Developing a method to map coconut agrosystems from high-resolution satellite images

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Abstract

Our study aims at developing a generalizable method to exploit high resolution satellite images (VHR) for mapping coconut-based agrosystems, differentiating them from oil palm agrosystems. We compared two methods of land use classification. The first one is similar to that described by Teina (2009), based on spectral analysis and watershed segmentation, which we simplified by using the NDVI vegetation index. The second one is the semi-automatic classification based on texture analysis (PAPRI method of Borne, 1990). These methods were tested in two different environments: Vanua Lava (Vanuatu; heterogeneous landscape, very ancient plantations) and Ivory Coast (Marc Delorme Research Station, monoculture, regular spacing, oil palm plantations); and their results were evaluated against manually digitized photo-interpretation maps.

In both situations, the PAPRI method produced better results than that of Teina (global kappa of 0.60 vs. 0.40). Spectral signatures do not allow a sufficiently accurate mapping of coconut and do not differentiate it from oil palm, despite their different NDVI signatures. The PAPRI method differentiates productive coconut from mixed plantations and other vegetation, either high or low (70% accuracy). In both situations, Teina's method allows counting 65% of the coconut trees when they are well spaced. To increase the method accuracy, we suggest (1) field surveys (for small scale studies) and/or finer image resolution, allowing a high precision in manual mapping with a better discrimination between coconut and oil palm, thus limiting the proportion of mixed pixels. (2) A phenological monitoring could improve the distinction between coconut and oil palm agrosystems. (3) Hyper-spectral images should allow extracting more precisely the respective signatures of both species. Another possibility would be (4) an object-oriented analysis as proposed by the eCognition software. Finally, (5) coupling the Lidar system with watershed analysis would allow a better characterization of coconut varietal types.

Keywords: coconut, oil palm, spectral analysis, textural analysis, VHR images, agrosystem, mapping

1. INTRODUCTION

The coconut palm (*Cocos nucifera* L.) is a perennial oleaginous plant. It is restricted to humid tropical climates, characterized by average temperatures between 21°C and 27°C and rainfall between 1500mm and 2500mm, evenly distributed across the year (Komba Mayossa, 2013). The coconut palm is considered as the tree of life. Indeed, all parts of the plant are valued at small or industrial scale, as it provides water, food, fiber, fuel, shelter, and drugs (Bourdeix et al., 2005). However, the main product remains its fruit, whose dried albumen is called coprah. Its production

is estimated at 61.7 million tons, with an average yield of 5.2 tons.ha^{-1}. Coprah plays an important role in the economy of several regions of the Pacific (e.g. Vanuatu, Tuamotu), Africa (e.g. Ivorian and Tanzanian coasts) and Asia (India and the Philippines).

Our study was placed in the context of the long-term management of coconut resources; including coconut genetic resources that are the focus of the international COGENT network. The distribution and potential of coconut orchards is important information for the 39 countries affiliated to COGENT.

Several studies have shown the capability of remote sensing to inventory and characterize plant resources. To evaluate and classify local plant biodiversity in southern Tunisia, Domaç et al. (2004) extracted spectral information from Landsat ETM^{+} images. Vintrou (2012) also used such images to characterize and map Malian agricultural systems based on millet, sorghum, and maize. Mougel et al. (2009) used Quickbird images to detect and recognize orchards and tree plantations south of Nîmes (France). A few studies have considered the case of the coconut palm. They were aimed at developing methods for the characterization of coconut agrosystems (Lelong et al., 2004); or developing algorithms to count coconut palms and produce density maps (Teina, 2009). Working on the spatial structure of agrarian systems in Melanesia, Lelong et al. (2004) concluded that their textural analyses did not allow mapping the various coconut agrosystems from multispectral images. Teina (2009) developed a robust method to map and inventory the coconut-based agrosystems in the Tuamotu. As the near-infrared band (important for analysis of plant biomass) was not available for his study, Teina had to use a principal component analysis (PCA).

The objective of the present study was to propose a simple and generalizable method for (i) mapping coconut palm agrosystems; (ii) differentiating this crop from the relatively similar oil palm, in two different agricultural contexts: Vanuatu, where the coconut palm is ancient and present at several stages of maturity, in a heterogeneous agricultural environment; and Marc Delorme Research Station, in Ivory Coast, where coconut palms are grown intensively, in pure stands, with regular spacing, in a homogeneous agricultural environment, close to oil palm plantations.

2. MATERIALS AND METHODS
2.1. Study sites
2.1.2. *Vanua Lava*

In the Pacific Ocean, the Vanuatu archipelago extends over 850 km and includes approximately 80 volcanic islands between the 13th and 22nd south parallels and between Solomon and Fiji islands (fig.1.a). It has an oceanic equatorial climate. Rainfall, humidity and average temperature increases from south to north. The Vanuatu population of 234,000 inhabitants is rural at 75 %. The economy heavily relies on the coconut palm, cultivated throughout the country. Our study was focused on Vanua Lava Island, one of the largest islands of Banks, located in the North of Vanuatu.

2.1.3. *Marc Delorme Research Station*

The Ivory Coast republic is a country of western Africa, with an area of 322,462 km² and an estimated population of 20,000,000 inhabitants in 2010. Two main climatic zones are defined. In the South, the climate is equatorial, with limited thermal variations (25-30°C), a very high moisture level (80-90%), and abundant precipitation, up to 2129 mm., In the North, the tropical savanna is characterized by high thermal variations (14-34°C), moistures of 60-70%, and rainfall

reaching 1200 mm (Koffi et al., 2013).The Marc Delorme Research Station (5°16'N and 3°51'O), founded in 1949, holds an international collection and coconut genebank managed by COGENT (fig.1.b). The station is located in the Lagoons district, 30 km from Abidjan. Its plantations occupy more than 1000 ha and are located near oil palm plantations. Our study focused especially on tall coconut (plot142) and dwarf coconut (plot 132) plots.

