Investigating the Use of High Resolution Multi-spectral Satellite Imagery for Crop Mapping in Nigeria

Crop and Landuse Classification using WorldView-3 High Resolution Multispectral Imagery and LANDSAT8 Data

Tunrayo Alabi, Michael Haertel and Sarah Chiejile

Geospatial Laboratory, International Instititute of Tropical Agriculture (IITA), PMB 5320, Oyo Road, 200001 Ibadan, Nigeria

Keywords: Crop Mapping, WorldView-3, LANDSAT8, Cassava, Maize, Nigeria, Land Cover Classification, Maximum Likelihood, Neural Network, Support Vector Machine.

Abstract: Imagery from recently launched high spatial resolution WorldView-3 offers new opportunities for crop identification and landcover assessment. Multispectral WorldView-3 at 1.6m spatial resolution and LANDSAT8 images covering an extent of 100Km² in humid ecology of Nigeria were used for crop and landcover identification. Three supervised classification techniques (maximum likelihood(MLC), Neural Net clasifier(NNC) and support vector machine(SVM)) were used to classify WorldView-3 and LANDSAT8 into four crop classes and seven non-crop classes. For accuracy assessment, kappa coefficient, producer and user accuracies were used to evaluate the performance of all three supervised classifiers. NNC performed best with an overall accuracy(OA) of 92.20, kappa coefficient(KC) of 0.83 in landcover identification using WorldView-3. This was closely followed by SVM with an OA of 91.77%, KC of 0.83. MLC performed slightly lower at an OA of 91.25% and KC of 0.82. Classification of crops and landcover with LANDSAT8 was best with MLC classifier with an OA of 92.12% , KC of 0.89. Cassava at younger than 3 months old could not be identified correctly by all classifiers using WorldView-3 and LANDSAT8 products. In summary WorldView-3 and LANDSAT8 data had satisfactory performance in identifying different crop and landcover types though at varying degrees of accuracies.

1 INTRODUCTION

Agriculture is crucial to man's livelihood as the major source of food. Feeding the growing human population which is expected to reach more than 9 billion by 2050 could pose a serious challenge in the midst of the uncertainties and complexities of the predicted future climate. There will be need to constantly boost agriculture production in a sustainable and efficient way (Foley et al., 2011). To achieve this, dependable, accurate and comprehensive agricultural intelligence on crop production is imperative. Agricultural production monitoring can support decision-making and prioritization efforts towards ameliorating vulnerable parts of agricultural systems. The value of satellite Earth observation data in agricultural monitoring is well recognized (Low and Duveiller, 2014) and a variety of methods have been developed in the last decades to provide agricultural production related statistics (Carfagna and Gallego, 2005)

Remotely sensed data from satellite platforms such as LANDSAT and SPOT have been used to inventory a wide variety of earth resources, including agricultural land and crops. The synoptic overview provided by these satellite systems at regular intervals has allowed farmers and agricultural scientists to obtain information concerning the condition of crops grown over a large area. Satellite imagery has been used for crop species identification and area estimation since 1970s. Much research has been carried out in the use of LANDSAT MSS and TM data to estimate and identify crops. Various authors have found out that within some reasonable limits of accuracy, crops can be identified in LANDSAT MSS, TM/ETM (Xavier et al., 2005; Yang et al, 2007) or SPOT imagery (Hanna et al., 2004; Xavier et al., 2005).

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Many researchers have reported the use of multi-temporal imagery within a given year to map agricultural crops (Brewster et al., 1999) which has tremendous advantages. However, in tropical environment, cloud cover can limit this approach.

Classifying remotely sensed data remains a challenge because many factors, such as the complexity of the landscape in a study area, selected remotely sensed data, and image-processing and classification approaches, may affect the success of a classification. Major limitations on crop identification with satellite imagery relate to the similarity of plant reflectance of different crops in the available spectral bands, field-to-field variability of plant reflectance of the same crops, the particular combination of crops grown in a given region, the pattern of individual crop phenology, spatial and spectral variability within fields (Buechel et al., 1989; Vassilev, 2013; Yang et al., 2007).

