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Determination of the age of oil palm from crown projection area detected from WorldView-2 multispectral remote sensing data: The case of Ejisu-Juaben district, Ghana

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ABSTRACT

Information about age of oil palm is important in sustainability assessments, carbon mapping, yield projections and precision agriculture. The aim of this study was to develop and test an approach to determine the age of oil palm plantations (years after planting) by combining high resolution multispectral remote sensing data and regression techniques using a case study of Ejisu-Juaben district of Ghana. Firstly, we determined the relationship between age and crown projection area of oil palms from sample fields. Secondly, we did hierarchical classification using object based image analysis techniques on WorldView-2 multispectral data to determine the crown projection areas of oil palms from remote sensing data. Finally, the crown projection areas obtained from the hierarchical classification were combined with the field-developed regression model to determine the age of oil palms at field level for a wider area. Field collected data showed a strong linear relationship between age and crown area of oil palm up to 13 years beyond which no relationship was observed. A user's accuracy of 80.6% and a producer's accuracy of 68.4% were obtained for the delineation of oil palm crowns while for delineation of non-crown objects a user's accuracy of 65.6% and a producer's accuracy of 78.6% were obtained, with an overall accuracy of 72.8% for the OBIA delineation. Automatic crown projection area delineation from remote sensing data produced crown projection areas which closely matched the field measured crown areas except for older oil palms (13+ years) where the error was greatest. Combining the remote sensing detected crown projection area and the regression model accurately estimated oil palm ages for 27.9% of the fields and had an estimation error of 1 year or less for 74.6% of the fields and an error of a maximum 2 years for 92.4% of the fields. The results showed that 6 and 11 year old oil palm stands were dominating age categories in the study area. Although the method could be reliably applied for estimating oil palm age at field level, more attention is required in improving crown area delineation to improve the accuracy of the approach.

1. Introduction

Palm oil is obtained from the African oil palm (*Elaeis guineensis* Jacq.); monocotyledonous perennial plants that are indigenous to West Africa but are now grown in more than 43 tropical countries mainly between 10°N and 10°S of the equator (Hardter et al., 1997). Annual global production and use of palm oil is over thirty-five million metric tons with Malaysia and Indonesia being leading producers, contributing over 80% of global production (Fitzherbert et al., 2008; Germer and Sauerborn, 2008). The total area under commercial oil palm production is over thirteen and a half million hectares (Butler et al., 2009). Consequently, palm oil is the second most important source of vegetable oil in the world after soybean (Tan et al., 2009). Due to increasing demands for palm oil as a food resource in China, India and South America and as biofuel in the European Union, global production has been increasing at a rate of 9% annually in the last three decades (Koh and Wilcove, 2008; Tan et al., 2009). This is mainly because oil palms have the highest potential yield per hectare of all sources of vegetable oil (Corley, 2009). The growth in area under oil palm has been associated with many and widespread environmental problems such as deforestation and associated biodiversity loss in tropical areas (Butler et al., 2009; Carlson et al., 2012; Fitzherbert et al., 2008; Stone, 2007).

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The ability of remote sensing data to automatically detect and quantify plant biophysical parameters and biochemical properties through direct spectral measurements and/or vegetation indices is very useful in agricultural, forestry, environmental and land governance applications. Remote sensing can be used for producing a resource inventory of location of oil palm fields, size of plantations and age of oil palms. As such, remote sensing techniques have been developed for various management aspects of oil palm production such as disease detection (Santoso et al., 2011; Shafri and Anuar, 2008; Shafri et al., 2011a), counting of number of trees (Jusoff, 2009; Shafri et al., 2011b), recognition of oil palm bunch types (Alfatni et al., 2013), yield estimation (Balasundram et al., 2013), biomass estimation (Morel et al., 2012; Thenkabail et al., 2004) and determination of age (Ibrahim et al., 2000; McMorrow, 1995, 2001). Various sensors and sensing platforms such as Landsat TM satellite imagery (McMorrow, 2001), Quickbird satellite imagery (Balasundram et al., 2013; Santoso et al., 2011), hyperspectral airborne data (Jusoff, 2009; Shafri and Anuar, 2008) and IKONOS satellite imagery (Thenkabail et al., 2004) have been applied in these applications.

Information about the ages of oil palm plantations is important for biomass estimation and carbon stock inventory for oil palm plantations, an important aspect to biodiversity conservation and reducing greenhouse gas emissions from palm oil production (Thenkabail et al., 2004). In addition, some oil palm plantations are very large (exceeding 1000 ha) and therefore detecting age of oil palms is important for ensuring optimal resource utilization and management of farm operations such as fertilization. Efficient farm management results in higher productivity per unit area, and this is important in meeting production targets without expanding area under production. Oil palm age detection is also useful in yield forecasting, which is useful in pre-harvesting and post harvesting operation planning and market intelligence necessary for economic planning at local and regional levels (Balasundram et al., 2013). Furthermore, due to increasing market demand for sustainably produced palm oil, determining age of oil palm at field level is important in assessing certification requirements such as those for Round Table for Sustainable Palm Oil Production (RSPO). Traditional approaches to making these inventories rely only on ground based survey data to obtain this information, which alone is expensive, time consuming, arduous and may not be able to cover large areas. Remote sensing therefore becomes useful as it can complement ground data by extrapolating information from field samples to a wider area.

One remote sensing approach to determine the age of oil palm and other agricultural and forestry plantation trees is determining the relationship between radiance of individual image bands or derived vegetation indices to age at stand level (Franklin et al., 2003; McMorrow, 1995). It was established for oil palm that there was a negative nonlinear correlation between Landsat TM radiance and age on all image bands meaning that reflectance diminished with age of oil palms at stand level (McMorrow, 1995, 2001). Another approach to determine age is to use supervised or unsupervised image classification algorithms to classify an image into discrete age categories or age classes (Thenkabail et al., 2004). This approach is based on the hypothesis that each age or age class has a significantly different spectral signature that can be used to separate it from the next. With the advent of high resolution imagery and advancement of techniques to handle and process such data, it may be possible to extend the determination of oil palm age to the extraction of plant biophysical properties such as height and crown projection area from high spatial and spectral resolution remote sensing data that are known to be directly related to age.

