Monitoring spatial accuracy of oil palm cultivation mapping in southern Cameroon from Landsat series images

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Abtract

Studying and mapping palm grove evolution allow understanding the impact related to its cultivation. Our study aims to map industrial palm grove using Landsat series images and measures the accuracy of the produced maps. It was carried out in SOCAPALM industrial plantation, located in southern of Cameroon. For the mapping and assessment of accuracy, per-pixel classification and confusion matrix method were used, respectively. We obtained high correlated maps (Kappa =0.92 in 2001 vs 0.86 in 2015). However, some confusions were observed between vegetation and oil palm classes for the two periods, affecting the maps accuracy. These confusions are caused by the presence of mixed pixels resulting from the spatial and spectral characteristics of palm groves, the method used to map and validate the map, and uncertainty related to dada. To increase the accuracy, we suggest (1) to use another mapping method such as super-resolution mapping, (2) develop a classification system of cartographic products.

Keywords
Elaeis Guineensis.Jaq, oil palm, remote sensing, spatial accuracy, monitoring.

I INTRODUCTION

Oil palm (Elaeis guineensis.jaq) is a perennial oleaginous plant from Central Africa. In Cameroon oil palm has a high economic importance with an industrialisation dating from colonial period (Elong, 2003). The incomes generated by oil palm cultivation have developed agro- industries such as SOCAPALM (Cameroonian Society of Palm groves). This activity in high-yield and low cost of returns (Riva, 2013), is behind of socio- environmental damages whom deforestation, loss of biodiversity, pollution, etc. Studying and mapping palm grove evolution allow understanding the impacts related to this culture. Our work is placed in the context of the long-term management of Oil palm resources in Congo basin. This paper is focused on the first part of this project: studying, mapping and monitoring SOCAPALM industrial palm groves using remote sensing. Several studies have shown the capability of remote sensing to map plant resources (Domaç and al, 2004; Li and al., 2015; Koh and al, 2011; etc.). The accuracy of the produced maps is main question for the study of evolution, mapping and characterization of palm grove, and for the reliability of our method.

This first part aimed to map palm grove and assess the spatial accuracy of produced map.

II STUDY AREA AND DATA

II.1 study area

Located in the Congo Basin, the Republic of Cameroon is a central African country with a surface area of 475,440 Km² and 20,000,000 inhabitants in 2015. Two main climatic zones are defined. In south the climate is equatorial and sub-equatorial, temperatures range between 25°C and 35°C, annual abundant precipitations up to 1000mm. In north the tropical climate is Sudanese (high temperatures and scarce rainfall) and Sahelian (irregular precipitations). SOCAPALM industrial plantations are located in south west of Cameroon, in the Ocean County, not far from the port city of Kribi (see figure 1).