2.2. VHR images

Two Very High Spatial Resolution images, from Pléiades and GeoEye-1, represent respectively Vanua Lava and Marc Delorme research station. These images were acquired on the 10th, (Pléiades) and 29th (GeEye-1) of October 2013. They are orthorectified and radiometrically corrected (Komba Mayossa, 2014)
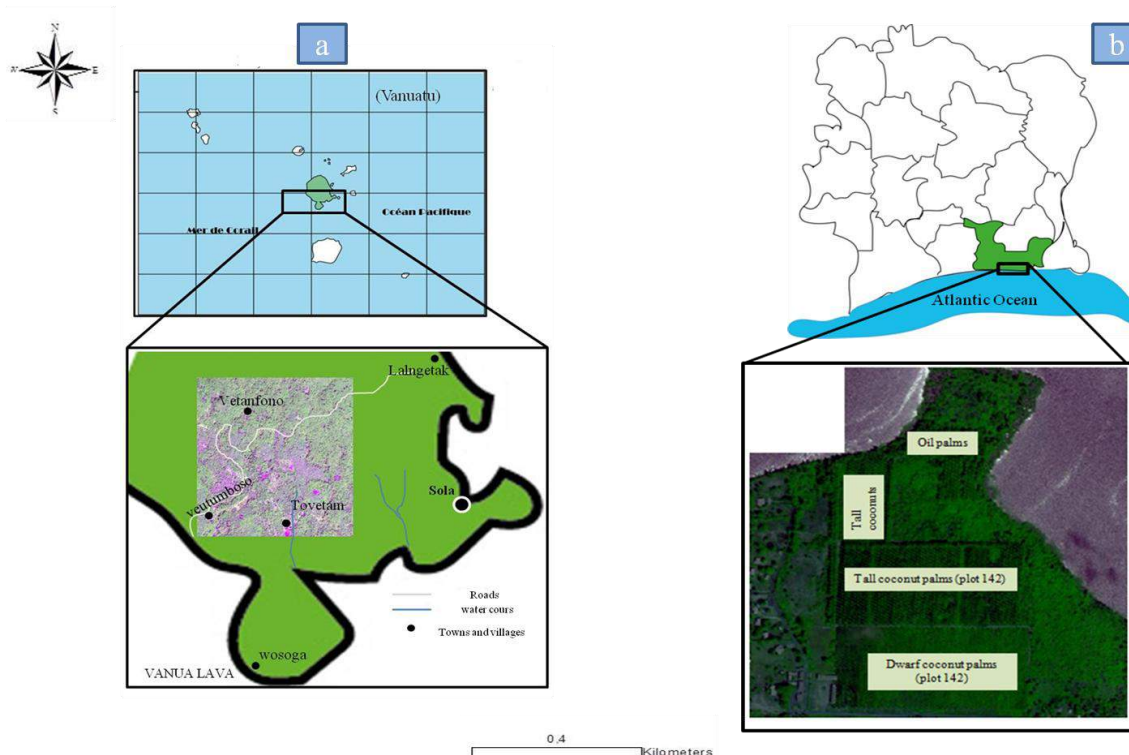

Figure 1: Study sites; a: Vanua Lava; b: Marc Delorme Research Station).

2.3. Preprocessing

We used a pansharpening method to improve the spatial resolution of the multispectral (2 m) image, merging it with the panchromatic image (0.5 m), by the Brovet transform (Lacombe, 2008). The function resamples automatically the four original channels in the maximal resolution by using several methods; in our case, the cubic convolution method was used, to obtain a multispectral image of 0.5 m of resolution in the blue, green, red and near-infrared channels. 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.

The vegetation index was calculated according to the equation NDVI = NIR-RED/NIR +RED NDVI . It allows characterizing the vegetation cover in terms of vigor (Pouchin et al., 2002). A visual analysis by photo-interpretation allows extracting several landscape characteristics. After

importing the image into the ArcGis software, we defined five Regions Of Interest (ROI), according to spatial organization of landscape: productive coconut palm, mixed coconut palm, high vegetation, low vegetation and bare ground / built-up areas.

2.4. Analyses

We used two main approaches to differentiate coconut palms from other types of vegetation. The first one aimed at extracting coconut palms by their spectral and textural signature to map them. Then, coconut crowns were isolated by the watershed segmentation process (Beucher , 1992). The second approach was based on textural analysis using the PAPRI method (Borne, 1990). These analyses were first developed on the Pléiades image for the Vanua Lava site, and second on the GeoEye-1 image of Marc Delorme station. The method architecture is presented at figure 2.

2.4.1. Extracting and counting coconut palms

We created a five-channel image (B, G, R, NIR, and NDVI), extracted spectral signatures from all channels, and computed radiance statistics.

The segmentation of coconut palms was carried out in three main stages. First, we produced a mask of coconut vegetation zones, applying a supervised maximum likelihood classification on VHR images (Teina, 2009). Then, we masked all the other classes (high vegetation, low vegetation, etc.) based on segmentation of coconut palm classes. This mask is called mask A.

