B. Morgan & J. I. Uitto (Eds.), *Sustaining the Future: Economic, Social and Environmental Change in Sub-Saharan Africa* (pp. 342-357). Tokyo: The United Nations University.

Gyasi, E. A. (2003). *The environmental impact and sustainability of plantations in Sub-Saharan Africa: Ghana's experiences with oil-palm plantations*: UNU Press.

Hardter, R., Chow, W. Y., & Hock, O. S. (1997). Intensive plantation cropping, a source of sustainable food and energy production in the tropical rain forest areas of southeast Asia. *Forest Ecology and Management, 93*, 93-102.

Härdter, R., Chow, W. Y., & Hock, O. S. (1997). Intensive plantation cropping, a source of sustainable food and energy production in the tropical rain forest areas in southeast Asia. *Forest Ecology and Management, 91*(1), 93-102.

Hay, G. J., & Castella, G. (2006). Object-based image analysis: strengths, weaknesses, opportunities and threats (SWOT). *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume No. XXXVI*(4/C42).

Hemery, G. E., Savill, P. S., & Pryor, S. N. (2005). Applications of the crown diameter–stem diameter relationship for different species of broadleaved trees. *Forest Ecology and Management, 215*, 285-294.

Hirschmugl, M., Ofner, M., Raggam, J., & Schardt, M. (2007). Single tree detection in very high resolution remote sensing data. *Remote Sensing of Environment, 110*(4), 533-544.

Holbech, L. H. (2009). The conservation importance of luxuriant tree plantations for lower storey forest birds in south-west Ghana. *Bird Conservation International, 19*(3), 287-308.

Ibrahim, S., Hasan, Z. A., & Khalid, M. (2000). *Application of optical remote sensing technology for oil palm management*. Paper presented at the 21st Asian Conference Remote Sensing Conference.

Kalliovirta, J., & Tokola, T. (2005). Functions for estimating stem diameter and tree age using tree height, crown width and existing stand database information. *Silva Fennica, 39*(2), 227-248.

Koh, L. P., & Wilcove, D. S. (2008). Is oil palm agriculture really destroying tropical biodiversity? *Conservation Letters, 1*(2), 60-64.

Lang, S. (2008). Object-based image analysis for remote sensing applications: modeling reality – dealing with complexity

Object-Based Image Analysis. In T. Blaschke, S. Lang & G. J. Hay (Eds.), (pp. 3-27): Springer Berlin Heidelberg.

Larsen, M., Eriksson, M., Descombes, X., Perrin, G., Brandtberg, T., & Gougeon, F. A. (2011). Comparison of six individual tree crown detection algorithms evaluated under varying forest conditions. *International Journal of Remote Sensing*, 1-26.

Laurance, W. F., Koh, L. P., Butler, R., Sodhi, N. S., Bradshaw, C. J. A., Neidel, J. D., Consunji, H., & Vega, J. M. (2010). Improving the performance of the roundtable on sustainable palm oil for nature conservation. *Conservation Biology, 24*(2), 377-381.

Leckie, D. G., Gougeon, F. A., Tinis, S., Nelson, T., Burnett, C. N., & Paradine, D. (2005). Automated tree recognition in old growth conifer stands with high resoluttion digital imagery. *Remote Sensing of Environment, 94*(3), 311-326.

Lillesand, T. M., & Kiefer, R. W. (2008). *Remote Sensing and Image Interpretation* (5th ed.). New York: Wiley & Sons.

Lunetta, R. S., Knight, J. F., Ediriwickrema, J., Lyon, J. G., & Worthy, L. D. (2006). Land-cover change detection using multi-temporal MODIS NDVI data. *Renewable and Sustainable Energy Reviews, 105*, 142-154.

Marshall, V., Lewis, M., & Ostendorf, B. (2011). Can 8-band Worldview-2 Imagery be used to discriminate an invasive grass species? *Digital Globe 8-band challenge*, 1-13.

McMorrow, J. (1995). Relation of oil palm spectral response to stand age. *International Journal of Remote Sensing, 16*(16), 3203-3209.

McMorrow, J. (2001). Linear regression modelling for the estimation of oil palm age from Landsat TM. *International Journal of Remote Sensing, 22*(12), 2243-2264.

