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A novel approach in monitoring land-cover change in the tropics: oil palm cultivation in the Niger Delta, Nigeria

***Stanley U. Okoro*[1], *Udo Schickhoff*[1], *Jürgen Böhner*[1], *Uwe A. Schneider*[2]**

[1] CEN Center for Earth System Research and Sustainability, Institute of Geography, University of Hamburg, Bundesstr. 55, 20146 Hamburg, Germany, stanley.okoro@uni-hamburg.de, udo.schickhoff@uni-hamburg.de, juergen.boehner@uni-hamburg.de

[2] CEN Center for Earth System Research and Sustainability, Research Unit Sustainability and Global Change, University of Hamburg, Grindelberg 5, 20144 Hamburg, uwe.schneider@uni-hamburg.de

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Abstract

The increasing demand for palm oil and bioenergy has promoted the expansion of tropical farmland covered with oil palms (Elaeis guineensis), resulting in increased competition with food production as well as environmental degradation. Moreover, oil palm cultivation may have increased greenhouse gas (GHG) emissions through deforestation. The overall impact estimation of oil palm related land-use change requires spatiotemporal land-use maps. So far, the Roundtable on Sustainable Palm Oil (RSPO) has not established guidelines on how to measure and evaluate oil palm related land-cover change. While remote sensing methods are suitable in general, the use of Landsat images in the tropics for the monitoring and modeling of land-cover changes has been restricted due to the influence of cloud cover. This study presents a novel approach for mapping tropical land-cover change using the Google Earth Engine (GEE) cloud-based platform and the System for Automated Geoscientific Analysis (SAGA) GIS. Spatiotemporal land-use and land-cover changes in relation to oil palm cultivation are assessed using a median pixel composite mosaic of Landsat 5, 7 and 8 image scenes for the time periods 1999-2005 and 2009-2015. The proposed approach yields an overall accuracy and kappa coefficient of 70.33 % and 0.62 for the first image composite period, and 84.5 % and 0.80 for the second image composite period respectively.

Zusammenfassung

Die steigende Nachfrage nach Palmöl und Bioenergie fördert die Ausweitung von mit Ölpalmen (*Elaeis guineensis*) bestandenen tropischen Nutzflächen und intensiviert zugleich Nutzungskonflikte mit der Nahrungsmittelproduktion sowie Umweltdegradation. Des Weiteren erhöht die Abholzung von Regenwald zur Errichtung von Ölpalmenplantagen in der Regel den Ausstoß von Treibhausgasen. Umfassende Wirkungsanalysen zur Ausbreitung von Ölpalmenplantagen benötigen Zeitreihen von Landnutzungskarten. Der Runde Tisch für nachhaltiges Palmöl (RSPO) hat bisher keine Leitlinien für die Evaluierung von Landnutzungsänderungen erstellt. Obwohl Fernerkundungsmethoden für die Beobachtung und Modellierung von Landnutzungsänderungen allgemein gut geeignet sind, wird die Nutzung von Landsat-Aufnahmen aus tropischen Regionen durch Bewölkung beeinträchtigt. Diese Studie präsentiert einen neuen Ansatz, welcher die Google Earth Engine (GEE) und das „System for Automated Geoscientific Analysis" (SAGA) GIS nutzt. Zeitlich und räumlich aufgelöste Landnutzungs- und Landbedeckungsänderungen durch den Anbau von Ölpalmen werden mit einem „*median pixel composite mosaic*" von Landsat-5-, 7- und 8-Szenen für die Zeiträume 1999-2005 und 2009-2015 erfasst. Für die erste Periode erreicht das Verfahren eine Gesamtgenauigkeit von 70,33 % und einen Kappa-Koeffizienten von 0,62. In der zweiten Periode steigen diese Werte auf 84,5 % und 0,80.

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1. Introduction

Traditionally, oil palm production has been a part of mixed farming activities in West Africa. However, in the current practice, most production has expanded as an industrial-scale mono-crop (*Corley* and *Tinker* 2016). This imposes greater environmental risk on local societies, particularly on those with limited economic capacities (*Colchester* 2011). Currently, oil palm cultivation is characterized by large monocultures of uniform age structure, low canopy, sparse undergrowth, a low stability microclimate and intensive use of fertilizers and pesticides. Land-cover patterns reflect the underlying natural and social processes which, thus, helps to provide essential information for modeling and understanding many phenomena on Earth (*Liang* 2008). Furthermore, understanding the complex interaction between human activities and global change requires the analysis of land cover data (*Gong* et al. 2013). The conversion of natural forest to agricultural uses such as oil palm etc., has been reflected in regional land-use maps in most of the tropical regions. This conversion can result in a series of negative impacts (*Carlson* et al. 2012), e.g., forest estate loss, social cost (private cost plus externalities as a result of forest to oil palm estate conversion), loss of biodiversity and ecosystem services, alternative revenue loss and greenhouse gas emissions etc. (*Sayer* et al. 2012; *Sheil* et al. 2009). To date, comprehensive regional land-use maps of the Nigerian Niger Delta which incorporate oil palm cultivation have not been produced. The lack of detailed land-use maps may be due to the limited availability of cloud-free satellite images and the unattractiveness of such studies for most private actors and non-governmental sectors. Consequently, scientists have not been able to carry out such research, possibly a result of the cost of acquiring high-resolution satellite images like IKONOS etc. in the region.

