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Determining Cashew Acreages in a Fragmented Landscape: Object vs. Pixel Based Classification

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Abstract: In Cote d'Ivoire, agricultural statistics about some major crops are just not available because government agencies in charge of survey have all been dismantled. This lack of data greatly affects planning and management of available land resources, estimation of agricultural output and proper decision making process. Cashew farming has recently been widely cultivated across large regions in the north of the country and its widespread adoption by the farmers raise question of arable land management. The main goal of the present study was to evaluate the spatial extent of this crop and by in large the main agricultural land cover types in the savannah region of northern Cote d'Ivoire. The objective was to determine which of the object-based and the pixel of classification methods could provide better estimates of agricultural land cover types in the study zone. In the fragmented landscapes observed in this region using the spatial attributes undoubtedly improves classification accuracy, thus leading us to favor the object-based classification approach over classical pixel-based classification. In this non-mechanized agriculture, small holdings dominated the agricultural landscape with yams farms varying between 0.8 and 2.5 ha. The object-based method predicted that 2.5% of the study area was occupied by cashew orchards or about 22,400 ha. With a better description of farm geometries, the object-based classification can be refined to yields accurate estimates and thus to be an efficient tool in agricultural data gathering process across large zones and particularly so when ground collection methods are inexistent.

Key words: Classification, pixel, object, cashew, savannah, Cote d'Ivoire

INTRODUCTION

Cashew cultivation has been re-introduced in Côte d'Ivoire in the early 90s. Since then, it has gained popularity among farmers in the northern region owing to favorable world market prices and suitable growing conditions. Especially in the northeastern region, the advent of this cash crop has disrupted a rather sustainable agricultural system which is traditionally based on annual cultivation of yam fallowed by a long period of fallow.

While no accurate farm data exist, empirical observations indicate a dwindling of arable lands in several villages as more and more cashew orchards are replacing fallows. Unfortunately, the dismantlement two decades ago of the government agencies in charge of farm data collection explains the lack of reliable records, a fact which obviously hampers proper decision making process related to food security, agricultural development and planning nationwide or at regional levels.

The rapid spread of cashew orchards in the region may have other long-term effects. Beyond land management or agricultural policy issues at the country level, agricultural land uses are also known to affect several environmental changes such as deforestation (Geist and Lambin, 2002) or local and regional climate change (Jianchu *et al*., 2005). A large scale cultivation of cashew in the region is expected to increase the woody vegetation in a savannah ecosystem, hence to affect local evapotranspiration (Oguntunde, 2007; Rodriguez *et al*., 2009) and to bring about land use land cover changes if the phenomenon perpetuates.

For Côte d'Ivoire which is coming out of a civil war, evaluating agricultural resources has become a necessity because the war has not only created internal migrations but it has also disrupted the production capacity of the country and particularly in the northern region which was economically stranded during the war. High resolution satellite imagery is an opportune alternative to ground collection of geo-spatial information of cashew orchards because of limited funding required to cover the large

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areas concerned by cashew cultivation. For example, digital imagery (e.g., Landsat) at a spatial resolution of 30 m or better can depict enough land surfaces disturbances such as farm lands, roads and fire burned areas.

Traditionally, land use land cover classes are derived from pixel-based classification methods applied to the images in a supervised way. While these methods use only the spectral attributes with no regard of likeness of adjacent pixels, the object based methods which are of recent use take into account both spectral and spatial attributes.

Merits of the object-based classification over the pixel-based classification are mentioned in the remote sensing literature. The gain in classification accuracy observed with object-based method is noticeable for very high spatial resolution data (Mantifar *et al.*, 2007; Mas and Gao, 2008).

The object-based method has been used to delineate land parcels in England, classify urban features (Fuller *et al.*, 2005; Mathieu *et al.*, 2007) or map large burned areas even with low resolution NOAA-AVHRR imagery (Gitas *et al.*, 2004).