It has been established in many plantation crops that there is a significant relationship between age and plant biophysical characteristics such as crown diameter, crown projection area, leaf area index, height and stem diameter (Kalliovirta and Tokola, 2005; Peper et al., 2001). The growth characteristics of oil palm can be divided into three stages; young, mature and old depending on the relationship between age and leaf area index as established from field studies (Breure, 1985, 2010; Gerritsma and Soebagyo, 1999). The leaf area index of oil palms has been observed to increase up to 10–12 years, after which the leaf area will remain constant or decrease (Breure, 1985; Van Kraalingen et al., 1989). Given the relationship between age and growth attributes of oil palm, combining a remote sensing method that can accurately detect oil palm crown projection area (or related biophysical attributes) with an empirical model that relate crown projection area to age provides a promising way of determine age of oil palm at field level from high resolution satellite imagery.

Use of high-resolution imagery such as WorldView-2 imagery processed through object-based image analysis (OBIA) provide a promising framework for determining age of oil palm at stand level through automatically extracting age-related parameters. Developments in OBIA have produced robust, reliable and automated routines for implementation of highly advanced algorithms (Blaschke, 2010; Navulur, 2007; Wang et al., 2013). An important aspect of OBIA is the inclusion of ancillary data such as texture, shape, size and relationships to image feature identification decisions (Blaschke, 2010). In feature identification decisions through OBIA, among the most important decision rules is the concept of scale, which defines the thresholds at which individual spatial or temporal features of an image can be treated as functionally homogeneous or heterogeneous (Addink et al., 2007; Blaschke, 2010; Gamanya et al., 2007; Wang et al., 2013). As such, the goal of a segmentation algorithm is to cut-up an image into uneven, non-random units based on spatial, functional and/or temporal heterogeneity functions and the resultant units are referred to as 'candidate objects' and these can be further purified into meaningful object features (Blaschke, 2010; Gamanya et al., 2007; Lang, 2008; Navulur, 2007). These object features can therefore be used in deriving image characteristics and meaning from satellite image data for use in decision making.

There have been significant developments in techniques for individual tree crown delineation from aerial imagery, satellite data and LIDAR data. These include analysis of crown texture in high resolution imagery to distinguish it from surroundings (Wu et al., 2004) and use of geostatistical methods that identify the apex of the crown first and then identify the crown boundary by determining the maximum rate of change across potential crowns (Feng et al., 2010; Pouliot et al., 2002; Song, 2007; Wang, 2010). Region growing techniques that identify and grow the local crown peaks (Brandtberg and Walter, 1998), detecting the local maxima and minima used for identifying the centroids and boundaries of the crowns (Culvenor, 2003b) and template matching algorithms (Erikson, 2004; Komura et al., 2004) have also been used in crown delineation. Other algorithms incorporated use of digital surface models in identification and delineation of individual tree crowns (Mei and Durrieu, 2004; Wolf and Heipke, 2007). Segmentation-based approaches that cut up the image according to spectral heterogeneity or homogeneity and then apply spectral, geometric, morphological, textural and other rules to identify tree crowns are increasingly being developed (Erikson, 2004; Whiteside et al., 2011; Wolf and Heipke, 2007). OBIA platforms have been able to incorporate many of these algorithms (spectral analysis, texture, morphology, geometry, colour) and thus making it possible to either choose one or combinations of techniques for individual tree crown detection. Although work on individual tree crown detection have been done for oil palm (Shafri et al., 2011b), the specific characteristics for mapping oil palm crowns in OBIA are not yet well established and the nature of oil palm crown presents further challenges compared to natural forests and other plantations for which research on crown projection area delineation has been done. In addition, much of the work relied on individual panchromatic or NIR bands for crown detection and no specific application of the detected crown area has been tested.

The main aim of this study was to develop and test a protocol to determine the age of oil palm by combining high resolution remote sensing extracted crown projection area to a field developed regression model that relate crown projection area to age. The method is demonstrated using a case study of Ejisu-Juaben district of Ghana. This was achieved through (1) determining the relationship between crown projection area and oil palm age through field data, (2) detecting crown projection are from WorldView-2 high resolution multispectral remote sensing data and (3) combining the remote sensing extracted crown projection area and the regression model to determine age of oil palm for a wider area. To test the potential use of the determined ages, we used oil palm ages as a proxy for time of land use/cover conversion to oil palm production which can be used in sustainability assessments and documentation of the growth in area under production.

2. Materials and methods

2.1. Study area

The study was carried out in Ejisu-Juaben district in the Ashanti Region of Ghana (Fig. 1). The district is located within longitude 6.42°N to 6.83°N and latitude 1.25°W to 1. 58°W, covering an area of about 64,000 ha. The topography is flat to undulating, with altitude ranging between 230 m and 300 m above sea level and has no major landform features. Dominant soil types are derived from pre-Cambrian rock formations such as granite, Birrimian, Tarkwaian and superficial deposits (Anornu et al., 2009). Soil fertility, agricultural productivity and cropping patterns are resultantly influenced by the distribution of these soil types. The climate characteristics are equatorial with high mean total annual rainfalls of above 1000 mm and high mean annual temperatures of around 26 °C (Anornu et al., 2009).