Satellite remote sensing technology provides promising approaches for monitoring land-cover change. In many studies in southeastern Asia, continuous observations of the land surface have been used to map oil palm cultivation (*Kamaruzaman* and *Setiawan* 2003; *Santoso* et al. 2011; *Tan* et al. 2012). The classifications of satellite imagery for land-cover mapping, however, often require extensive skills of an experienced environmental analyst (*Aitkenhead* and *Aalders* 2011). If such skills have not been available, land cover classification maps have been developed from ground surveys and base maps such as digital topographic maps. In addition, land-use maps and soil suitability agricultural maps (although not available for public use in the study area) have increased the accuracy of land-cover classification maps (*Razali* et al. 2014; *Reichenbach* and *Geng* 2003). Replacing or updating these maps with a large amount of remotely sensed data remains a very challenging task in land-use and land-cover mapping (*Franklin* and *Wulder* 2002). Different methods have been implemented; these can be divided into two categories: phenology and image-based approaches. The latter make use of spectral signatures to delineate different types of land cover, e.g. oil palm trees (e.g. *Shafri* et al. 2011; *Thenkabail* et al. 2004). The former relies on the temporal signal of optical sensors to identify various land covers using coarse resolution data from the Moderate-resolution Imaging Spectroradiometer (MODIS), e.g. *Gutierrez-Velez* et al. 2011. This is not ideal for monitoring oil palm distribution because the saturation of optimal images due to canopy closure causes a reduction in the possibility of detecting structural features (*Shafri* et al. 2011). Cloud cover issues are most common in tropical regions and have been a great challenge in land-cover monitoring. Due to the reduced monitoring options of cloudy images, Synthetic Aperture Radar (SAR) data were frequently used as a major alternative in tropical studies (*Koo* et al. 2012; *Li* et al. 2015, *Morel* et al. 2011). The reason for this has been attributed to SAR's all-weather and all-time capability. On the other hand, due to their coarse resolution of 50 m, SAR data are difficult to be used in a detailed monitoring of tropical land cover.

The GEE, which is an online environmental geoprocessing platform that incorporates data from the National Aeronautics and Space Administration (NASA) and the Landsat Program, has created an avenue which allows users to assess records of Landsat imagery and process them over its online platform. This process reduces users' computational processing times when analysing Landsat imagery, making global- and regional-scale Landsat projects achievable (e.g., *Hansen* et al. 2013).

The objective of this study is to provide a novel approach in monitoring and analyzing oil palm related land-cover issues in the tropics using Landsat data with a resolution of 30 m via GEE and SAGA GIS (*Conrad* et al. 2015). We implement the Voting Support Vector Machine (SVM) classifier in GEE to map oil palm plantation in the Nigerian Niger Delta. To investigate the biases of our classifier, the analysis of its error matrix which includes overall accuracy, user accuracy and producer accuracy and the computation of its kappa coefficient were performed.

2. Study area

The study area covers the southern part of Nigeria where the oil palm production is concentrated (see *Fig. 1*). Currently called the Niger Delta region, it is one of the world's largest acute fan-shaped river deltas. The settlements that are covered in this study include: Imo State, Abia State, Bayelsa State, Rivers State, Ondo state, Akwa Ibom state, Edo State and Cross River State. The Niger Delta is defined officially by the Nigerian government to extend over about 70,000 km^2 which is 7.5 % of Nigeria's total land mass. The region lies between 4.01°N and 7.90°N and between 4.50°E and 10.56°E in the West African section of the tropical rainforest belt and has a humid tropical climate. The area homes the country's wetlands which is also one the largest wetland in the world with a very high biodiversity rate. The riverine area of the Niger Delta is a coastal belt of swamps bordering the Atlantic Ocean. The swamps are vegetated tidal flats formed by a reticulate pattern of interconnected meandering creeks and tributaries of the River Niger. The Niger Delta has one of the highest population densities in the world with approximately 265 inhabitants per square kilometer. The population in the delta produces crops that are in high demand in the world market, such as palm oil and cocoa.

3. Materials and methods

3.1 Satellite data

Landsat 5, 7 and 8 orthorectified and coregistered scenes were used in this study, capturing identical