The segmentation process of the object-based method and the proper definition of the characteristics of the objects greatly affect the method. The object-based method is suited for cases where objects have well defined geometric shapes such as industrial farms or urban features. In the study area, farms have irregular shapes, variable sizes and fuzzy boundaries. Besides, the many farms randomly scattered around the region create a highly fragmented agricultural landscape.

The overall goal of the study is to determine the land acreage under cashew cultivation in the northeastern region of Côte d'Ivoire. The objective of the study is to compare the pixel and object-based classification methods using high resolution imagery (Landsat ETM+) in a fragmented agricultural landscape.

MATERIALS AND METHODS

The study area: The study site is situated in the northeast of Côte d'Ivoire, in the Zanzan department. With an estimated area slightly <9,000 km^2 i.e., 128 km (North-South) by 69 km (East-West), it stretches across latitudes 7°59' and 9°9'N and longitudes 2°37' and 3°15'W and encompasses the watersheds of two major rivers: the Comoe River (not visible in the image) and the Volta River (upper right section) (Fig. 1).

Both watersheds are divided by the paved road linking Bondoukou and Bouna, the two main cities of the Zanzan department. The road also separates the Comoe National park with its smooth texture from the humanized section consisting of scattered farms.

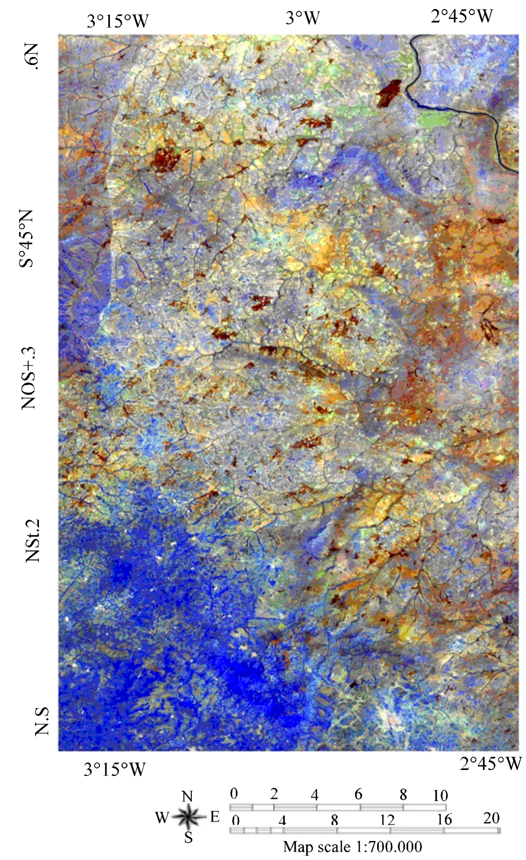

Fig. 1: False color composite (ETM+7-5-4 combinations) of the study site. The smooth portion on the upper left is the Comoe National park. The forest-savannah transition divide is neatly shown by Southeast-Northeast road linking Bondoukou to Bouna

The natural vegetation and expected agricultural land cover types: The dominant vegetation type, wooded savannah is generally a mixture of grassland and trees of varied kind and size. This is forest-savannah transition zone with the forest lying in the southeast corner of the study site. The savannah in the northern part is subject to annual wildfires. What the native vegetation would look like if fire alone was administered annually and in the absence of agricultural activities is exemplified by the vegetation of the park. Generally, the density of woody resource increases in a southward direction and remains high along river channels and on elevations which are spared by annual wildfires

Yam as the staple food and cash commodity is most dominant crop cultivated by the populations and all farming activities revolve around it. After land preparation in late September, yam is seed is lay dormant in the mount during the dry season. Emergence starts shortly after the onset of the first rains in late April. The crop reaches maturity in July or August. Cereal crops such as maize, millet and sorghum grown in association with yam or cassava supplement the diet of the local populations. Their growing cycle is limited to the rainy season. Hence, they do not constitute an agricultural cover type that can be observed in the imagery acquired during the dry season.