We used the Jeffries-Matusita distance (JM) to estimate the separability of ROI for each class (productive coconut palm, mixed coconut palm, high vegetation, low vegetation and bare ground / built-up areas; Teina, 2009). This average distance between two classes (Wacker and Langrab, 1972) takes values in the range [0; 2]. A value over 1.8 indicates a very good separability, a value under 1 indicates a poor separability.

Second, another mask was created (mask B) for low vegetation, as this class may disturb the analysis in coconut plantations. We used the Data range parameter (Anys et al., 1994), extracted from the occurrence matrix on a 3x3 pixel window, which allows identifying areas of high local variance. The resulting image was filtered using a convolution filter, Gaussian Low Pass, with a window size of 7x7 pixels. The mask B was applied on the near-infrared band of multispectral image.

Third, the final mask (mask C) was obtained by application of mask B onto mask A. Mask C was applied on our five-channel image, giving an image containing only coconut palms.

The last step allowed segmenting individual coconuts by the watershed process, a widely used method to isolate trees in satellite images (Beucher, 1992; Vincent and Soille, 1991). It was implemented using the Matlab codes developed by Teina (2009): the image was smoothed with a Laplacian morphological filter (window size of 3x3 pixels) to remove excessive variations in texture; then, individual trees were delineated with the TIDA algorithm (Culvenor, 2002), searching for local mimima and maxima in four directions. Local minima determine the centers of palm crowns, whereas maxima give their outlines.

2.4.2. Texture analysis by the PAPRI method

PAPRI (PAysages à Priori) is a texture-based classification method, allowing a landscape representation, from the spatial organization and the local distribution of radiometries. PAPRI was developed by Borne (1990) and applied in different contexts (Robbez-Masson, 1994; Borne et al., 2004; Viennois and Borne, 2014). A basis of reference textures is defined beforehand by drawing

representative polygons for each vegetation class. PAPRI uses a sliding window which travels through the image. Within this window, textural indexes and histograms are calculated. Then these parameters are compared to the reference textures, to produce the classification from local histograms and an index that characterizes the color mix. Because of difficulties related to heterogeneity, we proceeded to a PCA. The first component, accounting for 90% of the information, was retained. Our image was converted in 8 bits, saved in .bmp format, and then exported to the PAPRI software for texture classification.

We tested the method with different window sizes to evaluate the best texture expression. At the end of the process, PAPRI produced three files: landscape (classification result), distances (to assess the result), and a file describing window variations and a co-occurrence matrix to evaluate the classification inside the polygon. The darker the distance image, the better is the classification.

2.4.3. Automatic validation of classifications

To validate automatic classifications, two control areas in Vanua Lava and Marc Delorme station were digitized with ArcGis, in as many classes as estimated for each study site. Field data were also available for dwarf and tall coconut palms and for oil palms in the Marc Delorme study site. The resulting manual classifications could then be crossed with the automatic classifications to produce a confusion matrix and a kappa index.
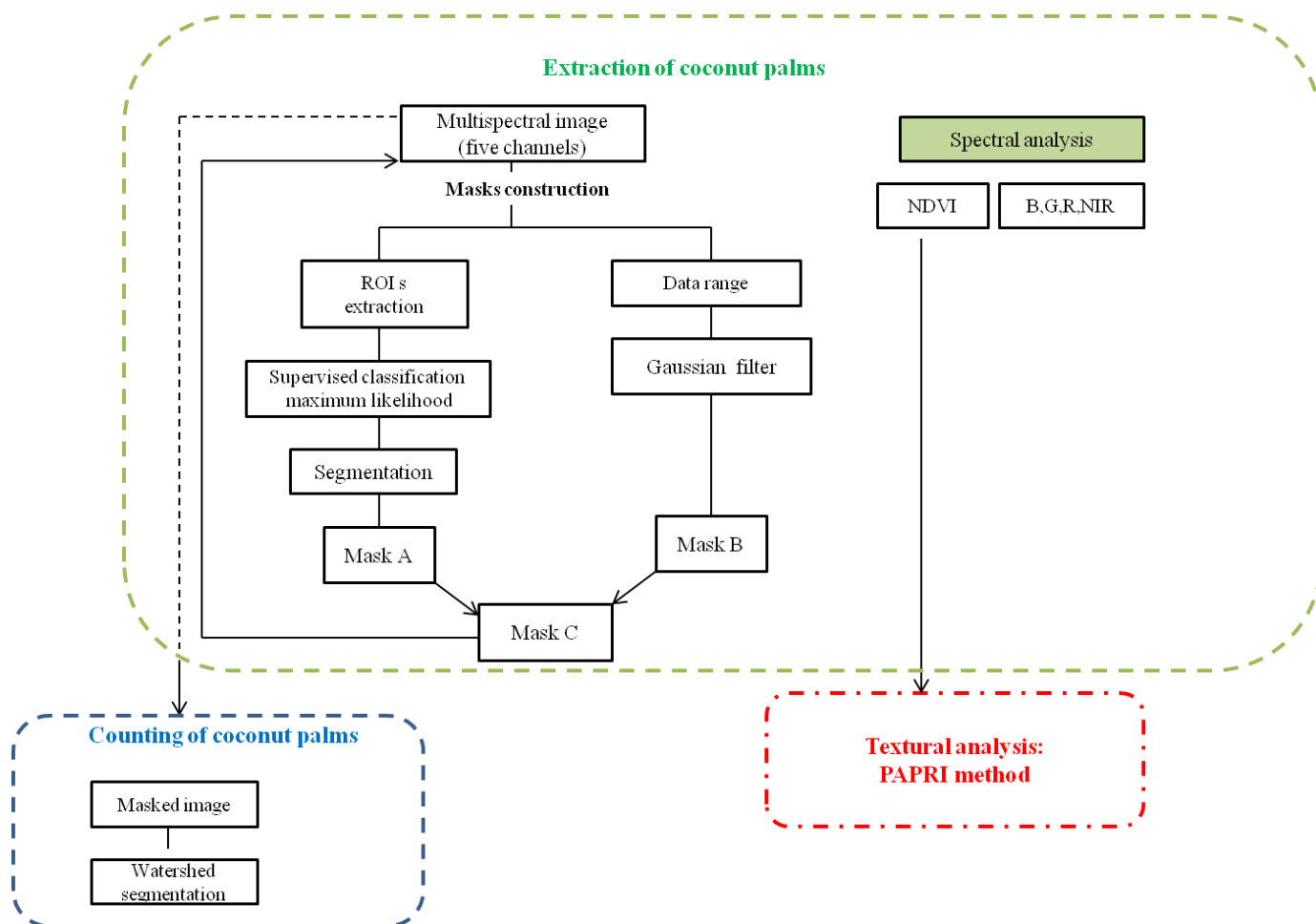