Moreover agricultural field in Africa are often small in size and very often many different plant species are found in a very small area (always the case if they are intercropped) which makes the homogeneous crop identification process rather difficult with coarse resolution satellite imagery (Campbell, 1996).

Advancements in digital image processing and geographic information systems (GIS) have increased the potential for deriving more accurate crop information from satellite imagery (Ehrlich et al., 1994; Rodrıguez et al., 2006).

High resolution satellite imagery offers more opportunity in crop identification. From 1999 when IKONOS was launched, several other High resolution satellites such as Quick Bird, WorldVIEW 1, 2 and 3 or Pleaides followed. The competition between these multi spectral platforms led to decreasing prices per km² with resolutions up to 30 cm per pixel.

Various researchers have evaluated the use of these modern satellite products for land cover types, crop classification in diverse regions of the world (Ozdarici-Ok et al., 2015; Srestasathiern and Rakwatin, 2014; Yang et al., 2007) but the use of these products for crop identification in humid regions like Nigeria and other tropical areas in West Africa has not been well documented.

Hence the objective of this study is to evaluate satellite images captured by the newly launched WorldView-3 sensor for crop identification and land cover classification in Nigeria as well as the use of LANDSAT8 OLI for landcover and cropland mapping.

2 STUDY AREA

The study location is the Ore Agricultural Village in Ondo state, Nigeria. The Agriculture village is dedicated to crop farming and animal husbandry and is situated on a 3000-hectare facility. The Ondo State Agricultural Village at Ore was created and started operation in 2011 as a tool for empowering the youth, the women and adults through agriculture and represents one of three integrated Agricultural villages established in the state that have been established in order to reduce unemployment among the younger population.

Participants at the village are drawn from young graduates who have just completed their Higher National Diploma and Bachelor degree and who are willing to take up agriculture as a career.

The natural vegetation of the site is tropical rainforest characterized by pockets of secondary forest and fallow regrowth. The area is characterized by a length of growing period of more than 270 days with humid forest ecology. The annual mean maximum temperature at the site is 31.5 °C while the minimum is 22.1°C. Mean annual rainfall is about 2067 mm. Rainfall starts around March and continues till middle of November. The topography of the land varies from nearly flat to moderately high slope. Mean elevation in the farm land is about 132 m above sea level with a mean slope of 8.7%. Nearly 25% of the study area has slope greater than 12%. Major soil type of the farm is Ferric Lixisols (Sonneveld, 2005). Soil texture is coarse loamy sand, imperfectly or poorly drained.

During the late season of 2014, Cassava and Maize were the major crops planted on the fields within the target area. Cassava *(Manihot esculenta)* is a perennial woody shrub with an edible root which grows in tropical and subtropical areas of the world. Cassava is the third largest source of food carbohydrates in the tropics, after rice and maize (Fauquet and Fargette, 1990). Cassava is a major staple food in the developing world, providing a basic diet for over half a billion people (It is one of the most drought-tolerant crops, capable of growing on marginal soils. Nigeria is the world's largest producer of cassava, while Thailand is the largest exporter of dried cassava.

In 2014, cassava and maize were planted during the late season of August through November. Specifically, the first batch of cassava was planted on September 10th and the second was planted on November 13th at end of rainy season. The total area of cassava planted was 219 Ha. Apart from the young cassava planted, matured cassava plots of between 12-15 months old were also found in the study area, often mixed with weeds. These matured cassava farms with weeds represent typical plots in West Africa. Farmers stop weeding their cassava field once they reach 5-6 months. During ground truth field visit several of such plots have been observed from which a few of them have been selected to serve as a training site for the classification process to be able to classify such ready for harvest cassava fields.

Maize was planted for late season from August 25th through September 30th. The total area of maize was 100 ha. Other non-crop land cover types were also classified. Such includes primary forest, degraded forest, roads, and rivers, mixed fallow/shrubby grassland and bare ground.

Figure 1: Study area showing WorldView-3 natural colour image acquired January 3rd, 2015.