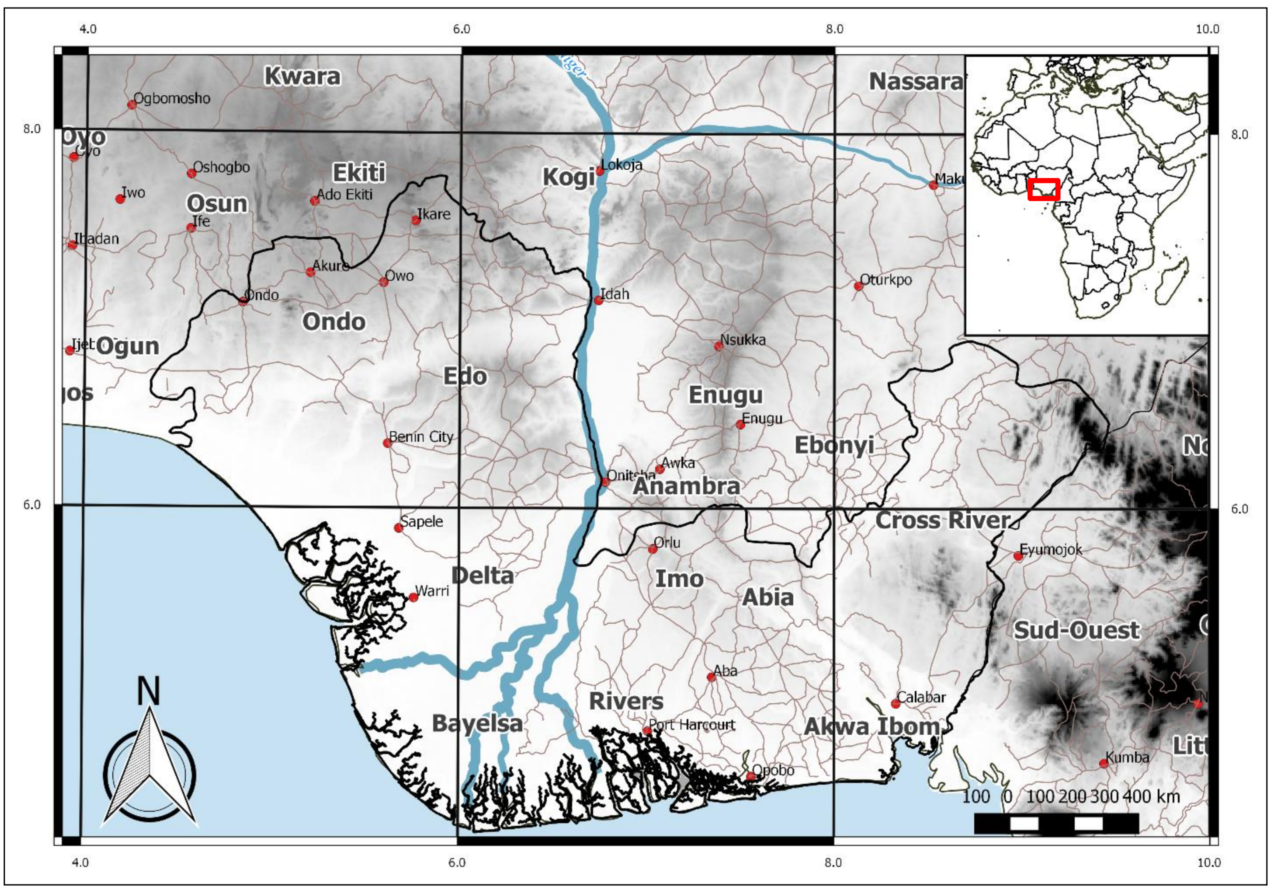

Fig. 1 Map of the study area

periods of calendar days (270-365) for 1999 through 2005 and 2009 through 2015. We did not consider using surface reflectance data following *Song* et al. (2001), who stated that an atmospheric correction was unnecessary for a change detection based on a classification of multitemporal composites in which multiple dates of remotely sensed images are rectified and placed in single dataset as long as the training dataset is derived from the image being classified.

We decided to work with the images of calendar days 270-365 in each year in order to avoid seasonality issues of oil palm reflectance values that may arise from seasonal variation of chlorophyll concentration, foliar pigments and other reflectance properties. We consider the image collection composite range used in this study as ideal for oil palm mapping studies. We worked with Landsat mosaic images only because they are consistent with a resolution of 30 m and the combination of different Landsat sensors has only minor effects on the output of the images. Landsat has a high degree of similarities among its different sensors (*Li* et al. 2014), a notable advantage compared to working with the fusion of Landsat and MODIS images with a coarser resolution of 50 m as in *Bisquert* et al. (2015).

3.2 Data pre-processing

Landsat 5, 7 and 8 data of the time periods from 1999 to 2005 and from 2009 to 2015 were combined in one mosaic by taking the median pixel from the entire Landsat image collection. The overall procedure is graphically represented in *Fig. 2* and involves nine steps. The first six steps were done in GEE and the remaining three in SAGA GIS.

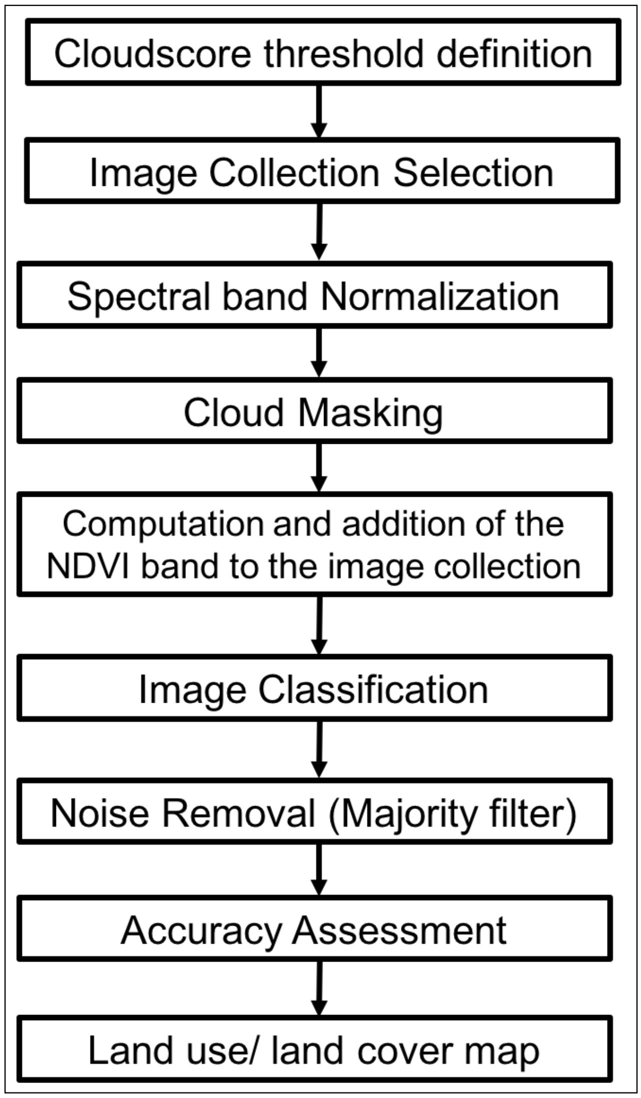

Fig. 2 Graphical representation of the processing approach

Spectral band normalization: Due to differences in the spectral band numbering system among the different Landsat missions – Landsat Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+) and Operational Land Imager & Thermal Infrared Sensor (TIRS) (*Li* et al. 2014) – a normalization process is required. Therefore, we carried out a normalization to make the images from the different sensors suitable for combination by matching the bands from the different Landsat sensors (e.g. red band from Landsat 5 to Landsat 7 red band).

Cloud score analysis: Cloud cover problems were tackled by using the simple cloud score algorithm implemented in the GEE. This algorithm computes a simple cloud likelihood score threshold that ranges from 0 to 100, making use of brightness, temperature and Normalized Difference Snow Index (NDSI). The algorithm is mainly intended to compare multiple looks at the same point for relative cloud likelihood. For this study, a cloud score threshold of 20 was used. The threshold is subjective; the choice, however, was based the visual interpretation of the Landsat images.

Training data: While focusing on oil palm plantation mapping, other land-cover types considered in this study include water (rivers, lakes, swamps), built-up areas (including bare lands), cropland (croplands that are not covered by oil palm trees) and forest. We incorporated the ground truth data, Google Earth data and Landsat image data in our training sample. The ground truth data were collected during a field work between November and December 2014.

Reference data: Due to the costs of acquiring reference data for using our sampling approach at a regional scale, we collected our reference data by combining Landsat image and Google Earth imagery. In a similar case, *Pulighe* et al. (2015) assess the horizontal accuracy of Google Earth images and conclude that they have an overall positional accuracy close to 1 m. This suggests that this is sufficient for deriving a reference data set for land-cover mapping. The sampling method used is the stratified random sampling method (*Husch* et al. 2003). The points were stratified according to the distribution of land-use/cover classes, in order to lessen the possibility of biases from misclassification. The choice of this sampling method was based on the recommendations of *Olofsson* et al. (2014) regarding good practices for estimating area and assessing accuracy of land cover and land use maps.