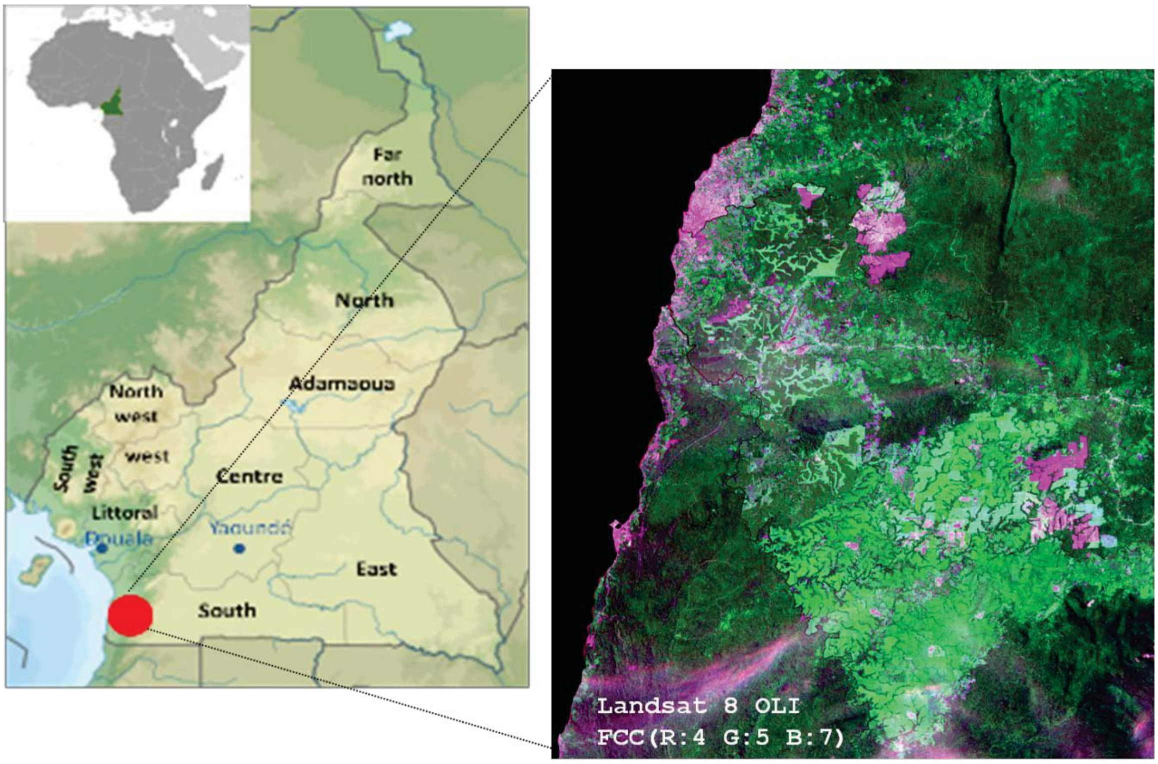

Figure 2: Localisation of study area, from CNRS ESPACE UMR 7300.

II.2 Data

Landsat 7 ETM+ and Landsat 8 OLI images of same season, but with different acquisition date were used (see Table 1). These images were acquired on the 26th April 2001 (ETM+) and 25th April 2015 (OLI), respectively.

Parameters	ETM+	OLI
Spectral range	0.45 -12.5µm	0.45-235µm
Spatial resolution	MS:30m/PAN:15m	MS:30m/PAN:15m
Swath width	183km	185km
Spatial coverage	Non-continuous	Non-continuous
Total number of bands	8	11
Mode	MS/PAN	MS/PAN
Date of acquisition of image	April 2001	April 2015

Table 1. Sensor specification of Landsat ETM^{+} and OLI.

III METHODOLOGY

Methodology adopted for this study is depicted in Figure 2. It involves mapping palm grove using spectral classification, evaluating the precision of produced maps for both Landsat images 2001 and 2015.

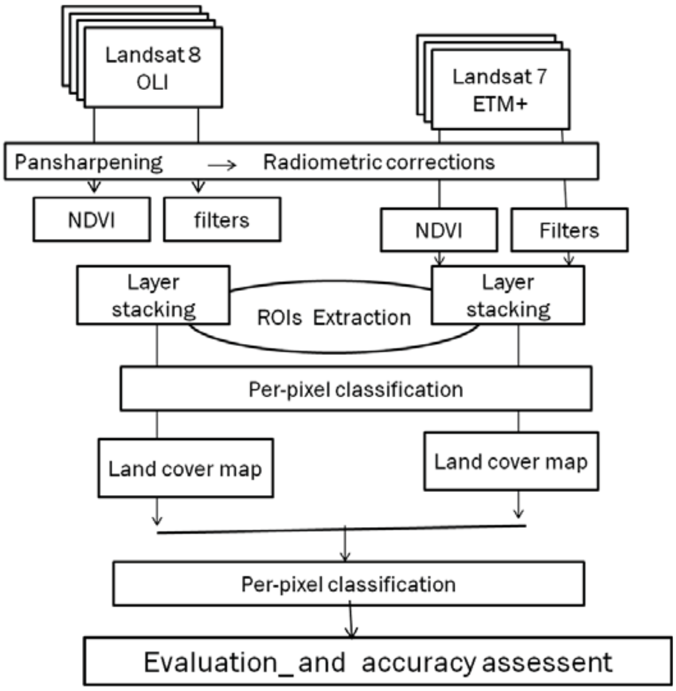

Figure 2: Flowchart of methodology adopted in this study.

III.1 Pre-processing

The pre-processing phase is composed of a chain of 6 calculs:

(i) Pansharpening method to improve the spatial resolution of the multispectral image (30m), merging it with the panchromatic image (15m), by the Brovet transform (Lacombe, 2008). The function resamples automatically the seven (Landsat 7) or eleven (Landsat 8) channels in the maximal resolution by using several methods; in our case, the cubic convolution method was used, to obtain a multispectral image of 15mx15m of resolution.