Mugo, J. M., Njunge, J. T., Malimbwi, R. E., Kigomo, B. N., Mwasi, B. N., & Muchiri, M. N. (2011). Models for predicting stem diameter from crown diameter of open crown trees in Sondu-Nyando River Catchment, Kenya. *Asian Journal of Agricultural Sciences, 3*(2), 119-126.

Navulur, K. (2007). *Multispectral image analysis using the object-oriented paradigm*. Boca: Taylor & Francis

Nellemann, C., Miles, L., Kaltenborn, B. P., Virtue, M., & H, A. (2007). *The last stand of the orangutan - State of Emergency: Illegal logging, fire and palm oil in Indonesia's National Parks*. Norway: United Nations Environemt Programme(UNEP).

Niccolai, A., Hohl, A., Niccolai, M., & Oliver, C. D. (2010). Integration of varying spatial, spectral and temporal high-resolution optical images for individual tree crown isolation. [Article]. *International Journal of Remote Sensing, 31*(19), 5061-5088.

Norris, K., Asase, A., Collen, B., Gockowksi, J., Mason, J., Phalan, B., & Wade, A. (2010). Biodiversity in a forest-agriculture mosaic - The changing face of West African rainforests. *Biological Conservation, 143*(10), 2341-2350.

OPRI (2003). Notes on oil palm, . Oil Palm Research Institute, CSIR.

Ozdemir, I. (2008). Estimating stem volume by tree crown area and tree shadow area extracted from pan-sharpened Quickbird imagery in open Crimean juniper forests. *International Journal of Remote Sensing, 29*(19), 5643-5655.

Padwick, C., Deskevich, M., Pacifici, F., & Snmallwood, S. (2010). *Worldview 2 pan sharpening*. Paper presented at the ASPRS Conference.

Partzsch, L. (2011). The legitimacy of biofuel certification. *Agriculture and Human Values, 28*(3), 413-425.

Peper, P. J., McPherson, E. G., & Mori, S. M. (2001). Functions for predicting diameter, height, crown width, and leaf area of San Joaquin Valley street trees. *Journal of Arboriculture, 26*(6), 306-317.

Phalan, B., Fitzherbert, E. B., Rafflegeau, S., Struebig, M. J., & Verwilghen, A. (2009). Conservation in oil-palm landscapes. *Conservation Biology, 23*(2), 244-245.

Pouliot, D. A., King, D. J., Bell, F. W., & Pitt, D. G. (2002). Automated tree crown detection and delineation in high-resolution digital camera imagery of coniferous forest regeneration. *Remote Sensing of Environment, 82*(2-3), 322-334.

Ravindranath, N. H., Manuvie, R., Fargione, J., Canadell, J., Berndes, G., Woods, J., Watson, H., & Sathaye, J. (2009). Greenhouse gas implications of land use and land conversion to biofuel crops. In Howarth RW & B. S (Eds.), *Biofuels: Environmental Consequences and Interactions with Changing Land Use*. New York.: Scientific Committee on Problems of the Environment (SCOPE), Island Press,.

Ray, T. W. (1994). A FAQ on vegetation in remote sensing (pp. 16). Carlifornia: California Institute of Technology.

Rogan, J., & Chen, D. (2004). Remote sensing technology for mapping and monitoring land-cover and land-use change. *Progress in Planning, 61*(4), 301-325.

Rosenqvist, Å., Milne, A., Lucas, R., Imhoff, M., & Dobson, C. (2003). A review of remote sensing technology in support of the Kyoto Protocol. *Environmental Science & Policy, 6*(5), 441-455.

RSPO (2007). RSPO Principles and Criteria for Sustainable Palm Oil Production, *Including indicators and Guidelines* (pp. 53): RSPO.

RSPO (2011). *Ghana national interpretation of RSPO principles and criteria for sustainable palm oil*.

Scarlat, N., & Dallemand, J. F. (2011). Recent developments of biofuels/bioenergy sustainability certification: A global overview. *Energy Policy, 39*(3), 1630-1646.

Shafri, H. Z. M., & Anuar, M. (2008, 20-22 Dec. 2008). *Hyperspectral Signal Analysis for Detecting Disease Infection in Oil Palms.* Paper presented at the Computer and Electrical Engineering, 2008. ICCEE 2008. International Conference on Computer and Electrical Engineering.