Signature analyses of reflectance values of land cover types: To determine and understand the spectral separability of the Landsat reflectance bands of the various land-cover types, to enable the choice and order of spectral bands to be used, the Landsat image reflectance at known land-cover types against the bands were plotted. Furthermore, the reflectance values against the different wavelengths at various land-cover types were also plotted.

Image classification: The approach is based on the supervised classification of multispectral, multisensor data, using the Landsat image collection of Landsat 5, 7 and 8 combined in one mosaic. Supervised classification is a method often used for the quantitative analysis of remote sensing images. It aims at grouping the spectral domain into regions that can be associated with ground cover classes of interest for a particular application (*Richards* 2013). The Landsat image bands were chosen and their arrangements were Near Infrared (NIR), Shortwave Infrared 1 (SWIR1), Red, Green and the computed Normalized Difference Vegetation Index (NDVI) band. The NDVI is an index of plant greenness, which is also an indicator of density of plants. It is calculated using the formula in *Equation 1*.

$$NDVI = \frac{NIR - RED}{NIR + RED} \qquad (Eq.\ 1)$$

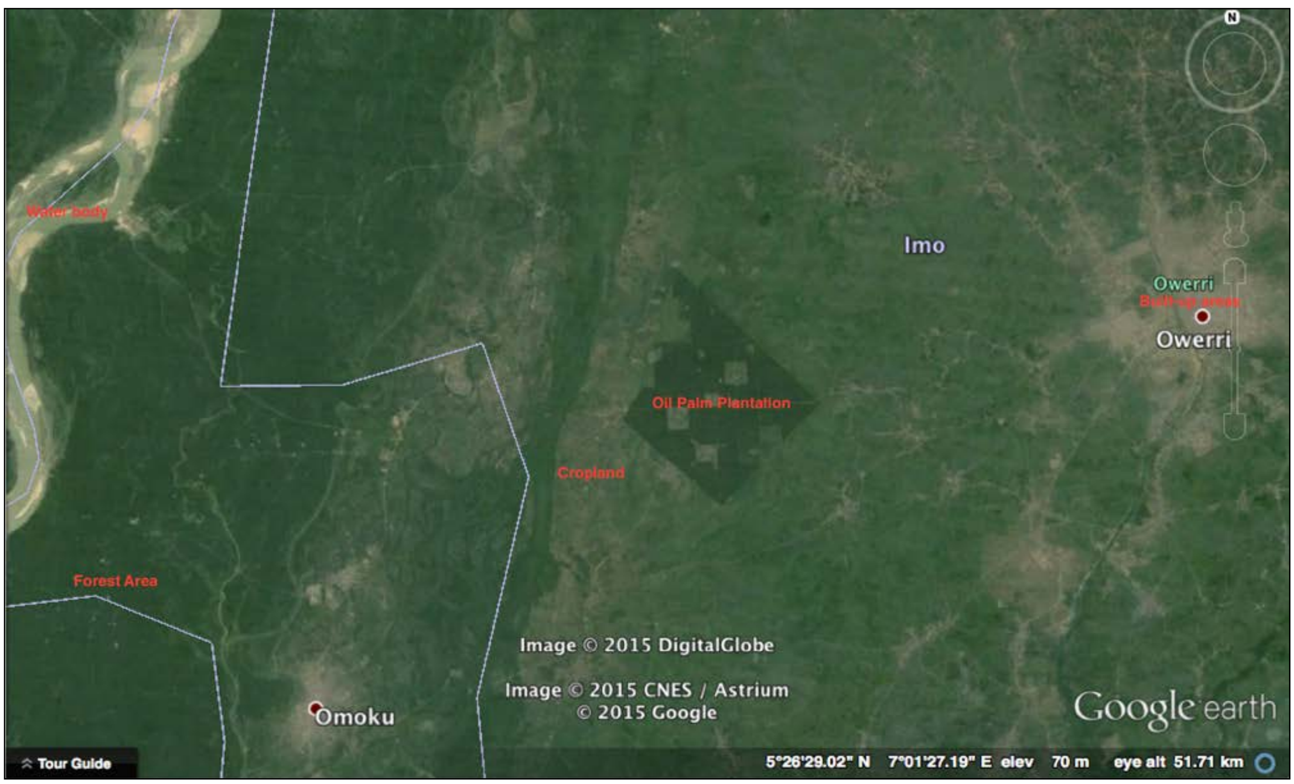

Fig. 3 Screen shot of a Google Earth image showing the various land-cover classes analyzed in this study

The classification scheme employed to create a land-cover/land-use map was a modification of *Omodanisi* (2013) to incorporate oil palm and cropland and to combine high forest and light forest in a single land-cover type (*Fig. 3*), thus differentiating between i) water bodies, ii) a built-up areas class which also includes bare ground, roads and building facilities, iii) cropland which includes all agricultural land that does not have oil palms planted as mixed crop, iv) forests, including primary and secondary forests, v) oil palms.

Classifiers voting support vector machine (SVM): The concept of SVM is based on decision plains that define decision boundaries. The classifier takes inputs from training data and makes predictions based on given inputs. The classes input is formed by relating the training data set to each pixel in an image (*Kavzoglu* and *Colkesen* 2009). The algorithm was first introduced as a machine learning method by *Cortes* and *Vapnik* (1995) based on a non-probability binary function because it predicts for each of a series of given inputs the possible input that the input belongs to. Originally, the approach was designed to solve binary problems. In remote sensing applications, however, the problem often involves multiclass/non-binary problems. Various approaches have been proposed to address multiclass problems (m-class), e.g. *Schölkopf* and *Smola* (2002), where the problem is usually split into a set of binary classifiers before combining them. The one-against-all classification strategy splits the problem into multiple binary sub-problems. The one-versus-one classification strategy creates *Equation 2* binary sub-problems and later combines the following adopting a majority voting scheme. The approach has shown to be more suitable for large problems like ours (cf. *Hsu* and *Lin* 2002). Its operation is carried out in feature space, where classes are separated by a boundary that is as wide as possible. Our choice of choosing this algorithm as classifier algorithm was based on the finding that it performs well in mapping oil palm plantation (*Li* et al. 2015; *Nooni* et al. 2014).

$$\frac{M(m-1)}{2} \qquad (Eq.\ 2)$$

3.3 Post-processing

Noise filtering (majority filter): In order to reduce noise in the classification result, we applied a majority filter algorithm as implemented in SAGA GIS in the post-processing, which removes isolated cells. The majority filter considered a search radius of 3 x 3 cells to improve the homogeneity of the classified raster.