Figure 2: General architecture of the method.

3. RESULTS

3.1. Classification based on spectral analysis

In Vanua Lava, while spectral bands of blue, green, red and near-infrared do not allow discriminating among vegetation classes, the NDVI variation curve allows discriminating among coconut palm classes, and differentiating coconut palm from high vegetation and bare ground. Figure 3.a shows average NDVI variation per class, between 0.1 and 0.8. The highest values are assigned to high (0.8) and low (0.7) vegetation; and the lowest ones (0.24) to the bare ground/built-up class. Thus, NDVI differentiates mixed (0.6) and productive (0.67) coconut palms.

In Marc Delorme station, NDVI ranges between -0.05 and 0.25 (fig.3.b). Varietal (tall vs. dwarf) separability among coconut palms is already visible with NDVI values of 0.14 for dwarf and 0.05 for tall coconut palms. The same holds true for lower crops (-0.005). The 'oil palms', high vegetation' and 'low vegetation', cannot be differentiated and get confused with coconut palm varieties, as their NDVI confidence intervals overlap. The spectral behavior of vegetation classes in the blue, green, and red channels does not allow differentiating them. Variation in the near-infrared spectrum is more comparable to that of NDVI, however only tall coconut palms may be distinguished.
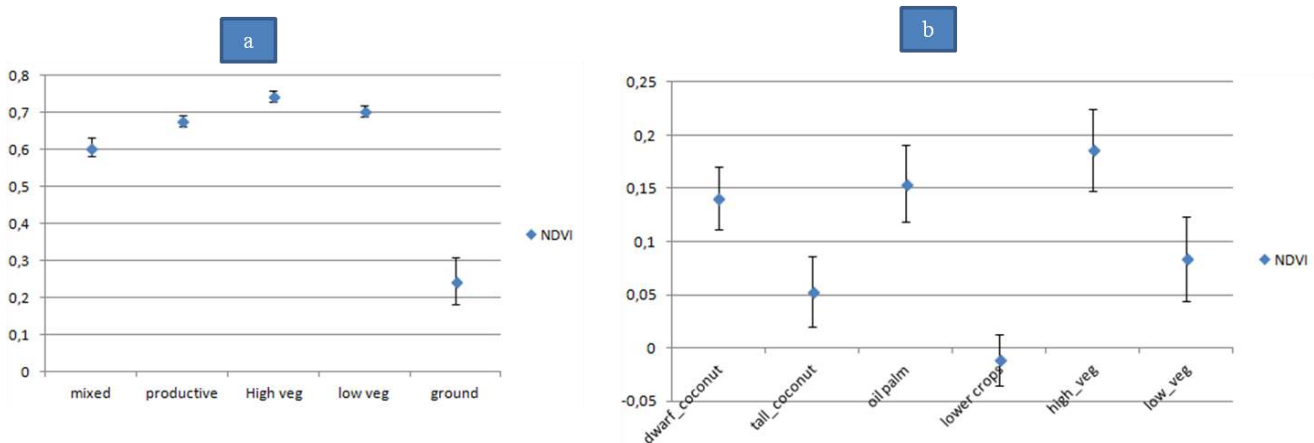

Figure 3: Average NDVI variation; a: Vanua Lava; b: Marc Delorme Research Station.

3.1.1. Classification by maximum likelihood and class separability

Figure 4 shows the classification result in Vanua Lava. Five classes are distinguished: (i) mixed coconut palm (trees, bare ground and coconut), (ii) productive coconut palm (densely planted coconut with rare vegetated ground), (iii) low vegetation (herbaceous layer and lower crops), (iv) high vegetation (trees), and (v) bare ground / built-up areas.