2.2. Multispectral remote sensing data

A WorldView-2 image (Digital Globe®) taken on the 4th of January 2011 was used in this study (www.digitalglobe.com). WorldView-2 imagery comprises eight spectral bands in the spectral ranges of 400–450 nm (Coastal blue), 450–510 nm (Blue), 510–580 nm (Green), 585–625 nm (Yellow), 630–690 nm (Red), 705–745 nm (Red edge), 770–895 nm (Near infrared 1) and 860–1040 nm (Near infrared 2) all at 1.84 m resolution and one in the panchromatic band (450–800 nm) at 0.5 m resolution. The image is cloud free and covered an area of 5200 ha. Pan sharpening of the image was done using the hyperspherical colour space resolution merge described by Padwick et al. (2010) as suitable for WorldView-2 imagery. The quick atmospheric correction model (QUAC) in ENVI 4.3 was used to approximate reflectance to top of the atmosphere reflectance by using the information contained within the image scene (ENVI, 2008).

Next, six ground control points collected using a GPS (Garmin® eTrex) at road intersections in the study area were used for geometric correction. A first order polynomial (Affine) transformation was used for geometric correction of the WorldView-2 imagery because the study area has a generally flat terrain. The transformation had a root mean square error of less than a pixel (0.26 m) which was considered adequate for the purpose of the study. The study was interested only in oil palm fields and therefore an oil palm and non-oil palm map was produced by digitising the boundaries of oil palm fields around GPS coordinates of oil palm fields collected during field work and previous oil palm studies in the area.

2.3. Field data collection

Field data were collected between 12 September and 14 October 2011 in the study area. Crown diameter and age of the oil palms was measured in 88 sample sites selected using stratified random sampling in corporate and smallholder plantations. Using a printed field map and a handheld geographic information system (HP iPAQ with ArcPad and Bluetooth GPS), the location of the selected sample sites was determined. On each field where the age of the oil palm could be established, three adjacent trees were randomly selected for measuring their crown diameters, and for that sample, GPS coordinates were taken from the central tree. 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. The two

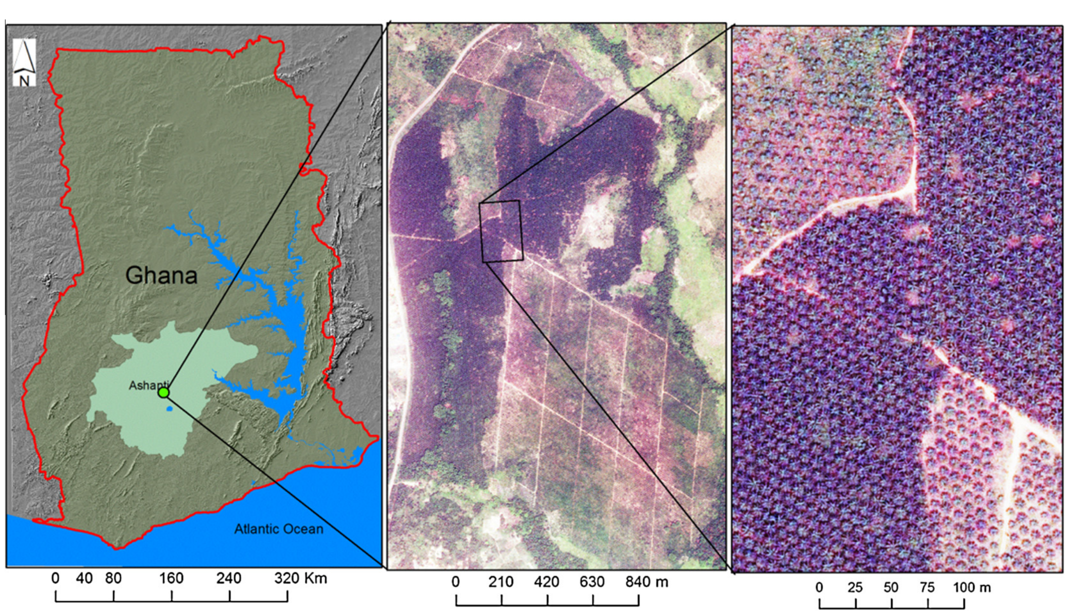

Fig. 1. A map of the location of the study area. Fig. 1a shows the location of Ejisu-Juaben district in Ghana and in Ashanti Region. Fig. 1b shows a sample oil palm farm covered by the WorldView-2 satellite image data and Fig. 1c shows a sample of oil palm crowns of different ages as shown on the WorldView-2 satellite image.

measurements intersected at a right angle. The information on ages of each oil palm stand was obtained through on-site interviews with farmers and extension workers. 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. In order to make sure that the 3 field measured trees at each stand are the ones identified on the image with the delineated crowns, a 17.5 m buffer was created around the stand centres and the trees extracted by masking with the buffer. It was determined that a buffer of 17.5 m was ideal because the plant spacing was 9 m with measurements taken from 3 trees giving a length of 27 m and therefore a 17.5 m buffer gave a circular stand diameter of 35 m covering the 3 oil palms measured in the field.

2.4. Generation and application of a regression model

From the field work, 88 plots were sampled, each with three trees. To convert the crown diameters to crown projection area, analysis of the relationship between measured diagonals showed that the crowns were circular and therefore the formulae for a circle was used for converting the crown diameters to crown projection area (CPA). The average CPA of the three trees was computed and used as CPA for that plot. A scatter plot of age and CPA was produced 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 regression model that can predict age from CPA from field data. The field data was randomly portioned into 60:40 for model building and validation respectively (Table 1). Residuals of the model were checked for normality using Lillilifor's test (Abdi and Molin, 2007). To assess the performance of the regression model, statistical analysis was done on the validation dataset. The coefficient of determination (R^2), significance of the regression ($\alpha = 0.05$), root mean square error, mean relative error and mean absolute error were used to determine the strength of the model in predicting age from crown area (Ozdemir, 2008; Suratman et al., 2004).