Accuracy assessment: Many factors affect the accuracy of an image classification, this includes preprocessing of remote sensing data, precision and resolution of remote sensing data and training sample selection. Accuracy assessment allows the analyst to compare certain pixel values in a raster layer to the reference pixels for which the class is known (*Mani Murali* et al. 2006), in order to establish the error margin of the classified image. This requires a simple cross-tabulation of the class labels allocated by a classification of the remotely sensed data against the reference data. The error matrix aids in quantifying image classification accuracy and its area estimation.

The accuracy assessment computation we carried out includes:

- **Confusion matrix**: The confusion matrix is calculated by comparing the location and class of each reference pixel with the corresponding location and class in the classification image.

- **Producer accuracy**: This is the measure that indicates the probability that the classifier has labeled an image pixel into class A given that the reference class is A.

- **User accuracy**: This measures the probability that a pixel is class A given that the classifier has labeled the pixel into class A.

- **Overall accuracy**: This is calculated by summing the number of pixels classified correctly, divided by the total number of pixels in that land-cover class.

- **Kappa coefficient**: The kappa coefficient (k) measures the agreement between the classification result with that of the reference pixels. Perfectly agreed means that the kappa coefficient tends to 1 or is very close to 1. It is calculated using the formula

$$k = \frac{\sum_{i=1}^{n} m_{i,i} - \sum_{i=1}^{n}(G_i\ C_i)}{N^2 - \sum_{i=1}^{n}(G_i\ C_i)} \qquad (Eq.\ 3)$$

where i is the class number, N is the total number of classified pixels that are compared to reference data, $m_{i,i}$ is the number of pixels belonging to the reference class i, which have been classified with a class i, C_i is the total number of classified pixels belonging to class i, G_i is the number of reference pixels belonging to class i.

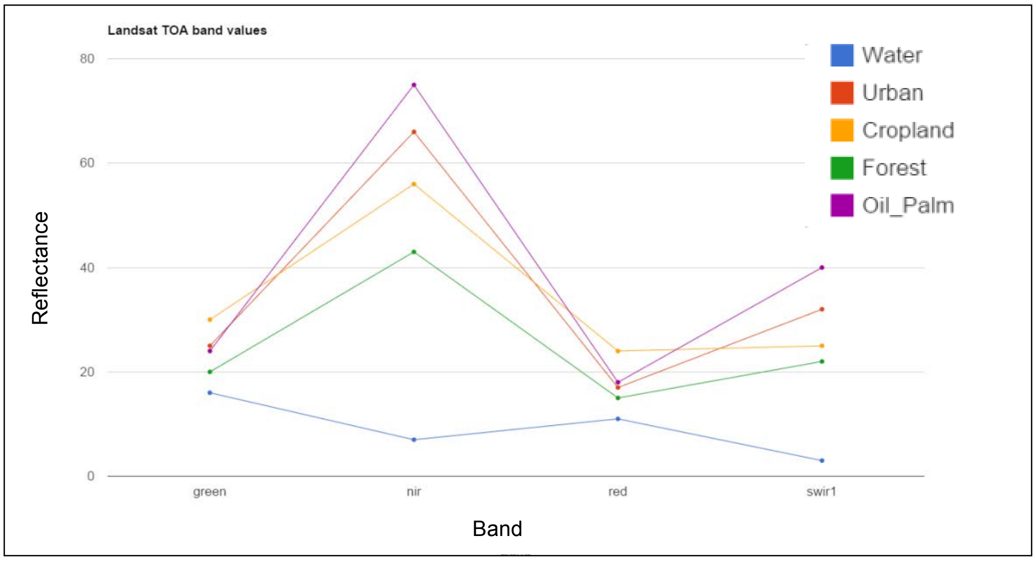

Fig. 4 *Landsat reflectance data for the various land-cover types*

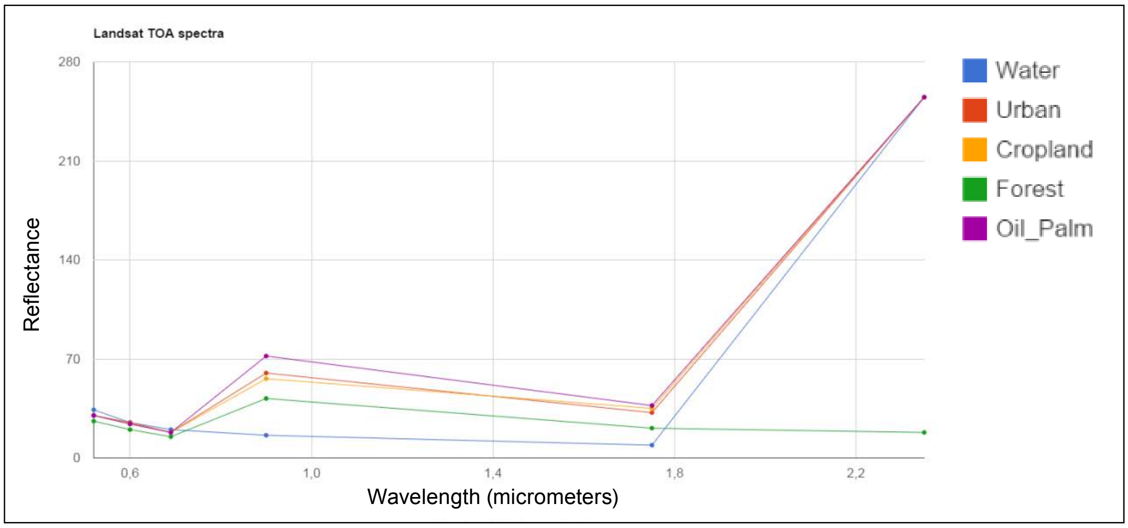

Fig. 5 *Landsat reflectance data for the various land-cover types plotted against wavelength*