Shafri, H. Z. M., Anuar, M., Seman, I. A., & Noor, M. (2011). Spectral discrimination of healthy and Ganoderma-infected oil palms from hyperspectral data. *International Journal of Remote Sensing, 32*(22), 7111 - 7129.

Shafri, H. Z. M., Hamdan, N., & Saripan, M. (2011). Semi-automatic detection and counting of oil palm trees from high spatial resolution airborne imagery. *International Journal of Remote Sensing, 32*(8), 2095-2115.

Sims, D. A., & Gamon, J. A. (2002). Relationships between leaf pigment content and spectral reflectance across a wide range of species, leaf structures and developmental stages. *Remote Sensing of Environment, 81*(2-3), 337-354.

Stone, R. (2007). Can Palm Oil Plantations Come Clean? *Science, 317*(5844), 1491.

Struebig, M. J. (2010). Reassessing the "real scenario" regarding the environmental sustainability of palm oil. *Renewable and Sustainable Energy Reviews, 14*(8), 2443-2444.

Suratman, M. N., Bull, G. Q., Leckie, D. G., Lemay, V. M., Marshall, P. L., & Mispan, M. R. (2004). Prediction models for estimating the area, volume, and age of rubber (Hevea brasiliensis) plantations in Malaysia using Landsat TM data. *International Forestry Review, 6*(1), 1-12.

Tan, K. T., Lee, K. T., Mohamed, A. R., & Bhatia, S. (2009). Palm oil: Addressing issues and towards sustainable development. *Renewable & Sustainable Energy Reviews, 13*(2), 420-427.

Thenkabail, P. S., Stucky, N., Griscom, B. W., Ashton, M. S., Diels, J., Van der Meer, B., & Enclona, E. (2004). Biomass estimations and carbon stock calculations in the oil palm plantations of African derived savannas using IKONOS data. *International Journal of Remote Sensing, 25*(23), 5447-5472.

Trimble (2010). *eCognition Developer 8.64.0: User Guide*. München: Trimble Germany GmbH,.

Turner, W., Spector, S., Gardiner, N., Fladeland, M., Sterling, E., & Steininger, M. (2003). Remote sensing for biodiversity science and conservation. *Trends in Ecology & Evolution, 18*(6), 306-314.

van Dam, J., Junginger, M., Faaij, A., Jurgens, I., Best, G., & Fritsche, U. (2008). Overview of recent developments in sustainable biomass certification. *Biomass & Bioenergy, 32*(8), 749-780.

Wang, L. (2010). A multi-scale approach for delineating Individual tree crowns with very high resolution imagery. *Photogrammetric Engineering & Remote Sensing, 76*(4), 371-378.

Whiteside, T. G., Boggs, G. S., & Maier, S. W. (2011). Extraction of tree crowns from high resolution imagery over eucalypt dominant tropical savannas. *Photogrametric Engineering & Remote Sensing, 77*(8), 813-824.

Wicke, B., Sikkema, R., Dornburg, V., & Faaij, A. (2011). Exploring land use changes and the role of palm oil production in Indonesia and Malaysia. *Land Use Policy, 28*(1), 193-206.

Wolf, B. M., & Heipke, C. (2007). Automatic extraction and delineation of single trees from remote sensing data. *Machine Vision and Applications, 18*, 317-330.

WRM (2010). Oil palm production in Ghana. *Oil palm production in Africa* Retrieved 3 January 2012, from http://oilpalminafrica.wordpress.com/2010/08/06/oil-palm-in-ghana/

Wu, W. C. (2009). Monitoring land degradation in drylands by remote sensing. In A. Marini & M. Talbi (Eds.), *Desertification and Risk Analysis Using High and Medium Resolution Satellite Data* (pp. 157-170). Dordrecht: Springer.

WWF (2007). *Rainforest for biodiesel?: Ecological effects of using palm oil as a source of energy*: WWF Germany/Switzerland/Netherlands.

Xiaoxia, S., Jixian, Z., & Zhengjun, L. (2005, 27 - 27 Aug). *A comparison of object-oriented and pixel-based classification approaches using Quickbird.* Paper presented at the International Symposium on Spatio-temporal Modeling, Spatial Reasoning, Analysis, Data Mining and Data Fusion, Beijing.