The re-introduction of cashew nut as a cash crop is one of the adaptation measures adopted by the farmers against climatic change. Decline in rainfall amount over the years and its erratic behavior have had farmers leaning towards drought resistant crops. For example, a less palatable but drought-resistant yam cultivar is widely grown in the region while several local varieties have now completely vanished. In all, two main agricultural land cover classes are expected in this image: yam farms and cashew orchards. The latter cover type stands out as patches of green vegetation. Their size and shape set them apart from land cover types such as forest or green woodland savannah or riparian forest.

Spectral discrimination of land cover types: During the dry season (from late September to early April), fresh yam farms are spectrally identical to bare soil while cashew orchards have their green foliage. Confusion among land cover classes is expectedly high between yam farms and bare soil on one hand and between cashew orchard and green vegetation (woody savannah or forest) one the other hand during the dry season. Both yam farms and cashew orchards spectrally contrast with the senescing grassland vegetation which is progressively devoured by wildfires. The front end of an active fire (visible on ETM + 7) helps to discriminate the dry grass from the burned areas and consequently to reduce any confusion between dry grass and yam farm features since there is no fuel on the yam farms to spark fire.

Digital imagery and software: Landsat-7 ETM + (Enhanced Thematic Mapper Plus) imagery acquired on February 2, 2000 was available. Spectral characteristics of Landsat's ETM + sensor are given at the following website (http://landsat.gsfc.nasa.gov/about/etm+.html).

Pixel-based classification methods were carried out on the digital image in ENVI 4.6.1. A specific feature extraction tool (ENVI ZOOM) available in ENVI was used for object-based classification.

Image rectification: Proper image registration is recommended prior to object-based classification (Grenier *et al*., 2008). Image to map rectification was made with 40 ground control points judiciously selected. A first order polynomial with the nearest neighbor resampling method was used and the root mean square error of the fit was below half the pixel size (i.e., 28.5 m).

Pixel-based classification: A supervised classification with a maximum likelihood classifier was initially used to map seven land cover types: water, green woodland savannah, cashew orchard, forest, yam farm, burned areas and dry wooded savannah. Finally, only the two agricultural land cover types (i.e., yam farms and cashew orchards) were retained while all the others were lumped into a single unclassified class. After yam harvest (from September to December), cassava or cashew is grown in the fallow land. However, the young seedlings do not provide a large soil cover and the barren soil dominates. Since the fallow is spectrally similar to the fresh yam farm, the yam cover type obtained here represents the yam acreage of two consecutive years. The single year yam farm acreage can also be perceived as the maximum annual increase in cashew acreage since yam fallows (some but not all) are turned into cashew orch. The amount of land cover type conversion will be investigated in a future study.

Object-based classification: The workflow starts by the image segmentation process (aggregating contiguous pixels having similar spectral, textural attributes). The only ancillary data imported in the workflow is an exclusion mask image of the human settlements. Scale level chosen for segmentation was initially 50 and later 70 in order to merge tiny objects. This optimum scale value is chosen such that few target cashew orchards were correctly segmented into distinct objects.

Rule based classification method with fuzzy logic algorithm is used instead of the supervised classification method because it is very hard to find enough cashew orchards well scattered across the whole region that can be used as training objects. The data about farm characteristics (unpublished data) also helped to build the rules for object discrimination.

The near infrared band when used in combination with other bands is very useful at distinguishing agricultural land cover types (Mas and Gao, 2008). Hence, it was a substitute for the Normalized Vegetation Index (NDVI) during the segmentation step of the feature extraction workflow. The band combinations used for image display during the segmentation process were ETM + 7, ETM + 5 and ETM + 4.

RESULTS AND DISCUSSION

Pixel-based classification classes, accuracy assessment: Upon visual inspection of the classified image, several features seem well identified. Among them are the forest at the bottom of the image, the burned areas (corroborated by their high normalized burn ratio) and the two most conspicuous water bodies consisting of the artificial lake situated north of the town of Bondoukou and the Volta

River. The Comoe National park predominantly occupied by woodland savannah is quite distinctive from the adjacent fragmented humanized section.