3 SATELLITE IMAGERY

3.1 WorldView-3

WorldView-3 was launched on 13th August, 2014 in California. It is the first multi-payload, super-spectral, high-resolution commercial satellite featuring 16 multispectral bands (eight in visible and NIR spectrum and eight in the SWIR spectrum). Operating at an altitude of 617 km, WorldView-3 provides 31 cm panchromatic resolution, 1.24 m multispectral resolution, 3.7 m short-wave infrared resolution, and 30 m CAVIS resolution. WorldView-3 has an average revisit time of <1 day (1m GSD) and is capable of collecting up to 680,000 km- per day.

A new tasking order for WorldView-3 image was placed at around October 2014 covering an extent of 100 km² which is the minimum extent for a tasking order from Digital Globe Inc. (Longmont, Colorado). Only the first eight multispectral bands of the WorldView-3 were purchased. The SWIR bands were not available for purchase at the time of order. Due to much cloud cover in the region, we could only obtain cloud free image on January 3, 2015. The geographic coordinates at the center of the area are (Longitude 4.7922047°E, Latitude 6.731706° N). The spatial resolution of the imagery was 1.24 m and the dynamic range of the data was 16 bits. Prior to delivery, the imagery was radiometrically and geometrically corrected and rectified to the world geodetic survey 1984 (WGS84) datum and the universal transverse Mercator (UTM) coordinate system of Zone 31N.

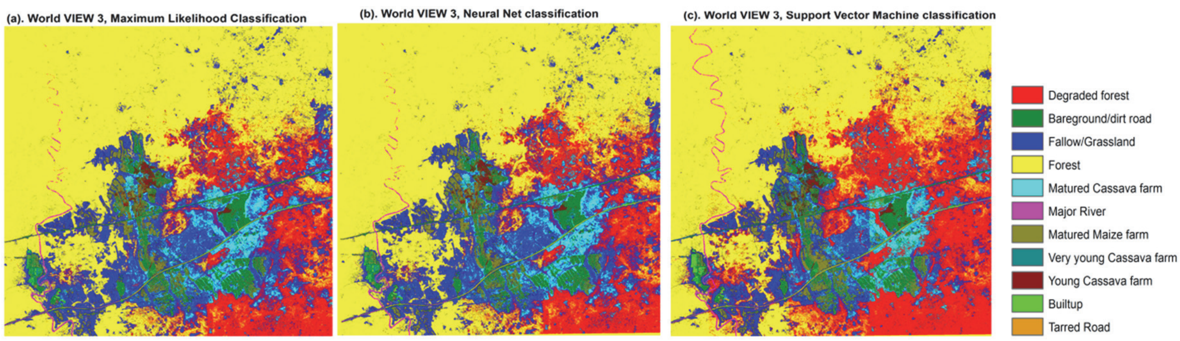

Figure 2: Classification results of WorldView-3 (a) Maximum Likelihood, (b) Neural Net and (c) Support Vector Machine.

Table 1: Specifications of eight multispectral and panchromatic bands of World-View 3 sensor.

Specifications	Multispectral sensor	Panchromatic sensor
Spatial resolution	1.24 (m)	40 cm
Radiometry	16 bits	16 bits
Spectral bands	1. Coastal Blue (400 to 450 nm) 2. Blue (450 to 510 nm) 3. Green (510 to 580 nm) 4. Yellow (585 to 625 nm) 5. Red (630 to 690 nm) 6. Red-Edge (705 to 745 nm) 7. NIR1 (770 to 895 nm) 8. NIR2 (860 to 1040 nm)	(450 to 800 nm)

3.2 LANDSAT8 Data

LANDSAT program of the United States of America is the longest running enterprise for acquisition of satellite imagery of Earth. On July 23, 1972 “the Earth Resources Technology Satellite” was launched. This was eventually renamed to LANDSAT. The most recent, LANDSAT8 was launched on February 11, 2013 which provided continuity in LANDSAT earth observation mission (Lulla et al., 2013). The LANDSAT8 orbits our planet every 99 min, covering the entire earth every 16 days except for the highest polar latitudes. LANDSAT8 follows a sun-synchronous orbit at an average altitude of 705 km and 98.2° inclination (Jia et al., 2014)