Change detection: Change detection is a process of identifying differences in the state of an object or phenomenon by observing it at different times (*Jensen* 1996). Change detection analyses can be deducted in many ways. In land-use/land-cover change analyses, three categories are mostly used: i) algebra-based approach image differencing, image regression, image rationing, vegetation index differencing and change vector analysis (*Singh* 1989); ii) transformation principal component analysis, tassled cap, Gramm-Schmidt and Chi.square test (*Nielsen* and *Canty* 2008); iii) classification-based spectral-temporal combined analysis, post-classification comparison, unsupervised change detection, hybrid change detection, artificial neutral networks and electromagnetic transformation (*İlsever* and *Ünsalan* 2012). We decided to work with post-classification comparison because this technique makes use of thematic maps (classified images) as input and does image differencing on a pixel-wise basis. The main advantage of post-classification comparison is that it avoids problems encountered at the image original pixel level, for example shadows and reflections (*Jensen* 1996).

4. Results and discussion

A total of five land-cover types were identified and classified in this study. These were water, built-up

Table 1 Land-cover/land-use change in the Nigerian Niger Delta

Land-cover class	1999-2005		2009-2015		Change	
	Area (ha)	%	Area (ha)	%	ha	%
Water	384918.52	3.59	415545.38	3.87	30626.86	7.95
Built-up area	468342.99	4.36	313990.09	2.92	-154352.90	-32.95
Cropland	4037477.94	37.66	4318065.23	40.28	280587.29	6.94
Forest	2917374.90	27.21	2824880.57	26.35	-92494.33	-3.17
Oil palm	2910695.95	27.15	2846329.03	26.55	-64366.92	-2.21

areas, cropland, forest and oil palm as shown in *Figure 4*. Following our approach, we were able to get little or no cloud cover in our image composite.

The plot of the reflectance values against the chosen Landsat image bands and reflectance values against wavelengths of the land-cover types at known points in our study area (*Figs. 4* and *5*) show a very clear spectral separability of the land-cover types within our chosen image bands. The near-infrared band has the highest spectral separability to distinguish among the different land-cover types. Thus, the band arrangement of the classification follows the order of its separability among the land-cover types.

In the 2005 land-cover map, cropland, oil palm, forest, built-up and water body occupy 37.66 %, 27.15 %, 27.21 %, 4.36 % and 3.59 % respectively (cf. *Table 1*).