Object-based classification (the two classes of concern): Since, the main task here is to extract the two agricultural land cover types mentioned earlier, spatial and spectral attributes which could uniquely help extract these features were sought.

Of the spatial attributes provided in ENVI feature extraction module, size and elongation attributes gave a better description of the farms. Minimum area of individual yam farms or cashew orchard was set to 1 ha (4 pixels).

A spectral separability test of the training sites of the pixel-based classification revealed that green orchards and woodland were the least distinguishable classes. Therefore, the spatial attribute elongation was used to discard narrow strips of woodlands along river channels which could be confused with orchards. This eliminates riparian forests from the cashew orchard cover type.

Estimation of agricultural cover types: Table 1 shows the relative importance of each agricultural land cover type for either classification method. For the pixel-based classification method, the cashew orchards and the yam farms account for 2.1 and 15.4% of the study site, respectively. The corresponding estimates for the object-based method are 2.5 and 6.7%.

While for the cashew orchard class, both classification methods yield comparable results, they show a striking difference for the yam farm class. The pixel-based method predicts more than the double of the other method for that cover type. This discrepancy results from the constraints imposed on the shape and size of the yam farms in the object-based method.

A survey (unpublished data) made from 30 randomly selected households shows that the size of yam farms varies between 0.8 and 2.5 ha and yam farms >10 ha are very unlikely and practically hard to achieve in this non-mechanized agriculture. Hence, these farm data enabled us to build the set of rules to identify farm objects in the object-based classification.

The lack of constraints on farm size in the pixel-based classification resulted in unrealistic farm sizes. For orchards, the lower and upper size limits were 0.8 and 15 ha, respectively.

The upper in area units, the total land acreages in 2000 for orchards and yam farms amount to 22,435 and 29,600 ha, respectively with the object-based method. Meanwhile, the pixel-based classification predicts 18550 ha for orchards and 68200 ha for yam farms.

Table 1: Percentage of each agricultural land cover type for both classification methods

Methods	Yam farms	Orchards	Total
Pixel-based method	15.4	2.1	22.1
Object-based method	06.7	2.5	09.2

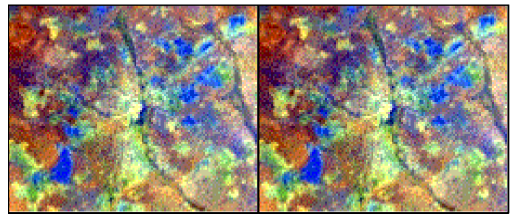

Fig. 2: Two small images depicting the spatial arrangement of cashew orchards (blue blobs) around two villages (brighter spot in the middle)

Spatial extent of cashew orchards and relative their importance in the region: Cashew orchards are widely spread across the region but specifically in the neighborhood of villages. The northern section is the least cultivated to cashew and the forest-savannah transition zone being the most active site.

When cashew land acreage is expressed as a percent of the total land area in the study, the value obtained Table 1 is not alarming yet. However, a close inspection shows that belts of cashew orchards exit around some villages and particularly those situated closer to the Ivorian-Ghanaian border Fig. 2. Perhaps, the proximity of the Ghanaian market must have sparked the early interest in cashew farming in these border villages.

We can ascertain that in 2000, there was not enough evidence that land shortage have resulted from the introduction of cashew farming across the whole study region.

Accuracy assessment of classification: In the Comoe Park which is a protected zone, there ought not to be any agricultural activities and in fact, there are none reported. Of the two classification methods, the object-based method predicted the least (very dismal) agricultural activity in the park.

In the pixel-based method, many pixels from the park were wrongly assigned to agricultural land cover classes and hence, this misclassification inflates the commission errors of both agricultural land cover types. Moreover, the increase of false positive responses for orchards in the park in the pixel-based classification method makes it less desirable than the objet-based method.