The data quality (signal-to-noise ratio) and radiometric quantization (12-bits) of the LANDSAT8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) are higher than previous LANDSAT instruments (8-bit for TM and ETM+). The OLI sensor aboard LANDSAT8 has nine bands for capturing the spectral response of the earth's surface at discrete wavelengths along the electromagnetic spectrum. Additionally, the TIRS sensor aboard LANDSAT8 collects information at two discrete wavelengths within the thermal infrared portion of the electromagnetic spectrum. These wavelengths have been chosen carefully based on years of scientific research. For the study area, cloud free LANDSAT8 images with path/row: 190/55 acquired on December 14, 2014 and January 15, 2015 was downloaded from the “earth explorer” website (http://earthexplorer.usgs.gov/).

4 METHODS OF IMAGE CLASSIFICATION

As an image analysis software EXELIS ENVI 5.2 was used to classify both satellite images. Many different supervised classification techniques are available in ENVI 5.2 including minimum distance, Mahalanobis distance, maximum likelihood, neural networks, and support vector machine. Maximum likelihood is probably the most commonly used classifier even though other classifiers may offer advantages for some applications. In this study the following algorithms are explored: Maximum likelihood (MLC), Support Vector Machine (SVM) and Neural Network (NNC) due to their high performance reported in literature (Foody & Mather, 2004, Pal and Mather, 2005, Omkar et al, 2008).

The **Maximum Likelihood Classifier** (MLC) is a well-known parametric statistical classifier and is widely used for pattern classification (Duda and Hart., 1973). A normal distribution is assumed for the input data which include two parameters - mean vectors and covariance matrices of the class distributions are estimated and used in the discriminant functions. MLC is generally accepted as a standard against which the performance of other classification algorithms is compared with (Omkar et al, 2008).

Support Vector Machine (SVM) is a supervised classification method derived from statistical learning theory that often yields good classification results from complex and noisy data. It separates the classes with a decision surface that maximizes the margin between the classes. The surface is often called the optimal hyperplane, and the data points closest to the hyperplane are called support vectors. The support vectors are the critical elements of the training set (Vapnik, 1979; Zhu and Blumberg, 2002). SVM can be adapted to become a nonlinear classifier through the use of nonlinear kernels. While SVM is a binary classifier in its simplest form, it can function as a multiclass classifier by combining several binary SVM classifiers (creating a binary classifier for each possible pair of classes). ENVI’s implementation of SVM uses the pairwise classification strategy for multiclass classification. SVM has been shown to also work well for crop classification (Foody and Mather, 2004; Pal and Mather, 2005; Jia et al., 2014)

Artificial Neural Networks (ANNs) were originally designed as pattern-recognition and data analysis tools that mimic the neural storage and analytical operations of the brain. ANN approaches have a distinct advantage over statistical classification methods in that they are non-parametric and require little or no a priori knowledge of the distribution model of input data. Additional superior advantages of ANNs include parallel computation, the ability to estimate the non-linear relationship between the input data and desired outputs, and fast generalization capability. Many previous studies on the classification of multispectral images have confirmed that ANNs perform better than traditional classification methods in terms of classification accuracy, such as maximum likelihood classifiers (Yuan et al. 2009). More detailed discussion on ANNs can be found in Lippmann, 1987 and Richards and Jia 2006. In a recent work Sandoval et al. 2014 used ANNs to perform crop classification and obtained satisfactory results.