2.5. Oil palm crown projection area delineation

2.5.1. Image segmentation

Object based segmentation was implemented in eCognition Developer (Trimble 2011), an object based image analysis system. To reduce computation overload, only five of the eight WorldView-2 bands were used (Near infrared -1, Red edge, Red, Green and Blue). Of the 8 WorldView-2 bands, these were found most relevant for vegetation and background analysis based on the descriptions by Marshall et al. (2011) and Digital Globe (2009) on the potential uses of the WorldView-2 bands. Multiresolution image segmentation, a bottom-up region merging image segmentation method that applies the spatial clustering technique was used (Addink et al., 2007; Comer and Delp, 1995). In this approach image objects are created by pair-wise clustering beginning with single-pixel objects and merging with or separating from surrounding pixels using neighbourhood statistics (local optimization). The clustering is started at random seed points aiming at maintaining similar object sizes in the image and terminates when the smallest increase of homogeneity exceeds a user defined threshold (called scale parameter) (Addink et al., 2007; Benz et al., 2004; Darwish et al., 2003).

The segmentation process was influenced by the scale parameter, colour (spectral properties) and shape (smoothness and compactness). The appropriate scale parameter for use in multiresolution segmentation was determined through the Estimation of Scale Parameter (ESP) tool, a method developed by Dragut et al. (2010). This tool estimates the most appropriate scale parameter for an image scene by generating sample objects at different scales and then calculating local variance. The basis of this approach is that local variance increases with increase in scale parameter and therefore, the most appropriate scale parameter at which segmentation of the image is best is at the smallest scale parameter with the highest rate of change in variance (Dragut et al., 2010). The NIR band was given a weight of 3 while the other bands were given a weight of 1 [3:1:1:1:1] as done by Shafri et al. (2011b) because vegetation reflectance is more distinguished in the NIR band than in the other bands.

2.5.2. Hierarchical rule-based delineation of oil palm crowns

Scene-based semantics and decision rules based on logical conditions and expert knowledge were used to further purify the segmented objects into oil palm crowns. Based on the visual and statistical properties of the candidate crowns, three categories of objects were distinguished at each stand. These were the crown cores (local maxima) where reflectance in the NIR, Red edge, and Green; and vegetation indices (Simple Index, Normalized Difference Vegetation Index and Red Edge Normalized Vegetation Index) were high. The second was the edges of the rachis where leaf density is lower. Unlike in the crown cores and the rachis edges, some segments showed none to very low vegetation characteristics and were therefore considered background features. 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, human constructions and water). The NIR thresholds used for this classification depended on the factors above. As shown in Fig. 2, the NIR reflectance closely followed the structure of oil palm crown and the minimum reflectance able to separate between two potential crowns could be determined from the NIR profile.

In order to restrict the potential crowns above the minimum possible crown sizes, a threshold of 40 pixels (based on minimum crown projection area obtained in field work) was used to combine potential crown objects into candidate crowns. Only candidate crowns with an elliptic fit (given the standard spacing and

Table 1
Descriptive statistics of the field data used in developing and testing the regression model.

Variable	Data	n	Mean	Min	Max
Age	Training	53	9.7	2	21
	Validation	35	9.2	3	21
CPA	Training	53	58.5	8.2	104.6
	Validation	35	57.2	16.4	102.7

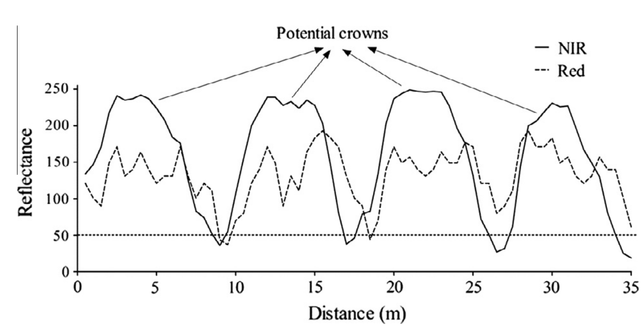

Fig. 2. Spatial reflectance profile in the NIR and Red bands of oil palm crowns.

uniformity of plants the crowns were assumed to be elliptic to circular) above 0.8 were retained. Elliptic fit describes how well the segmented objects are able to fit into an ellipse of their similar size and proportions, and an elliptic fit of 0 indicates no fit while 1 indicates a perfect fit. Therefore, setting 0.8 as the elliptic fit would retain objects that resemble the shape characteristics expected on oil palm crowns. This was done to remove irregular segments created within canopies.

We applied the watershed transformation described by Tarabalka et al. (2010) and Meyer and Beucher (1990) to the segmented objects in order to separate some of the potential oil palm crowns that were co-joined after the initial segmentation. Since it is known that the watershed transformation usually results in over-segmentation (Derivaux et al., 2010; Tarabalka et al., 2010), we applied a minimum oil palm crown diameter restriction of 5 m (giving 10 pixels) based on field work data to confine the outputs to reasonable sizes. After watershed transformation, the closed-object morphology algorithm was then applied on the result to create closed circular objects that represent individual oil palm crowns. The morphology algorithm was important in adding neighbouring objects to the oil palm crown to correct any over-segmentation that could have resulted from the watershed transformation. The resulting objects were cleaned up to remove non-representative objects (too small to be an oil palm crown) and exported as vector layer (Fig. 3).

2.5.3. Accuracy assessment

We first evaluated the accuracy in terms of the producer's accuracy (the proportion of the oil palm crown and non-crown area on reference data that was correctly mapped as oil palm crown and non-crown respectively), user's accuracy (the proportion of the mapped oil palm crown and non-crown area that was oil palm crown and non-crown area respectively on reference data) and overall accuracy (the proportion of the oil palm crown and non-crown area mapped correctly) (Olofsson et al., 2013). An error matrix was developed by overlaying the mapped oil palm crown area and non-crown area with reference crown and non-crown areas to determine the numbers of pixels overlapping (and not overlapping).