Classes are difficult to separate. Thus, JM distances are 1.25 for productive and mixed coconuts; 1.54 for mixed coconuts and high vegetation; 1.61 for high and low vegetation. This is the better result that could be obtained. Confusions are expected between mixed and productive coconut palms on one hand and high and low vegetation on the other hand. Referring to the manual map, overall accuracy (fig.4.c.) is 58% (for $1.6.10^6$ pixels) with a kappa of 0.4. It should be noted that overall accuracy and kappa index increase according to the way ROIs are sampled. With smaller ROIs, the overall accuracy increases to 85%, with a kappa of 0.71.
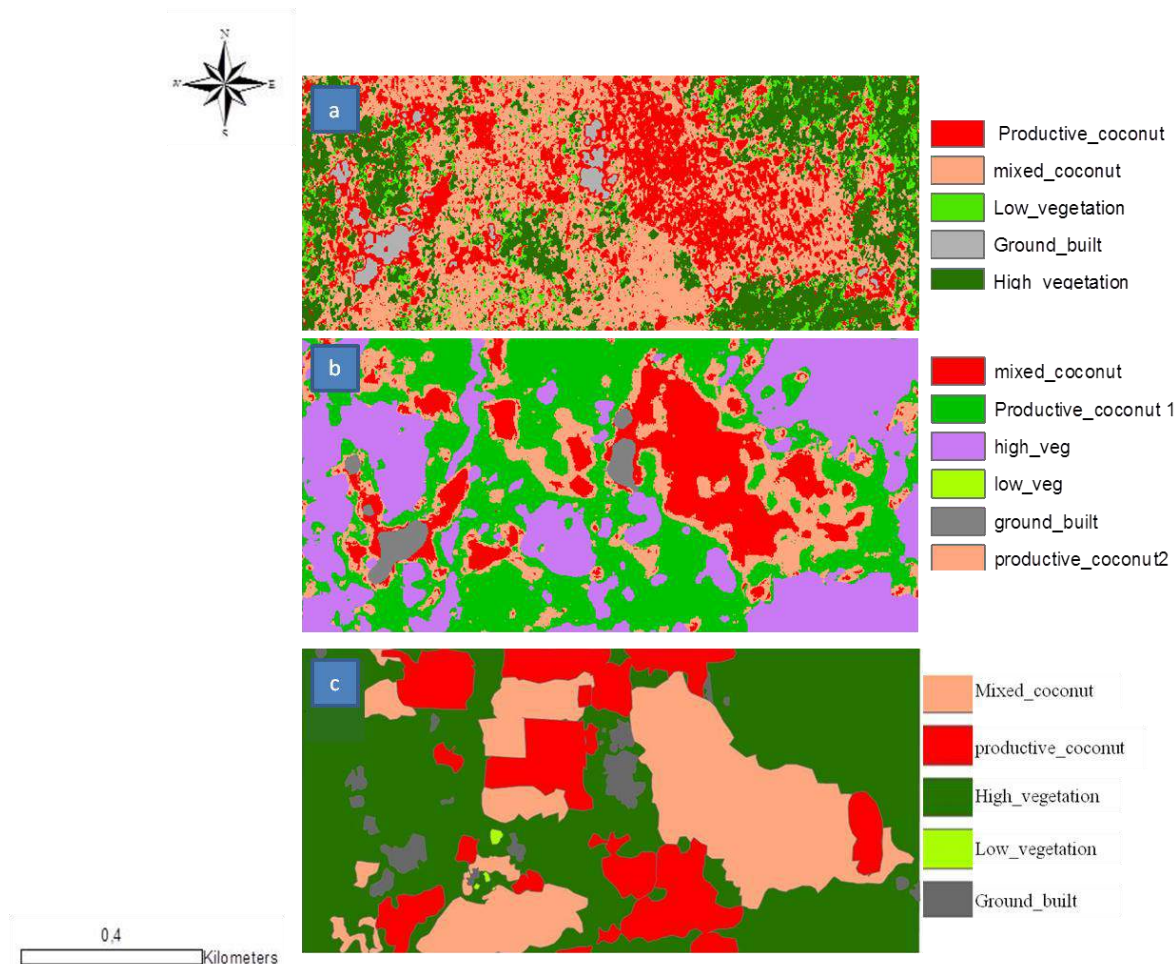
Figure 4: Classification results for Vanua Lava; a: Maximum Likelihood classification; b: Textural classification by the PAPRI method; c: manually digitized map.

Figure 5 shows the classification result for Marc Delorme station. A JM distance of 0.5 indicates poor separation between oil palms and coconut palms. Classification errors are also committed between dwarf and tall coconuts; however, tall coconut palms of plot 142 are well recognized (fig.5a). Overall accuracy is 57% (for 3.10^6 pixels) with a kappa of 0.48. With an automatic validation, defining smaller ROIs, the overall accuracy increases to 85% and kappa to 0.71.

3.2. Classification based on texture analysis

As the tests undertaken on the multi-spectral image had not been satisfactory, the PAPRI analyses were only performed on the first component of the PCA and the NDVI image. The parameters used were: a minimum size of 21 and a maximum of 51 pixels; a step of 16, a rejection threshold of 100%, and a texture coefficient of 50.

For the textural analyses, the productive coconut class was divided into productive coconut 1 and 2 on the basis of different textures.

In general, large window sizes induce a loss of precision in the definition of plot limits. The results roughly reflect reality, with a consequent increase in recognition rate by class in both agricultural contexts, as compared to small window sizes. As for the maximum likelihood classification in the spectral analyses, our textural classification efforts were confronted to

confusions among species (coconut palms, oil palms, and vegetation), and coconut varietal types (fig.5.b).