4.1 Supervised Classification

Ground truth field visit was conducted on 4 February, 2015 from which georeferenced photos of each crop and landcover type were collected. These photos were used for developing training sites for each crop or cover type class. Eleven cover types were identified: Matured maize class consisted of maize at full maturity by 3 January 2015 when WorldView-3 image was taken, though a few of them would still maintain some green colour by December 14, 2014 when the first LANDSAT8 data was acquired. Young cassava class are 3 month old cassava by January 3, 2015 when WorldView-3 image was taken. Very young cassava class consisted of cassava planted in the first and second week of November, 2014 and were just one and half month old by January 2015. This class consists more of bare ground. Matured cassava class consisted of those that were observed on the field planted over a year before January 2015. This class shows typical matured cassava fields mixed with weeds, shrubs and trees. Other land cover types identified on the land are: Degraded Forest, Primary Forest, Fallow/grassland, Built up, Major River, Bare ground/dirt road and Tarred road.

Supervised training sites were created using online digitizing in ArcGIS 10.3 on known crops or cover types with the aid of ground truth geotagged photos.

Training samples were created proportional in size and number to each land cover type extent.

Supervised classification using Maximum likelihood algorithms in ENVI 5.2 with default parameters; probability threshold set to none and data scale factor of 1 was used to classify the eight multispectral bands of WorldView-3 and LANDSAT8 OLI into the eleven classes. Coastal blue band was removed initially to see whether its exclusion will improve accuracy of classification, but it was found that using all bands gave a slightly higher accuracy using confusion matrix tool accuracy assessment. Hence eight bands were used for WorldView-3. A similar procedure was followed for LANDSAT8 classification. Coastal aerosol band 1 and Cirrus band 9 were removed from supervised classification after the method of Jia et al., 2014, but it was found that the accuracy dropped slightly when these bands were removed. Hence all the multispectral bands (bands 1-7, 9) of LANDSAT8 OLI data were used in the classification except the thermal bands (TIRS 1&2).

Neural Net classifier in ENVI 5.2 was used to apply a multi-layered feed-forward neural network classification. An eleven layer multi-layered Neural Network has been used for this eight-class satellite image classification problem. The input layer consists of eight neurons representing the eight bands of the multi-spectral data. The output layer has eleven neurons, representing the eleven crop and cover type classes. For this study, we used only a single hidden layer perceptron network based classifier, with eight neurons in the hidden layer. ENVI implementation of Neural Net allows choosing between a logistic or hyperbolic activation function. A logistic activation function was selected due to its superior performance over the hyperbolic function. There are four important parameters that need to be set; namely training threshold contribution, training rate, training momentum and RMS exit criteria. By a process of iteration to optimize these parameters, default values set by ENVI were found to give best results except for training threshold contribution that gave best performance when it was set to 0.65. These values were employed for classification for WorldView-3 and LANDSAT8.

Support Vector Machine (SVM) is a supervised classification method derived from statistical learning theory that often yields good classification results from complex and noisy data (Pal and Foody, 2012, Jia et al., 2014). It separates the classes with a decision surface that maximizes the margin between the classes. The surface is often called the optimal hyperplane, and the data points closest to the hyperplane are called support vectors. The support vectors are the critical elements of the training set. SVM can be adapted to become a nonlinear classifier through the use of nonlinear kernels. The radial basis function Kernel (RBF) is the default in ENVI. This has been found to give the best results by many authors (Hsu et al., 2010, Jia et al., 2013). The RBF kernel non-linearly mapped samples into a higher dimensional space so the RBF could handle the case when the relationship between class types and attributes was not linear. Second, the RBF kernel had fewer numerical computational difficulties. The penalty value C and kernel parameter γ were the two parameters used for the RBF kernels, set to default values of 100 and 0.125 respectively as a result of our iteration process to optimize them.

5 RESULT AND DISCUSSION

Figure 2 presents the results of the three algorithms in classifying the crops and land cover types in the study area. Clearly, forest and degraded forest land cover types dominate the entire area. Primary forest occurred mainly in the northern and western part of the land while degraded forest existed mainly in the south eastern part of the land. Fallow/grassland appeared to be third largest among the land cover type and it spread mainly around the cropped area. Generally all three supervised classification techniques seem to agree in discriminating the land cover types in the area by visual interpretation of figure 2(a)-2(c). A closer view of the classification result is presented in Figure 3 (a-k). Figure 3a-d presents a natural colour image of WorldView-3 image taken on January 3, 2015 and the classification results of all three algorithms of an area planted with young cassava and very young cassava. Clearly all three classifiers were able to discriminate young cassava class better than they did very young cassava. Very young cassava category was mainly confused with the bare ground/dirt road class expectedly since this class had little vegetation cover. This result implies that WorldView-3 multispectral products can identify cassava when it is above 3 months old.