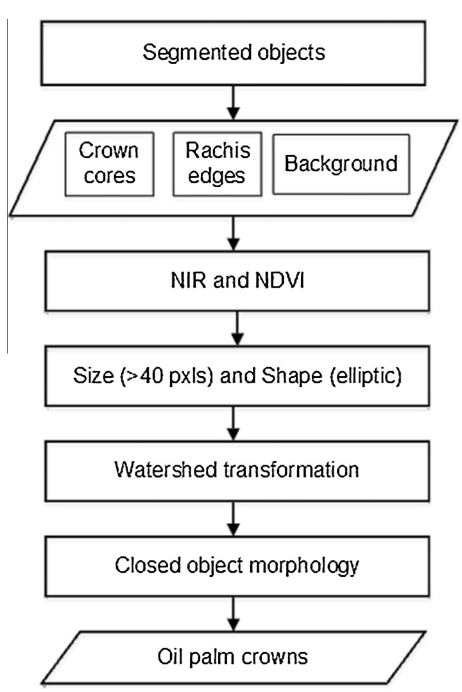

Fig. 3. Flow chart of the delineation of oil palm crowns showing the different steps.

We also compared the spatial and positional matching of the delineated crowns and reference objects using the D (which measures goodness of fit between reference crown objects (x_i) and remote sensing delineated crown objects (y_j)) as described by Clinton et al. (2010). To get the D, over-segmentation and under-segmentation are determined first as metrics defining the overlap between crown objects and reference crowns. For all objects where the centroid of x_i is in y_j, the centroid of y_j is in x_i, area $x_i \cap y_j \geqslant 0.5$ and area $y_j \cap x_i \geqslant 0.5$, over-segmentation and under-segmentation are defined after Clinton et al. (2008) as:

$$\text{Over-segmentation}_{ij} = 1 - \text{area}(x_i \cap y_j)/\text{area}(x_i) \quad (1)$$

$$\text{Under-segmentation}_{ij} = 1 - \text{area}(x_i \cap y_j)/\text{area}(y_j) \quad (2)$$

Since over-segmentation and under-segmentation are properties of segments, we averaged them according to the number of objects in each age category and for all x objects interacting with y objects to obtain their values for each age class and for all of the test data.

We then combined the measures (over-segmentation and under-segmentation) into one metric; a root mean square (D) suggested by Levine and Nazif (1982) as in Eq. (3). The D is a scaled measurement of error [0, 1] and, where $D = 0$ there is a perfect match between segmentation objects and reference data (0% error and 100% accuracy) and where $D = 1$ shows non-representativeness of the segmentation (100% error and 0% accuracy) (Clinton et al., 2010). This method automatically compares, for all objects created, the area of overlap between the extracted object and the reference object, the area of reference object not covered by extracted object and the area of extracted object not corresponding to the reference object as a single measure of accuracy.

$$D = \sqrt{\frac{\text{Oversegmentation}^2 + \text{Undersegmentation}^2}{2}} \quad (3)$$

We also determined the percentage of delineated oil palm crowns that were able to achieve 50%, 60%, 70%, 80%, 90% and 99% overlap with the reference objects for each age class by intersecting them with the reference objects.

As a further validation, comparison of the remote sensing crown extraction method and the reference sampled field measurements was done. The remote sensing extracted crown were compared with the field measurements at plots with reference data (Wang, 2010). The correlation coefficient (r) and the significance of the correlation were used as a measure of the strength of the correlation between the delineated and field measured crown area, indicating the quality of the delineation. The size of delineated crowns was used to determine the age of oil palm at each stand through application of the field developed regression model.

3. Results

3.1. Oil palm crown area delineation

Comparing the spatial matching of delineated crown pixels with reference oil palm crown pixels produced a user's accuracy of 80.6% and a producer's accuracy of 68.4% while comparing the spatial matching of non-crown pixels on delineated crowns against non-crown pixels on reference objects resulted in a user's accuracy of 65.6% and a producer's accuracy of 78.6%. The overall accuracy of the delineation was 72.8% (Table 2).

Using the D, an overall delineation accuracy of 0.69 ($D = 0.31$) was achieved (Fig. 4) from using OBIA to obtain oil palm crown area. The highest accuracy of 0.89 and 0.86 were obtained for 6 and 7 year old palm oil stands respectively. The lowest accuracy of 0.41 ($D = 0.59$) was obtained for the 13 year old stands mostly due to over-segmentation (Table 3).

Using the percentage of overlap between the delineated crowns and reference crowns, the highest percentage of crown objects achieving at least 50% overlap with reference objects was for 13+ year old oil palms (100%) followed by 6 year old oil palms (96.7%, Table 3). The least accuracy at the 50% threshold was for 12 year old oil palms where only 61% of crowns achieved 50% overlap with reference crowns. The percentage of crowns overlapping with reference oil palm crowns decreased as the threshold of overlap increased from 50% to 99% in all age categories with the highest percentage of crowns achieving at least 99% overlap being 40% for the 6 year old oil palms crowns. None of the 5 year old palm crowns achieved a minimum of 99% overlap between the delineated crowns and reference crowns. For all the oil palm stands, 81.3% of delineated crowns achieved at least 50% overlap with reference crowns and only 23.6% achieved at least 99% overlap with reference crowns (Table 3).

3.2. Relationship between field measured crown area and age

A positive linear relationship was observed between age and crown area up to 13 years and no apparent relationship was observed between age and crown area from 13 years onwards (Fig. 5). We therefore decided to fit a linear model between age and crown area up to 13 years. This was because older classes beyond 13 years could not be reliably segmented A significant relationship was obtained between age and area ($R^2 = 0.88$, $p < 0.001$). Therefore, Eq. (4) was obtained from field-measured crowns as a function for predicting oil palm age from crown projection area (Eq. (4));

$$\text{Age(years)} = 0.59 + 0.15 * \text{CPA}(\text{m}^2) \qquad (4)$$

A RMSE of 1.3 years, MAE of 0.8 years (10 months) and a percentage error of 8.2% were obtained when the regression model was applied on independent data.