In Vanua Lava, overall precision is 70%, for a kappa of 0.63. Mixed and productive coconuts are recognized with respective accuracy rates of 60% and 93%. The kappa value is explained by confusions between mixed and productive coconuts (34%), productive and high vegetation (75%), as well as by confusions between bare ground and built-up areas on one hand and productive and mixed coconut palms on the other hand. For the Marc Delorme station, textural analysis discriminates 65% of oil palms, while the remaining 35% get confused with tall (16%) and dwarf (19%) coconuts. For varietal distinction, 58% of tall coconuts and 69% of dwarf coconuts are discriminated, with 10% confusion between dwarf and tall coconuts. This gives an overall accuracy of 56% and a kappa of 0.56.
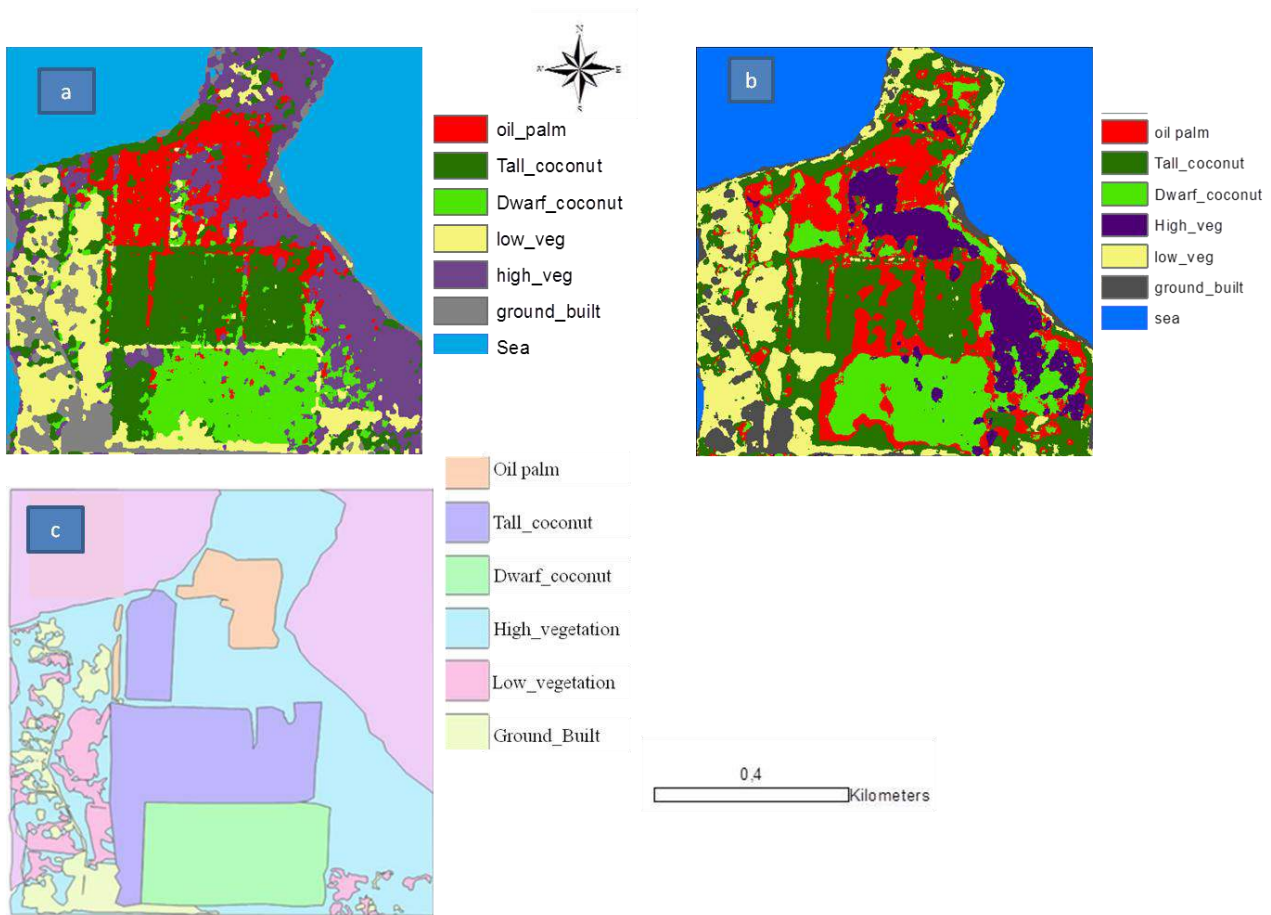

Figure 5: Classification results for Marc Delorme Station; a: Maximum Likelihood classification; b: Textural classification by PAPRI method; c: manually digitized map).