Although the three classification techniques were able to distinguish from other land cover types such as degraded forest and forest, they could not clearly discriminate them from fallow/grassland. This is probably due to spectral similarities between fallow/grassland and matured cassava category which are mainly mixtures of perennial shrubs and weeds. LANDSAT8 OLI classification results of the same matured cassava area present a better performance (Figure 3i-k). With LANDSAT8, the coarser spatial resolution smoothed out the noisy pixels and produced more realistic results from the three classifiers for the matured cassava farm area. This result is similar to what Yang et al, 2007 obtained while they aggregated Quick Bird imagery of spatial resolution of 2.8m to 11.2, 19.6 and 30m from 2.8m to 11.2 m and 19.6 pixel sizes improved overall classification accuracy in crop identification in South Texas. LANDSAT8 of 30 m pixel size identified matured cassava farm more realistically than WorldView-3 at 1.6m spatial resolution.

0 to 0 present the accuracy assessment confusion matrix for WorldView-3 image classification by Maximum likelihood classifier (MLC), Neural Net Classifier (NNC) and Support vector Machine classifier (SVM). Overall accuracy of the three classifiers are higher than 90 % with NNC having the highest accuracy of 92% followed by MLC. The kappa coefficients are equally high, greater than 0.81 for all three classifiers, though NNC still had the highest at 0.833. The high kappa coefficients indicate that all three classifiers performed at over 80% better than if the pixels have been randomly assigned.

The producer's accuracy is a measure of omission error and it indicates the probability that pixels that belong to the ground truth class and the classification technique has failed to classify them into the proper class. This ranged from 44.6% to 99.8% for MLC, 7.3% to 99.6% for NNC and for SVM 12.3% to 99.3%. The lowest producer's accuracy occurred for the very young cassava category for all the three classifiers indicating the most difficult class to identify is the very young cassava, although MLC performed best in classifying this category at about 45% accuracy. The highest confusion with this class came from young cassava category and followed by matured maize for MLC while it was confused mostly with matured maize and bare ground classes for NNC. SVM confused this class with bare ground class mostly and closely followed by matured maize.

This is not unexpected since this class has a lot of bare ground in the class due to sparse vegetation of cassava at this stage of less than 2 months old. Confusion with matured maize is probably due to the fact that some of the matured maize plots