(ii) Radiometric corrections, images were calibrated in radiance by applying the equation:

L=a*CN+b, where *CN* is the digital count, *a* is the gain and *b* is the bias. The coefficients *a* and *b* of sensor calibration are given in the metadata files. The luminance ($W.m^{-2}.sr^{-1}$) was calculated for each band.

(iii) As the presence of cloud (30% of cloud cover) and water area, may disturb the analysis, they were masked.

(iv) The vegetation index was calculated according to the equation: NDVI=NIR-RED/NIR+RED. It allows characterizing the vegetation cover in terms of level of Chlorophyll (Pouchin and al., 2002).

(v) To improve the detectability of objects, (Gadal , 2003) convolution filters were used: morphological (maximum filter) and directional filter with a kernel size of 3x3 pixels.

(vi) Eight regions of interest (ROIs) were defined according to the spatial organisation of landscape: growing, young, and mature oil palm, low vegetation, forest, bare ground/built-up areas and waterway.

III.2 PROCESSING

III.2.1 Palm grove mapping

First, we created an image with B, G, R, NIR, SWIR and NDVI channels, masked water area, extracted spectral signatures from all channels and computed radiance statistics. Second, to estimate ROIs separability, Jeffries-Matusita distance (JM) was used. This average distance between two classes (Wacker and Landgrab, 1972) takes values in the range [0-2]. Value over 1.8 indicates a very good separability, a value under 1.8 indicates poor separability.

Third, supervised maximum likelihood classification was applied on filtered channel and on other channels of the image.

III.2.2 Validation of classification

To validate produced maps, control areas were digitized with Arcgis GIS software in eleven as estimated for each image. The resulting manual classifications could then be crossed with the maximum likelihood classification result, to produce a confusion matrix and Kappa index.

III.2.3 Analysis of maps accuracy

The conventional methods of accuracy assessment of thematic maps were employed: confusion matrix (Congalton, 1991). The confusion matrix gives an overall evaluation of map accuracy and for classification results of each thematic class.

Kappa index assesses the correlation between obtained results (maps produced) and the ground truth. Kappa takes values in the range [0-1] and it's divided into five categories: very low agreement from 0 to 0.20; weak correlation from 0.21 to 0.40; moderate correlation from 0.41 to 0.60; substantial correlation from 0.61 to 0.80; high correlation from 0.81 to 1. This index (equation 1) is expressed in terms of overall accuracy observed (equation 2) and expected (equation 3).

$$K = \frac{a-b}{1-b} \quad (1)$$

$$a = \frac{1}{N}\sum_{i=1}^{NC} x_{ii} \quad (2)$$

$$b = \frac{1}{N^2}\sum_{i=1}^{NC} (x_{i+} . x_{+i}) \quad (3)$$

Were <NC> is the number of classes; <N> the total number of observations; <x_{ii}> the number of observations in the row i; < x_{+i}> and <x_{i+}> total observations in the line i.

IV RESULTS AND DISCUSSION

IV.1 Classification by maximum likelihood and classes'separability

In general, the computed JM index to assess ROIs separability shows that, ROIs defined have good separability. Thus, JM distances are 1.99 for growing and young oil palms; but poor separability between forest class and mature oil palm. Confusions are expected between these last two classes (see Table 2).

IV.2 Accuracy and thematic confusions analysis

For both Landsat 8 and ETM+ images, maps produced have very good accuracy (see Table 2) with 90% in 2001 and 80% in 2015, respectively. Different classes of palm grove are recognized: 99.67% for growing oil palm, 80% for mature oil palm and 93.42 %, for mature oil palm in 2001. The same trend was obtained in 2015. Kappa values shows high correlation: Kappa = 0.92 (2001) and Kappa= 0.86 (2015).
However, despite of the high values of Kappa, some thematic confusions are observed between oil palm classes, or oil palm and vegetation classes. For example, we observed confusions between forest and mature oil palm (17%); or between young and growing oil palm (5.4%).
During the classification process, some pixels belonging to mature palm, where classified in to forest classes, for example.

The quality of classification is directly related to class separability, which itself depends on the variation among pixel from different classes as compared to within-class pixel variation. On one side, uncertainty to the data including several factors such as variable incidence, shading effects contribute to within class heterogeneity and alter the specificity of the signal.