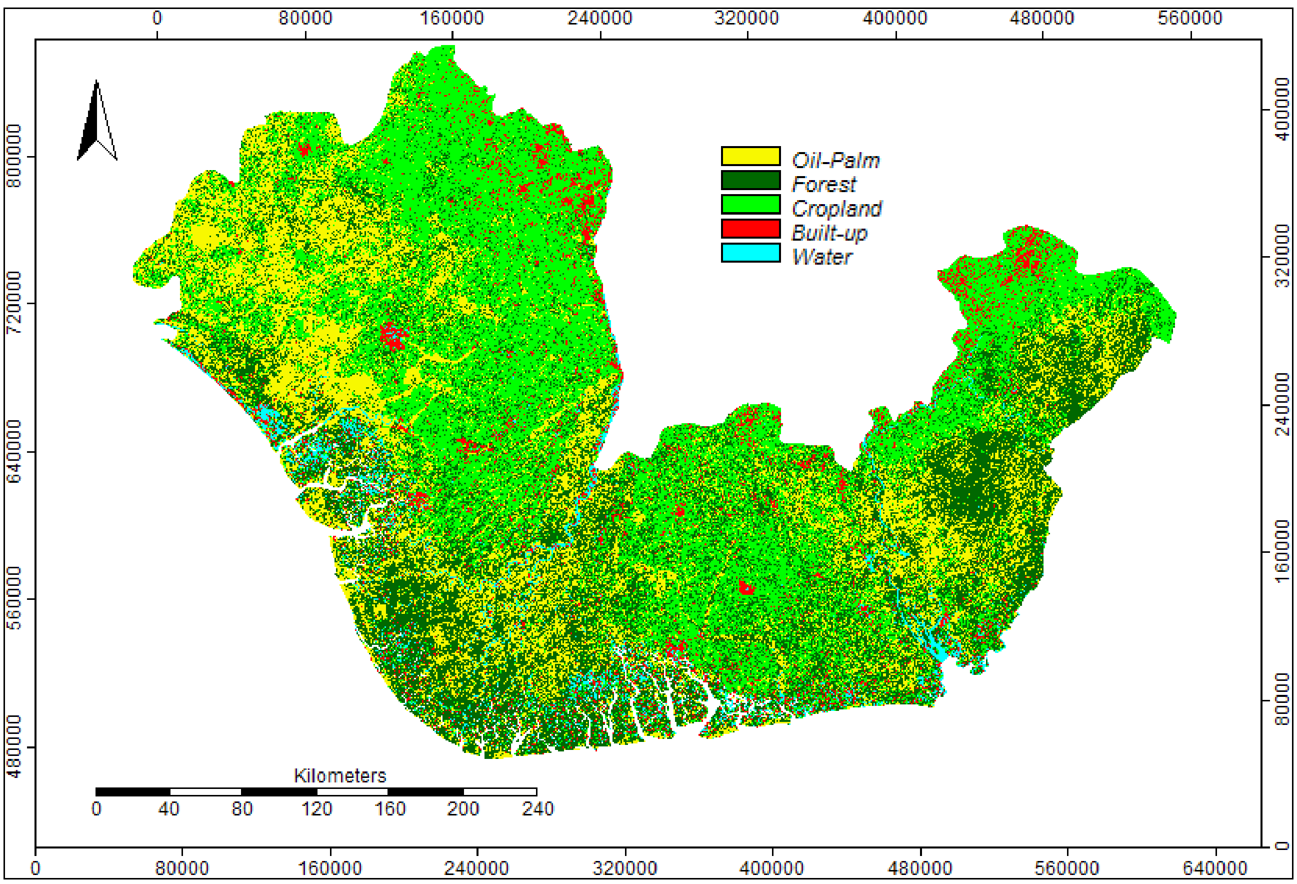

Fig. 6 Land-use/land-cover map based on the 1999-2005 median composite

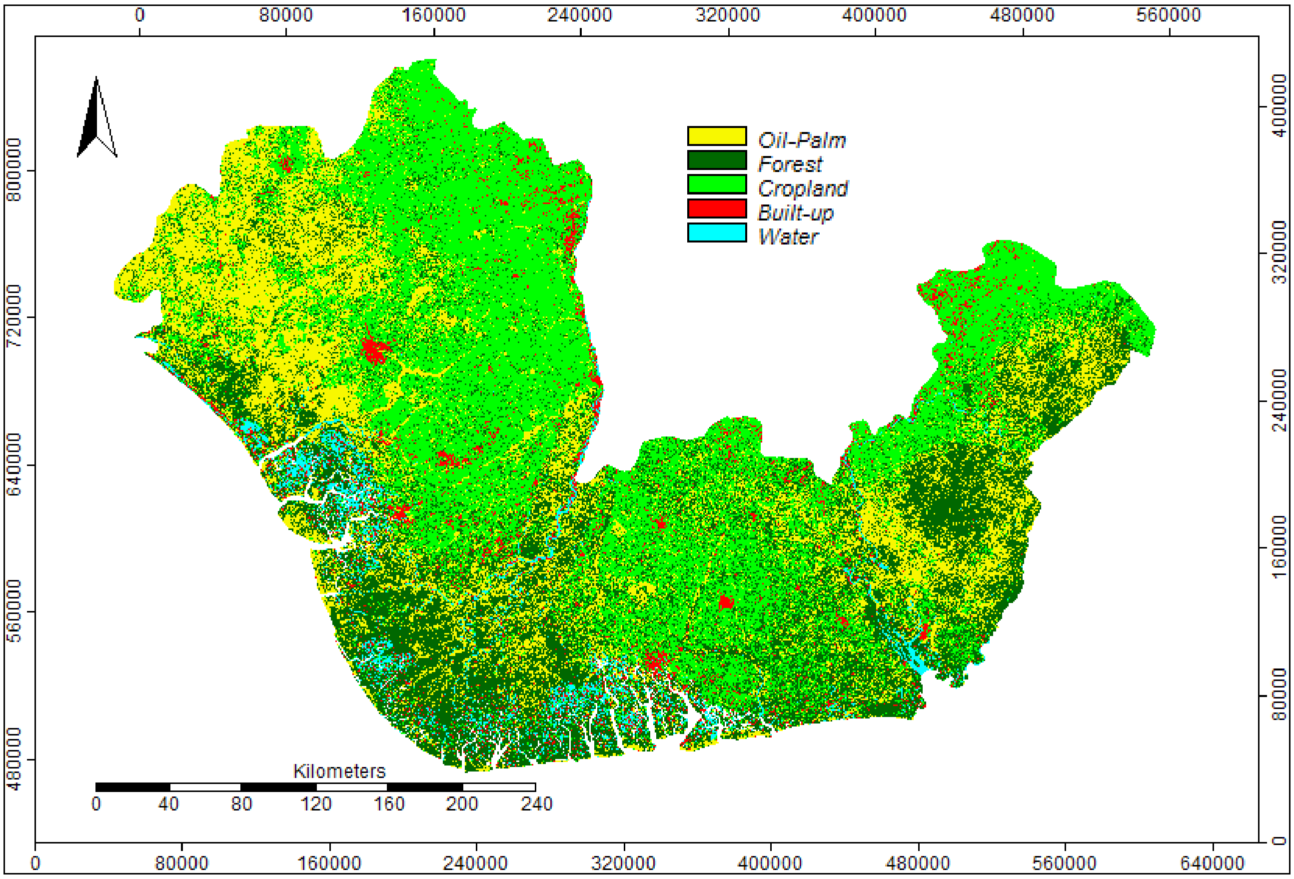

Fig. 7 *Land-use/land-cover map based on the 2009-2015 median composite*

According to the results obtained for the 2015 land-cover map, cropland occupies 40.28 %, oil palm 26.55 %, forest 26.35 %, built up area 2.92 %, and waterbodies 3.87 % of the study area (cf. *Table 1*). It could be observed from our maps for both years that the oil palm plantation operations are mostly concentrated at the western and eastern parts of our study area (*Fig. 6* and *Fig. 7*). The larger forest extent was observed in the eastern part, where the altitude is slightly higher.

The result of the post-classification comparison approach employed for the detection of land-cover changes is shown in *Table 1* and *Fig. 8*. It is clearly observed that forest had a decrease of 3.17 % from 2005 to 2015, which is very significant compared to the time interval. Field observations and research findings reveal that the high rate of change observed in the forest area has to be attributed to the conversion to cropland and to oil palm cultivation. Our findings are in line with those of *Abbas* (2012) in his study of a smaller area within our study area. Cropland experienced an increase, which has to be largely attributed to forest area decrease, reflecting, according to the locals, the governmental policies on agriculture (see also *Orimoogunje* et al. 2013). The decrease in built-up area resulted from the conversion of bare lands into mostly agricultural land. According to our analysis the land-cover type that was most heavily converted to oil palm cultivation and cropland was forested areas (cf. *Fig. 8*). Other land-cover changes encountered include: from cropland to forest, built-up areas to cropland (which is basically the cropland areas that were initially cleared for cultivation during the first image acquisition period), cropland to built-up areas which is due to the increase in urbanization. Our study also reveals an increase in water body area.

The accuracy of the classification results for land-cover maps for 2005 and 2015 is reported in *Tables 2* and *3* respectively. The producer accuracy for all the land-cover types for the 2015 land-cover map ranges from 74.69 % to 90.00 % and the user accuracy from 72.72 % to 97.82 %. Our approach was able to produce an overall accuracy of 84.51 % with a Kappa coefficient of 0.80.