A qualitative appreciation of the results is not enough to judge the quality of the classification. A rather unbiased quantitative approach is needed and the confusion matrix is the common method of accuracy assessment (Congalton, 1991) which must be done for both the pixel-based and object-based classification. Classification accuracy was assessed using a total of 80 samples randomly selected within a 35 km by 20 km section in the middle of the image.

Access to inner areas of the Comoe park was restricted and because of limited financial resources available, not so many samples could be gathered from the upper right edge of the image. Object (yam farm or orchard) identification was made with the help of farmers who could recall what they grew on the training sites. Written land records do not exist but farmers can easily trace back their farming history with great accuracy. The overall classification accuracy and the Kappa coefficients of the object-based classification were 73 and 54.8%, respectively. Comparatively lower values, 68 and 46.6% were obtained for the pixel-based classification approach (Table 2). Based on these accuracy values, it can be inferred that the object based classification yields better results and this confirms early finding by Mas and Gao (2008). One of the reasons of the improved accuracy of the object-based method is the reduction of effects of spatial autocorrelation, an important phenomenon in pixel-based classification.

Adjacent objects contrarily to pixels are more likely to be non-correlated. In general, the user accuracies for both land cover classes were high (>99%) in both classification methods. In other words, the commission errors were low, suggesting that pixels classified as a given land cover type were truly of that cover type. Meanwhile, the lower producer accuracies (or high omission errors) obtained imply that ground samples were likely to be misclassified in both classification methods. Most of these misclassified pixels fell in the unclassified.

The producer accuracy is about the same for the yam farm class in either classification method; i.e., 80% (object) vs. 83 (pixel).

Only with the orchard class is there a big discrepancy in producer accuracy between the two methods (i.e., 61% for object-based vs. About 40% for pixel-based) and this difference in producer accuracy accounts for most of the difference in accuracy between the object and the pixel-based methods. Since image classification accuracy seems limited by the accuracy of the orchards class (particularly, the producer accuracy) spatial attributes of orchards must be properly defined when using the object based classification. As orchards become larger and larger every year, they are expected to be easily distinguishable from the woodland savannah as their shapes become increases and tree crowns overlap, orchards will have unmixed spectral signature since they make homogenous canopies. Yam farm pixels were spectrally distinguishable from all other land cover types. Therefore, the probability of a yam farm pixel to be misclassified was much lower compared to the orchard pixels which could be confused with the woodland savannah or at a lesser extent, the green forest cover type. Moreover, the lower misclassification errors for the yam farms indicate that the judicious use of Landsat imagery at this stage of the dry season along with the object based classification method could prove as an effective method to estimate agricultural land parcels of annual crops in the savannah region of northern Cote d'Ivoire. For perennial crops such as cashew, perhaps better estimates of land acreages would be obtained with the study of a series of images.

Table 2: percent accuracy of both classification methods

Methods	Overall accuracy (%)	Kappa coefficient (%)
Pixel-based method	68	46.6
Object-based method	73	54.8

CONCLUSION

Compared to the traditional pixel-based classification method, the object-based classification yielded better results in delineating the two main agricultural land cover types in this region dominated by small holdings. The gain in accuracy of the object-based classification method was mainly due to the increase in producer accuracy of the orchards class. Further improvement of the object-based classification hinges upon the accurate definition of the spatial attributes of the cashew orchards and their spectral discrimination against the green woodland cover. Moreover, more sophisticated spatial or textural attributes must be elaborated in the feature extraction module for an accurate description of the complex patterns of farms in this region. From this study, it can be inferred that in 2000, only two to three percent (i.e., 20,000 ha) of the study site was devoted to cashew cultivation. This figure was not alarming then but may now be, 10 years later. Hence, the next step is to further investigate the current trend of cashew farming activities in the region and its impact on the management of available arable land resource.

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