3.3. Coconut palm segmentation

The result of coconut segmentation by the watershed method is not uniform across the image, with cases of both over-segmentation and sub-segmentation (fig.6). Crowns are generally well detected when coconut are spaced, while overlapping palms generate errors. Overall, the method is able to count 65% of the coconut palms.
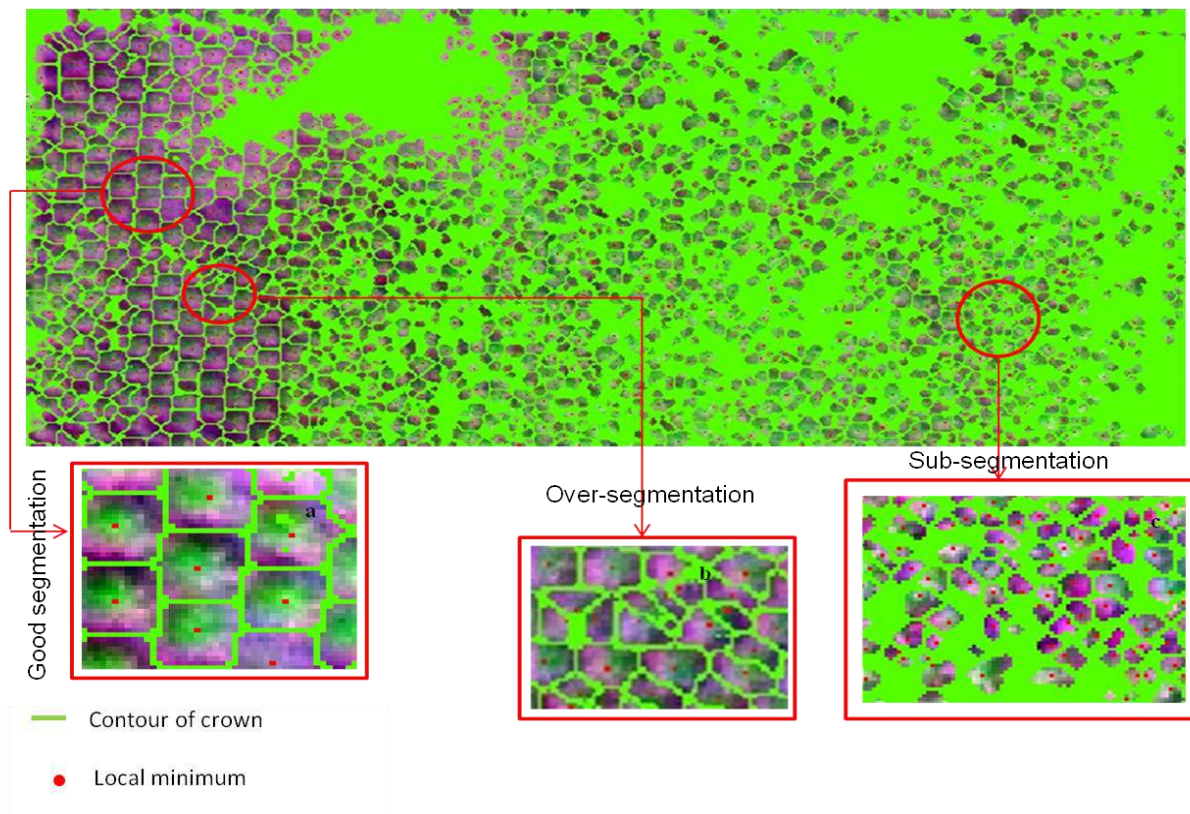
Figure 6: Watershed result (Marc Delorme station).

4. DISCUSSION

In their study of Melanesian agrosystems, Lelong et al. (2004) conclude that the CLAPAS method (derived from the PAPRI method) does not allow mapping the various types of coconut from multispectral images, while Teina (2009) developed a robust method to map and count the coconut-based agrosystems in the Tuamotu islands. We have resumed their efforts, aiming at a better and more generalizable method to map coconut agrosystems and differentiate them from oil palm plantations, testing and improving different processes for extracting, counting and classifying coconuts based on either spectral or textural analyses. Although they are still insufficient for an automatized high precision mapping of coconut agrosystems, our results are encouraging, as they open prospects either for further improvements of the methods, or for envisaging the assessment of coconut resources with less precision but at a much wider scale. In this perspective, we shall outline our main results, identify their main shortcomings and propose possible improvements to overcome them.

4.1. Spectral analysis

In the heterogeneous landscape of Vanua Lava we could use the Jeffries-Matusita index to separate two classes of coconut agrosystems, with different spectral behaviors: mixed and productive coconut palms. They present different vegetation indices (NDVI), thanks to the specific reflectance of their components: soil and trees for mixed coconut orchards, and low vegetation for productive coconut orchards. A maximum likelihood classification allows an accuracy of 57% for mixed coconut and 68% for productive coconuts. Thus, the spectral signatures of these two classes do not allow a precise mapping of coconut agrosystems in a heterogeneous landscape.

By its well-defined spatial organization, the homogeneous agricultural landscape of the Marc Delorme station allowed testing spectral analysis in the case of mono-specific plantations. It also allowed addressing two further questions: the distinction between the two main coconut varietal types, and the distinction of the coconut palm from a botanically very similar crop, the oil palm. The answer was not very encouraging, as overlapping NDVI values hampered a clear separation of the corresponding spectral classes, leading to confusions in the classification.

Spectral analysis was also combined with watershed segmentation, using the TIDA delineation algorithm, to count coconuts and map their density. In both study sites, the algorithm identified 65% of coconuts. Our results show that the method is effective only for places where coconuts are well spaced. When they are too close, they cannot be individually segmented. Furthermore, the algorithm does not work regularly across the image, which presents over-segmented and sub-segmented areas. A study on Babassu palm detection (*Attalea speciosa* Mart.) in Brazil presented the same difficulties (Demagistri et al., 2014).

The use of the vegetation index simplified the method developed by Teina (2009). As the infrared band was not available for their study, this author had to use a PCA to discriminate coconut palms. Indeed, we have noticed the relatively more important contribution of the near-infrared band in the discrimination between coconuts and other landscape components (high vegetation, low vegetation and built-up areas).

Using the NDVI allows differentiating coconut palms from high and low vegetation (Vanua Lava), as well as discriminating between coconut varietal types (tall and dwarf in Ivory Coast), however the differentiation between oil palm and coconut palm is not possible. The discriminating power in this band is related to differences in canopy chlorophyll density, among oil palm, coconut, and high and low vegetation. However the spectral variations in blue, green, red and near-infrared channels show that these classes, which can be separated from their plant density, are not necessarily in the short or long wavelengths.