3.3. Estimating oil palm age from OBIA delineated crown area

Comparing the delineated and field measured crown areas showed a strong relationship between field measured crown area and delineated crown area ($R^2 = 0.81$, $r = 0.9$, $p < 0.0001$, Fig. 6a). However, the results showed that estimating oil palm age from this approach overestimated the age of younger oil palm (less than 8 years) and underestimated older stands (12+ years, Fig. 6b). For the 13 year old stands, the spread between the field measured and delineated crowns was apparent where the field measured crown area was over 80 m^2. As expected, older oil palm stands did not show any direct relationship between crown area and age.

The estimation showed that 6 and 11 year old oil palm plantations dominate the area under oil palm with 16.7% (116.7 ha) and 14.6% (101.5 ha) respectively (Table 4, Fig. 7). This indicates that there were more new oil palm plantings in 2000 and in 2005. Comparing the actual ages and the estimated oil palm ages showed that the error ranged between an under estimation of 4 years to an over estimation of 3 years in oil palm age (Fig. 8). The age estimation was accurate for 27.9% of the stands, within ±1 year accuracy for 74.6% of the stands and within ±2 year accuracy 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 palm plantations. The approach tended to over-estimate the age of younger oil palm while underestimating that of older stands.

Table 2
Error matrices (in terms of number of pixels) for the crown and non-crown classification of the WorldView-2 image. The matrix was produced by comparing the number of pixels in the delineated crowns intersecting with reference crowns and number of pixels in non-crowns intersecting with non-crown in reference data. In this matrix, the delineated pixels are rows while the reference pixels are columns.

	Crown	Non-crown	Total	User's	Producer's	Overall
Crown	37,316	8968	46,284	80.6	68.4	72.8%
Non-crown	17,256	32,896	50,152	65.6	78.6	
Total	54,572	41,864	96,436			

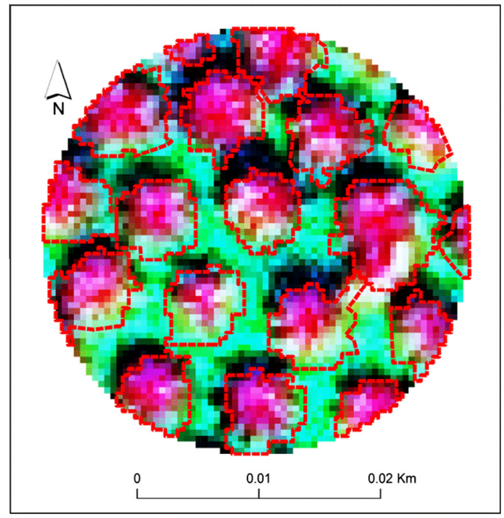

Fig. 4. Delineated crowns on a false colour composite (NIR1–Red–Blue) of the WorldView-2 image.

3.4. Applying the determined age for determining conversion time

The distribution of the oil palm according to the estimated time planting obtained from remote sensing estimated ages was obtained for oil palm field in the study area. The area and percentage planted in each time period is shown in Table 4. The results showed that the largest area development in terms of new oil palm plantings occurred in 2005 with 116.7 ha (16.7% of area under oil palm in the area) followed by plantings in 2000 with 101.5 ha (14.6% of area under oil palm in the area). The least in area were the 2 year old oil palm plantations with only 4.8 ha (0.7% of area under oil palm in the area).

4. Discussion

4.1. Oil palm crown area delineation

One of the most important basis for many of the individual tree crown delineation approaches is that the centre of a tree crown is brighter than the edges or boundary between tree crowns (Culvenor, 2003a) which was demonstrated by sample spatial profiles of oil palm crowns in this study, providing a foundation for individual oil palm crown delineation. The overall accuracy (72.8%), the segmentation goodness of fit (0.69) and the correlation between delineated and field measured crown area (0.9) on a scale of [0, 1] indicates the successful delineation of individual tree crowns using an object-based analysis. These results may give an impression that the performance of the delineation was good, but as Wolf and Heipke (2007) rightly observed, the results on individual tree crown delineation are difficult to standardize and to 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 used in this study is

Table 3
Number of stands, number of objects per stand and segmentation goodness of fit (D) for each age class and for all stands. The percentage of oil palm crown objects achieving minimum overlaps of 50%, 60%, 70%, 80%, 90% and 99% overlap with reference crowns for validation data is also shown.

Age	No. of stands	No. of objects	D	Accuracy	Percentage delineated crowns overlapping with reference crowns by given percentages					
					50%	60%	70%	80%	90%	99%
2	2	28	0.25	0.75	75.0	71.4	67.9	57.1	39.3	28.6
3	3	54	0.34	0.66	85.2	72.2	63.0	46.3	31.5	14.8
4	2	31	0.4	0.6	64.5	64.5	58.1	51.6	41.9	12.9
5	2	29	0.38	0.62	62.1	55.2	55.2	51.7	20.7	0.0
6	2	30	0.11	0.89	96.7	93.3	83.3	83.3	73.3	40.0
7	6	110	0.14	0.86	92.7	90.0	85.5	84.5	78.2	27.3
8	4	81	0.25	0.75	85.2	84.0	81.5	76.5	60.5	34.6
12	4	77	0.36	0.64	61.0	54.5	48.1	48.1	45.5	20.8
13	2	31	0.59	0.41	100.0	100.0	93.5	83.9	71.0	16.1
All	27	471	0.31	0.69	81.3	77.1	71.8	66.9	55.4	23.6