On the other side, as some component may be common to different classes, (for example low vegetation pixels in the growing or young oil palm classes), distinct classes may share mixed pixels (Komba Mayossa, 2014).
On the validation map side, ground truth plays an important role in map accuracy. The knowledge of ground is an important key; the results were obtained from validation of digitized map and classification result. Landsat image, have 30mx30m of spatial resolution. The photo-interpretation is difficult especially in a heterogeneous landscape, as our study area where errors during the sampling step, cannot take to account within-plot heterogeneity. Thematic confusion caused by the presence of mixed pixels affects map accuracy (Chitroub, 2007). These mixed pixels result from spectral and spatial characteristics of the landscape studied objects, and from the method used to map.

IV.3 Prospects

The maps obtained have a good accuracy, but some thematic confusions were observed.
One limitation of spatial accuracy of oil palm grove mapping is bound to class heterogeneity, attendant mixed pixels and the method used. Several ways for improvement are possible. At first, per-pixel classification assumes that each pixel represents a single class only. Maximum likely hood algorithm, used to map palm grove, ignores the mixed pixel problem. One of the solutions is to use a technic which allows mapping at the sub-pixel scale, such as super-resolution mapping (Priyaa and sanjeevi, 2013; Muad and foody, 2010). Second, as the map validation method improves or decreases the accuracy of produced map, the development of a classification system of cartographic products can be most interesting. Indeed, further studies should be focused on the evaluation of reliability of the produced map by this classification system (Chalifoux and al, 2006).

Map 2001

GROUND TRUTH	**Growing Oil palm**	**Young Oil palm**	**Mature Oil palm**	**Low Vegetation**	**Shady Forest**	**Forest**	**Ground Built1**	**Ground Built2**	**Ground Built3**	**Waterway**	TOTAL
Growing Oil palm	**99.67**	2.87		0.01							102.25
Young Oil palm	0.33	**93.42**		5.4							99.15
Mature Oil palm			**80**		10	2.22					92.32
Low Vegetation		3		**94.59**		1.70					100
Shady Forest			2.88		**84.15**	7.07				6	100.12
Forest			1.22			**88.99**					112.45
Ground Built1							**100**				106.45
Ground Built2								**100**			100
Ground Built3									**93.55**		93.55
Waterway										**94**	94
TOTAL	100	100	100	100	100	100	100	100	100	100	**1000**

Overall accuracy 90% / Kappa=0.92

Map 2015

GROUND TRUTH	**Growing Oil palm**	**Young Oil palm**	**Mature Oil palm**	**Low Vegetation**	**Shady Forest**	**Forest**	**Ground Built1**	**Ground Built2**	**Ground Built3**	**Waterway**	TOTAL
Growing Oil palm	100										100
Young Oil palm		**100**		0.04							100
Mature Oil palm			**99.51**		1.58						101.13
Low Vegetation				**100**							100
Shady Forest					**97.55**	12					99.15
Forest			0.49		2.01	**97.22**					99.63
Ground Built1							**100**				100
Ground Built2								**100**			100
Ground Built3									**100**		100
Waterway										**100**	94
TOTAL	100	100	100	100	100	100	100	100	100	100	1000

Overall accuracy 80% / Kappa=0.89

Table 2. Confusion matrix and Kappa index (Land cover map 2001 and 2015)