Global change and energy transition have triggered a lot of land-use/land-cover changes. The RSPO has not yet come up with a standard to map and monitor oil palm plantations. There is a serious concern that palm

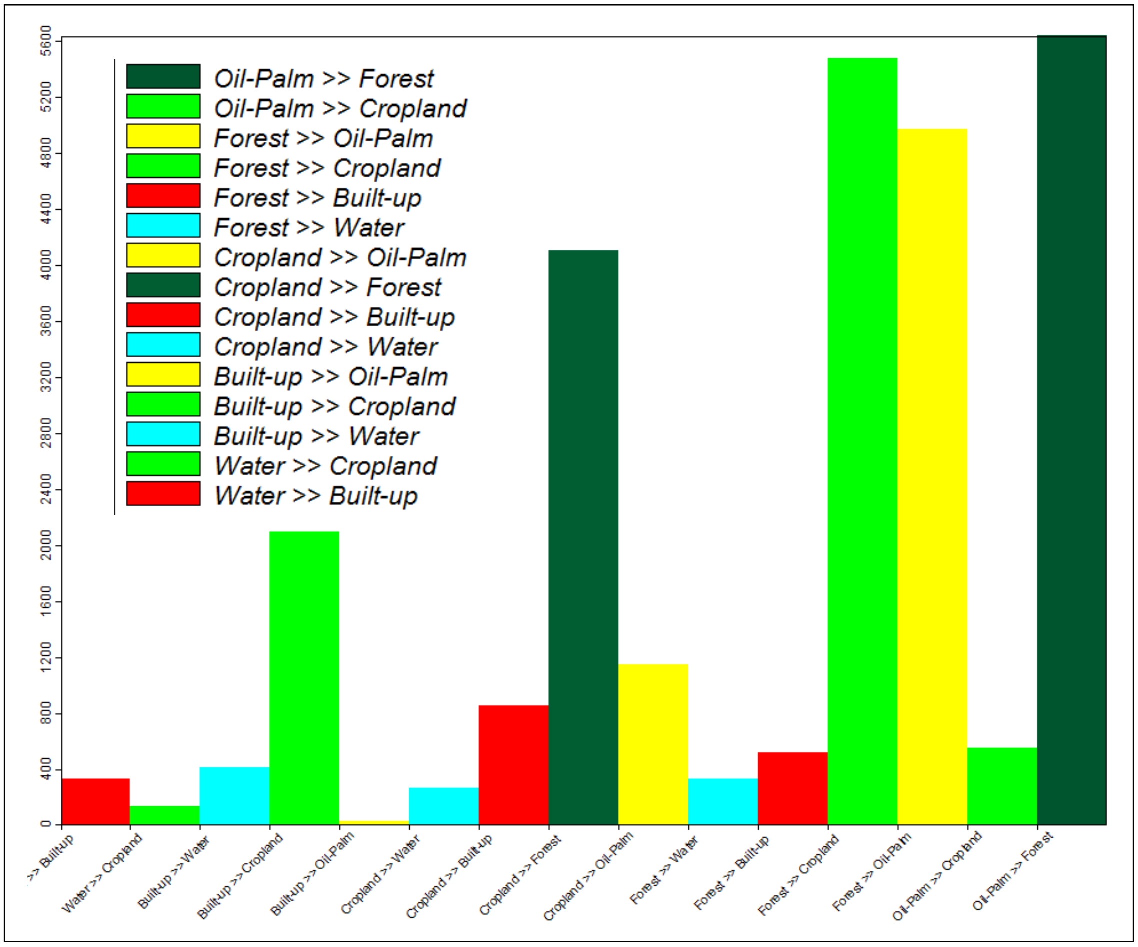

Fig. 8 Land-use/land-cover change 2005-2015

oil production is largely unsustainable, with issues relating to deforestation, biodiversity, soil degradation, water quantity, local people, land rights and many other aspects. The development of new plantations has resulted in the conversion of large areas of forests with a high conservation value and threatens the rich biodiversity in these ecosystems. Many of these social, ecological and environmental impacts of oil palm production can be associated with land-cover and land-use change in connection with bioenergy production (*Elbehri* et al. 2013). Bioenergy-related land-use decisions may affect local, regional and global social, ecological and environmental systems. Therefore, sustainability is a big challenge with regard to the increased development of bioenergy production. It is important to develop a standard approach that aids in the determination of the main resource availability (land).

To investigate the environmental and social impacts of unsustainable oil palm cultivation for bioenergy production, the land-use/land-cover maps of oil palm production are among the data basically needed. To this end, our study has come up with an approach to get rid of cloudiness challenges in mapping oil palm trees in the tropical region at a regional scale using Landsat images. This tool is useful when the land cover is very heterogeneous, and thus requires a medium- to fine-image resolution. Therefore, our approach could serve as a baseline for policy makers, land managers in the tropical region to map and monitor land-use/land-cover change on a local to regional scale.

5. Conclusions

Oil palm related land use/land cover change can be monitored in the tropics at a regional scale by using a median composite image, combining Landsat 5, 7 and 8 data in a single mosaic via GEE and SAGA GIS. The approach assists in getting rid of cloud problems in tropical regions, which also helps in understanding the nature of change in the use of land

Table 2 Confusion matrix for land-use/land-cover map 1999-2005 composite

	Water	Built-up	Cropland	Forest	Oil palm	Classification overall	Producer accuracy (%)
Water	61	1	0	37	1	100	61.00
Built-up	4	61	13	3	2	83	73.49
Cropland	0	8	78	10	8	104	75.00
Forest	2	1	3	66	21	93	70.96
Oil palm	0	0	12	17	73	102	71.56
Truth overall	67	71	106	133	105	483	
User accuracy (%)	91.04	85.91	73.58	49.62	69.52		

Table 3 Confusion matrix for land-use/land-cover map 2009-2015 composite

	Water	Built-up	Cropland	Forest	Oil palm	Classification overall	Producer accuracy (%)
Water	90	2	0	8	0	100	90.00
Built-up	1	62	17	3	0	83	74.69
Cropland	0	0	89	8	7	104	85.57
Forest	1	0	0	80	8	89	89.88
Oil palm	0	0	8	11	83	102	81.37
Truth overall	92	64	144	110	98	478	
User accuracy (%)	97.82	96.87	78.07	72.72	84.69		

resources. This approach can also facilitate proper planning, management and regulations of the use of land resources now that there is a quest for energy transition due to climate change. The change detection analysis shows that there is a decrease in the forested area in the study area, with a much greater forest area that changes to oil palm than other land-cover types. The overall classification accuracy is sufficient in order to establish management strategies based on the map results.

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