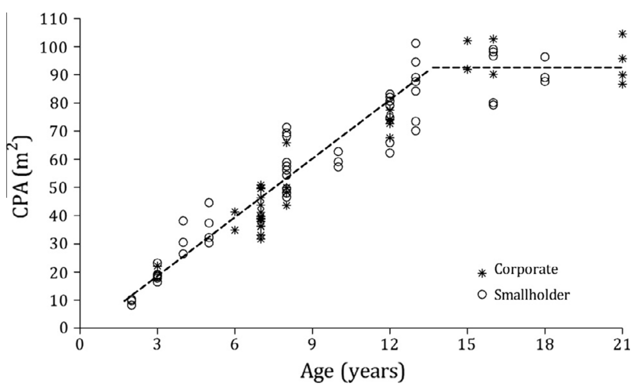

Fig. 5. Relationship between field age and CPA obtained from fieldwork showing that the relationship between age and CPA saturated from 13 years for both smallholder and corporate farms.

relatively new to the field, having been developed by Clinton et al. (2010) and still to be widely applied for comparison.

The results showed no linear 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 palm could be easily delineated as there are no problems of overlapping branches and shadows cast upon other palms. Shadows may have made young oil palm crowns seem larger than they actually are resulting in overestimation in younger oil palm plantations. The lack of a direct relationship between age and accuracy suggests 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 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 more accuracy for younger age classes (Ibrahim et al., 2000; McMorrow, 2001; Thenkabail et al., 2004). The spectral and spatial characteristics of the oil palm 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 as was observed in this study. However, these findings that there is no linear relationship between the age of the oil palm and delineation accuracy are based on a very small sample and are therefore not conclusive.

The NIR was most consistently able to separate oil palm crowns from background. Other studies found 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). Due to the fuzziness of leaf density gradient from the crown centre, it is difficult to figure out exactly where the crown ends. This is made even more complicated where there is undergrowth. Although the fuzziness of the edges of tree crowns in terms of reflectance may be the general spatial reflectance profile for trees (Hirschmugl et al., 2007; Pouliot et al., 2002; Wolf and Heipke, 2007), it could be more problematic in delineation of oil palm given their star-shaped form compared to conoid and hemispherical forms common in other trees. Therefore spectral diversity in hyperspectral data could provide added abilities for oil palm crown delineation.

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 during the cropping season. It is therefore recommended to test if accuracy of oil palm crown delineation is affected by seasonality. The problems of shadows and overlap-

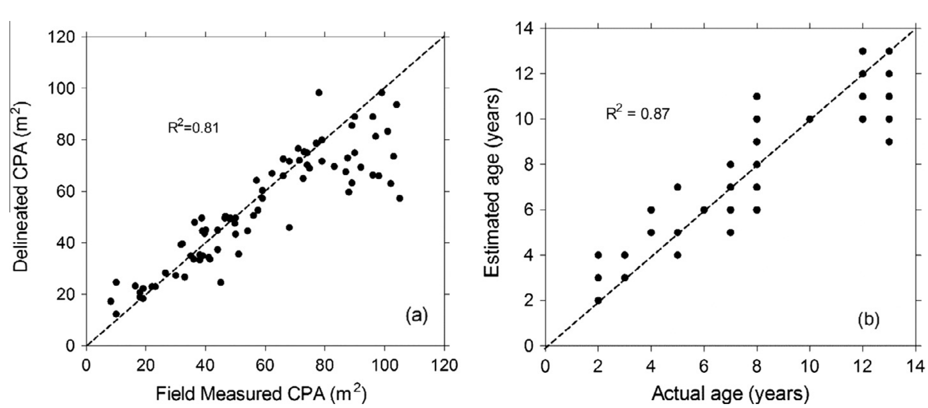

Fig. 6. Relationship between field and remote sensed parameters. Fig. 6a shows the relationship between the field measured CPA and OBIA delineated. Fig. 6b shows the relationship between actual oil palm ages and remote sensing estimated CPA.

Table 4
Determined age, year of planting, area of new planting and total area under oil palm.

Age (years)	Estimated planting year	Area of new plantings (ha)	% Of total	Total area (ha)
13+	1998	48.4	6.9	48.4
12	1999	47.6	6.8	96
11	2000	101.5	14.6	197.4
10	2001	35.4	5.1	232.9
9	2002	55.7	8.0	288.6
8	2003	79.6	11.4	368.2
7	2004	82.6	11.9	450.8
6	2005	116.7	16.7	567.5
5	2006	37.9	5.4	605.4
4	2007	62.5	9.0	667.9
3	2008	24.2	3.5	692.0
2	2009	4.8	0.7	696.8

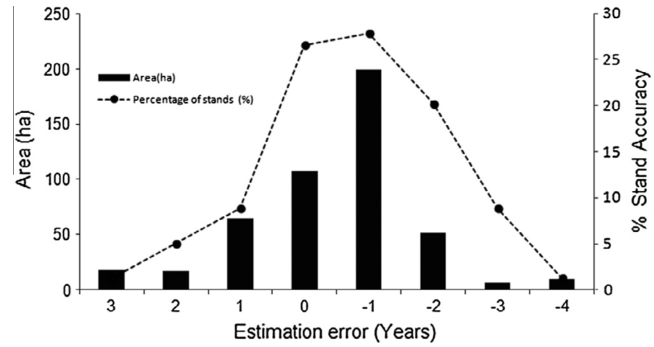

Fig. 8. Application of the remote sensing determined ages showed the distribution of oil palm ages and area under each age in the study area.

ping branches may be particular for older age classes (>13 years) while site characteristics are more important for young age categories less than 13 years. The shadow effect may probably explain the delineation error reported for older oil palm. 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. Although satellite overpass times are programmed to be mainly in the mid-morning (1047 h for this image) to minimize on shadow effect, the problems of shadow cannot be fully eliminated in dealing with remote sensing imagery.