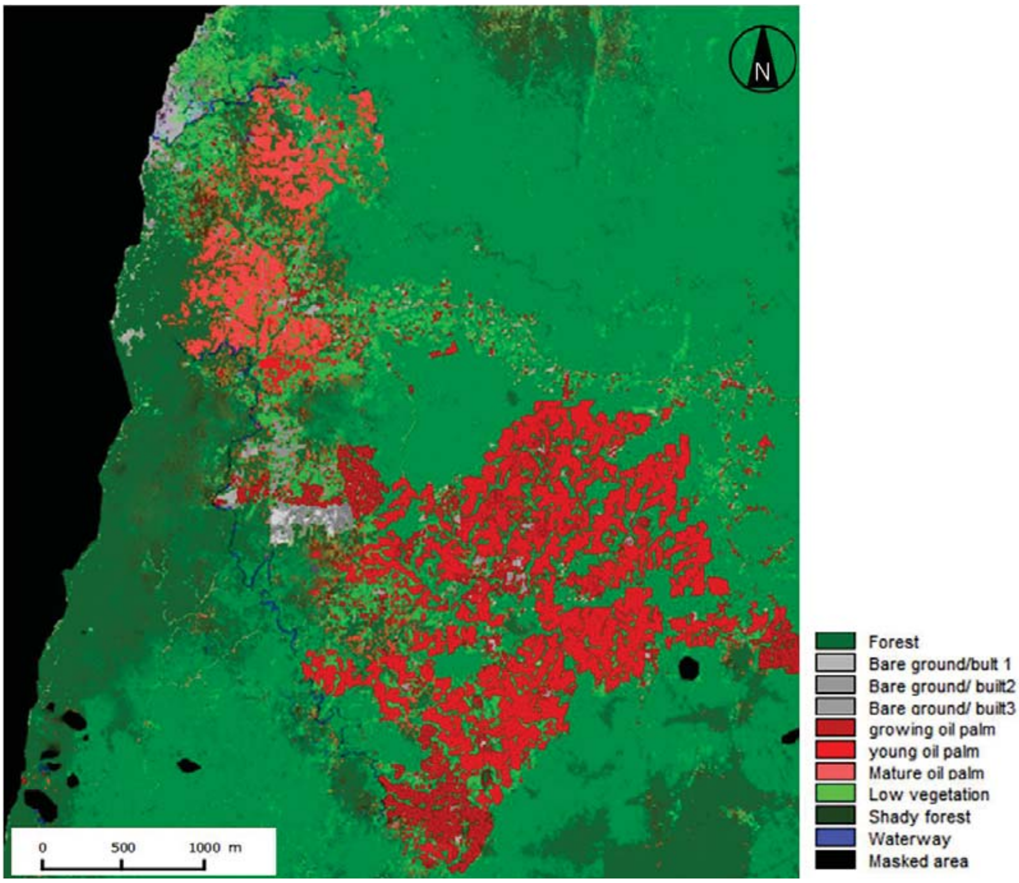

Figure 3: Landsat map in 2001(Landsat 7 ETM+), from CNRS ESPACE UMR 7300.

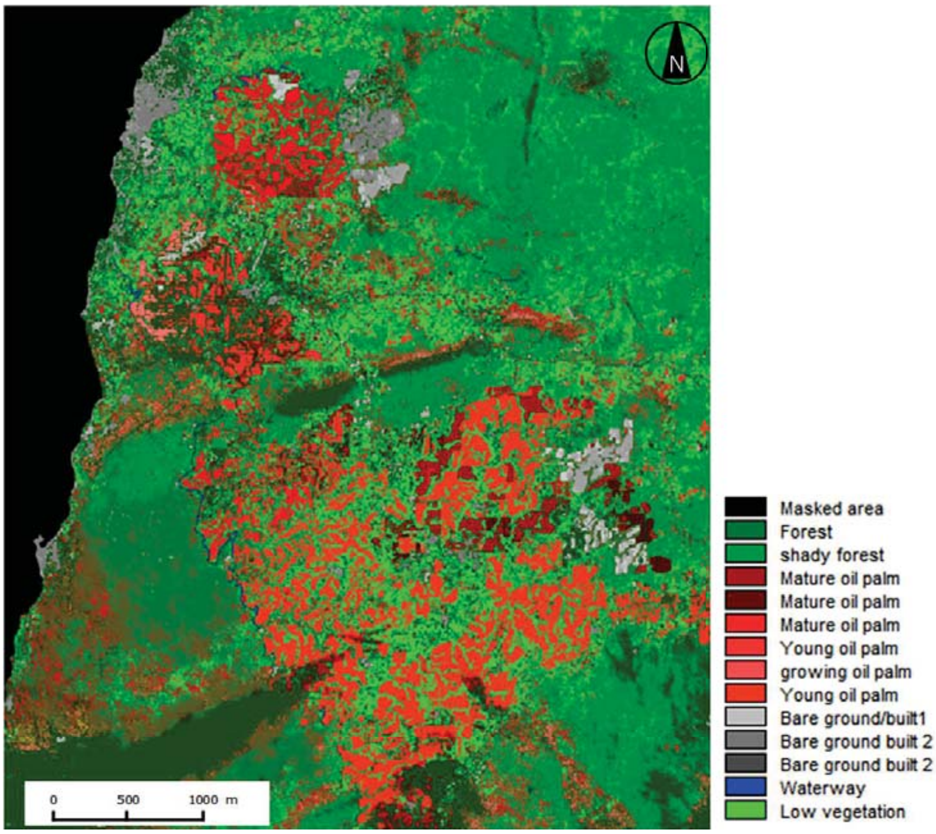

Figure 4: Landsat map in 2015 (Landsat 8 OLI-TIRS), from CNRS ESPACE UMR 7300.

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