4.2. Textural analysis

Textural analyses offer better perspectives than spectral approaches for high-resolution mapping of coconut palms at a local scale. Indeed, our study shows that it is possible with the PAPRI method, using the first component of PCA or by defining polygons on NDVI images. Thus, the use of polygons for classification on the NDVI image constituted a clear improvement as compared to the method used by Lelong et al. (2004) for their textural analyses of Melanesian coconut agrosystems. Better results were obtained using large sliding windows, with a texture coefficient of 50. The increase of window size improves texture expression and minimizes confusion rate per class, at the expense of precision. This improvement was obtained using a PCA or NDVI image. Besides, NDVI allowed a higher overall accuracy in the classification.

If we compare kappas for spectral (0.4) and textural (0.63 and 0.56) analyses, the PAPRI method produces the best classification. However, whether by spectral or textural analysis, there still remains some confusion between coconut and oil palms.

4.3. Sources of errors

4.3.1. *Problem related to data and the method*

For both sites, low kappa values find their origin in the training areas used to initiate the classification as well as in the manual maps produced for its validation.

The classification quality is directly related to class separability, which itself depends on the variation among pixels from different classes as compared to within-class pixel variation. On one side, several factors such as variable incidence, palm inclination, or shading effects contribute to within- class heterogeneity and alter the specificity of the signal. On the other side, as some components may be common to different classes (e.g low vegetation pixels in the mixed coconut class), distinct classes may share "mixed pixels" or "mixels." Other mixels can be linked to transition zones between classes and/or between plots. These mixels resulting from the radiometric integration of several objects cause difficulties in the definition of the classes and, therefore, in their recognition (Chitroub, 2005).

On the validation map side, it must be kept in mind that its construction involves a precise demarcation of plots and their constituent elements. The photo-interpretation is difficult, especially in heterogeneous landscapes. Errors are inevitable during the digitalization step, which cannot take into account within-plot heterogeneity (e.g. presence of a tree in the middle of a coconut grove). The problem is even more important in transitional areas (boundaries between plots associated with different classes) and unrecognized elements (shadows, paths, streams, etc.).

4.3.2. *Problems bound to the segmentation algorithm*

As segmentation depends on the number of detected minima or local maxima, which are themselves a function of the texture, counting errors are related to the textural heterogeneity of the image, with over-segmentation in its highly textured parts. As for the sub-segmentation, it stems from the limitations of the classification; the algorithm does not operate in areas masked by mistake.

4.4. Prospects for improvement

We saw that one of the major limitations of the classification is bound to class heterogeneity and attendant mixels. To limit their influence, several areas for improvement are possible. At first, for small-scale studies, ground surveying will improve the delineation of training areas (ROI) to initiate the classification. Artenatively, a higher number and diversity of ROI may result in more homogenous classes (Desmier et al. 2011). A finer resolution of the image would also allow a better identification of objects and reduce edge effects and the proportion of mixels. The best option is to use a multispectral image, with the same resolution as for the panchromatic image (0.5 m). This would avoid the need for a spectral and spatial information fusion method (pansharpening), with the attendant noise and loss of spectral information.

To increase classification accuracy, to reduce errors bound to noise (mixels), it would be advisable to reduce the dynamics of the image, in the preliminary processing phase. Filters may help in homogenizing texture. Images may be processed in a system of color other than RVB, like HSV.

To distinguish among species or varieties of palms/trees, another track to consider would be a spectral study based on hyper-spectral images. Their hundreds of spectral bands will allow extracting finer signatures and improving discrimination. A phenological monitoring (monitoring

of spectral signatures over time, at several stages, such as fruit production or yellowing of leaves), may also exploit the differences between two species.

For coconut palms counting, the main problem is over-segmentation. At this stage too, filters reducing the image dynamics would be useful to regulate minima and maxima, so controlling the number of basins.

Our classification method is essentially based on the spectral information associated with each pixel; it does not take into account all the spatial structure information that can be extracted from very high resolution images. For example, to differentiate coconuts varieties between them (tall and dwarf), results from the watershed segmentation process could be better exploited. Indeed, segmentation defines the outlines of areas, but does not characterize them. At the end of the watershed process, we obtain basins for dwarf and tall coconuts plots. By associating with each basin the radius corresponding to the palm crown size of each coconut, or using several other discriminatory criteria for size or by coupling to LIDAR data, a better differentiation should be possible. Going further along this lane of improvement, the use of an object-oriented classification approach, as the one based on the e-cognition software, or an extraction module like ENVI FX, may be particularly adapted to the coconut and other palms.

4.5. Prospects for studies at wider scales

We have explored the potential of remote sensing for mapping coconut resources using Very High Resolution images, and shown that we can indeed distinguish various coconut palms agrosystems, even in heterogeneous landscapes, as in Vanua Lava. However, before this can be achieved automatically at a very fine scale, as needed for local studies, the method must be refined, and we have suggested several alleys for further improvement. Other developments will be necessary to work at much wider scales. Thus, if the objective is monitoring the potential of coconut in the large zones of production in India, many problems and methodological limitations faced in Vanua Lava lose much of their importance. For example, as the inventory of regional resources cannot be based on the production of each coconut palm or on the exact density of each plot, a problem of over-segmentation or sub-segmentation will have little impact on the mapping of the coconut monoculture. Instead, an important technical challenge will be to integrate the distribution of coconuts agrosystems into a Geographic Information System, which also takes into account environmental and technical characteristics associated with them. Ground and soil databases exist, as well as potential distribution models of the species and the evolution of its production according to the climate (Komba Mayossa, 2013; Kumar and Aggarwal, 2013). In this context developing mapping methods which allow the necessary change of scale, becomes as important as or even more important than to achieve high accuracy in Very-High Resolution mapping.

Acknowlegdement

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