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, this study showed that there are many factors that are different at each stand such as the presence of weeds or intercropping. Thus a method for delineation that considers each field's characteristics is likely to perform better than a blanket approach. This is, however, something that is not known in advance and depends on field observations or local expert knowledge. Then, preliminary stratification can be applied before delineation in order to adjust segmentation and delineation parameters such as scale parameter accordingly. Whiteside et al. (2011) for instance used tree density to adjust parameters. More rigorous image preparation methods applied before segmentation such as texture analysis and edge enhancement may also be useful in improving the performance of the delineation of individual crowns as done by Shafri (2011b).

4.2. Relationship between CPA and age

A linear relationship between age and oil palm crown area until 13 years and no relationship thereafter concur with the relationship determined by McMorrow (2001) with field measurements done in Malaysia. Thus, the growth of crown projection area with age in oil palm may be more dependent on the physiology of the oil palm than on geographical characteristics. 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 as pruning especially when applied over larger areas (Breure, 1985). The error of the model in predicting oil palm age could therefore be explained by the variability in these factors at each measured stand.

A second order polynomial that follows the saturation could have produced a model able to predict oil palm age even a bit beyond the age of 13 years until the relationship between CPA and age really saturates. However, this could have produced more errors in the prediction for the younger ages through error

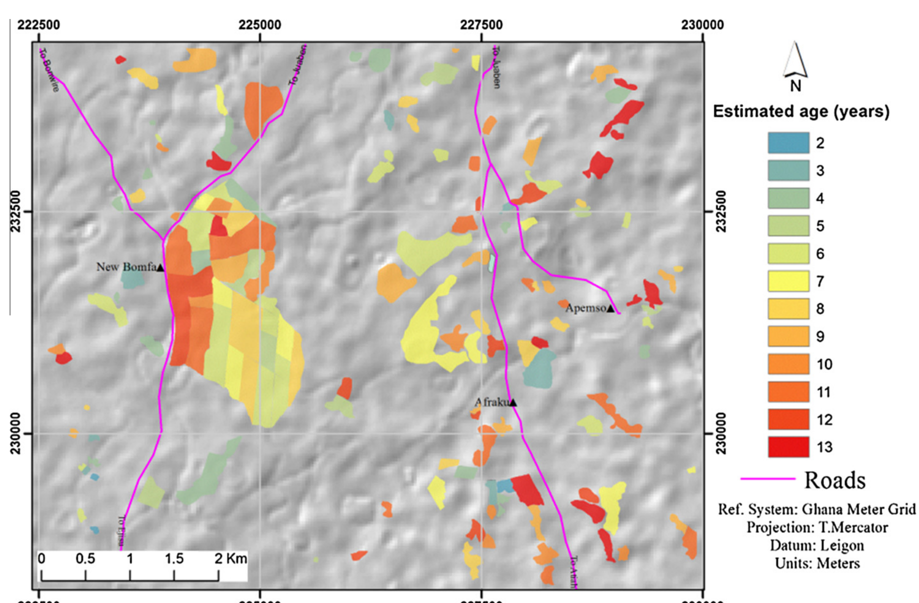

Fig. 7. Distribution of estimated age of oil palm in the study area.

propagation and a linear function is more parsimonious. Linear functions have been widely and reliably used as functions for predicting other plant parameters from crown area or crown diameter. Other studies have applied other functional forms such as 'flexible' models, second-degree polynomials, power functions and others (Avsar, 2004; Chase and 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.

4.3. Estimation of oil palm age and conversion time

It was shown that it is possible to determine the age of oil palm from combining remote sensing crown area to statistical models. The age determined from this stand-based approach can be useful in understanding the general age categories of oil palm for environmental monitoring, as part of a certification process, as a validation for the information that managers or farmers provide and for studies that require insight in oil palm developments over larger areas such as strategic impact assessments and spatial planning. However, the approach presented in this paper has its limitations as errors could stem from both the field model and from the crown area delineation. Part of the age prediction errors in this study are from the fact that there was some time difference (7 months) between field work and the date of the satellite image was taken.

The estimations showed that the dominant age classes in the study area were 6 and 11 years old (planted in 2005 and 2000). These findings concur with reports that as a result of the President Special Initiative (PSI) in Ghana, 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 to 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 is therefore very useful for analysing the effect of policies such as the PSI (from 2003) or the multilateral development funding by the World Bank (from 1998) on the sector. The ages determined in this approach could thus be potentially useful for analysing the impacts of these initiatives on the environment across space and time. For example, large scale support for small-holder oil palm farmers may result in a large number of small oil palm plantings scattered over an area which will have clearly different effects on e.g. biodiversity compared to the development of one large oil palm plantation.

5. Conclusions

The study concluded that there is potential in using object-based image analysis and an empirical model to determine the age of oil palm at field scale from high resolution satellite imagery. Many factors however affect the delineation accuracy and the most significant are stand characteristics particularly undergrowth (weeds and intercrops). The density of undergrowth differs in each field and a stand-level approach was found more suitable. The linear function relating age to CPA was found useful to predict the age of oil palm per field with accuracy of ±1 year up to 13 years, which happened to coincide with the age where delineation accuracy is also acceptable. However, statistical functions that could extend the prediction beyond 13 years could improve the useful of the field model relating age to CPA that will be combined with remote sensed crown area. The method demonstrated here uses spectral information to obtain spatial information that can be used for determining characteristics of target features. This indirect approach has the possibility of discrete age modelling. However, it must be noted that errors in the biophysical model can be carried forth to the remote sensing approach (which has its own errors), resulting in error propagation. The age map produced from this approach is useful for a wide range of age-related applications in the oil palm management.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.isprsjprs.2014.07.013. These data include Google maps of the most important areas described in this article.

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