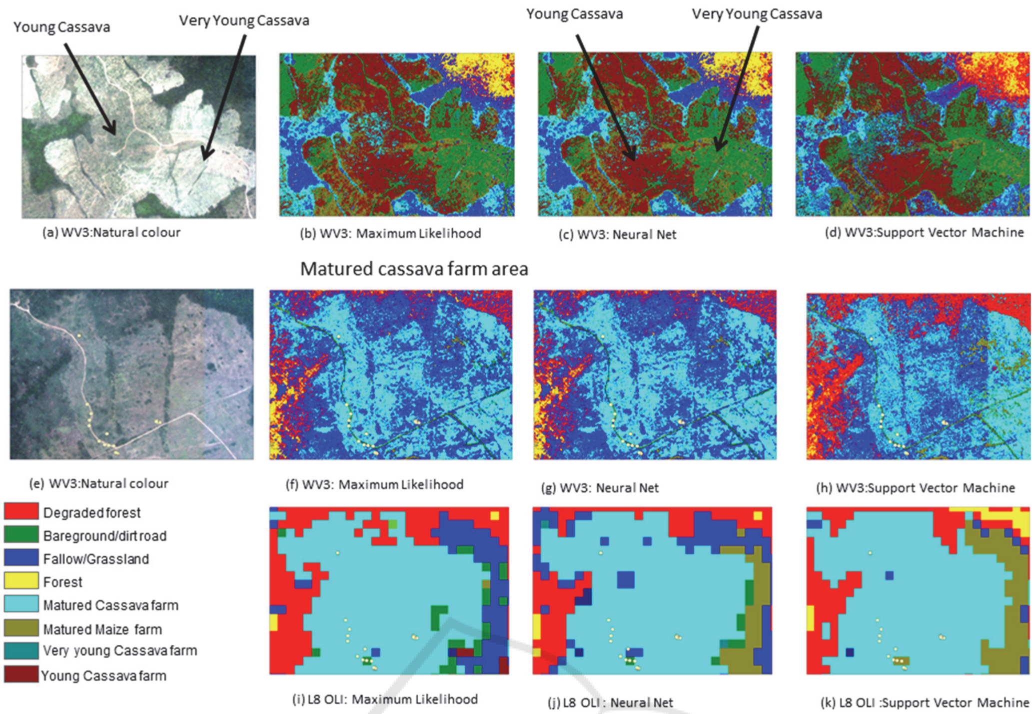

Figure 3: (a) WorldView-3 natural colour image taken January 3, 2015, (b) Maximum Likelihood, (c) Neural Net, (d) Support vector machine classification of an area of young cassava and very young cassava. (e) WorldView-3 natural colour image, (f) Maximum Likelihood, (g) Neural Net, (h) Support vector machine classification of a matured cassava farm area. (i) Maximum likelihood, (j) Neural Net and (k) support vector machine of the same matured cassava farm area using LANDSAT8, OLI captured on January 15 2015.

have been harvested at the time of image capture exposing more bare ground in these plots. From Table 2-4, it is also clear that the three classifiers identified the Forest, Built up, Major River and Tarred roads categories correctly at a producer's accuracy of higher than 97% implying that the probability of using WorldView-3, 8- band multispectral image to identify those classes are above 95%. A similar look at the user's accuracy, which is a measure of commission error and indicative of the probability that a category classified on the map actually represents that on the ground reveals that it ranged from 35 to 100% for MLC, 64 to 100% for NNC and 44 to 100% for SVM. Clearly four of the eleven land cover categories (Forest, Major River, Tarred Road and Built up) were the easiest to identify with both user's and producer's accuracy higher than 95% for all the three classifier algorithms. The low producer's accuracy and user accuracies for the three cassava categories (very young cassava, young cassava and matured cassava) suggests that cassava crop is the most difficult to differentiate among the eleven landcover categories. The very young cassava and young cassava were mostly confused with bare ground, matured maize and fallow/grassland by the 3 algorithms although MLC produced least confusion. Young cassava as well was often confused with bare ground and matured maize. This is because these two cassava crop categories have significant bare ground exposure. The matured cassava category was confused mainly with degraded forest and Fallow/grassland under MLC classifier, while it was mainly confused with Fallow/grassland for NNC and SVM classifiers. Spectral similarity between matured cassava and fallow/grassland is expected since both consist of shrubby vegetation and grasses. Most of the matured cassava plots were also mixtures of weeds and cassava which is a shrubby crop. This is the normal practice in West Africa where weeds in cassava farms of over 10 months are no longer controlled since the farmers know the weeds competition with cassava at this stage is very negligible.

MLC correctly identified matured cassava at a producer accuracy of 83% whereas only 63% of those pixels called matured cassava on the map are actually matured cassava on the ground. Similarly NNC identified this class at producer accuracy of 70% with a user accuracy of 67%, while SVM

Table 2: Confusion matrixes for crop and landcover classification of the WorldView-3 using the Maximum Likelihood classifier.

Class category	Degraded forest	Bare ground/ dirt road	Fallow/ Grassland	Forest	Matured Cassava	Major River	Matured Maize	Very young Cassava	Young Cassava	Built up	Tarred Road	Total	***User accuracy (%)***
Degraded forest	14,205	2	1,683	2,191	1,379	8	0	0	1	0	0	19,469	***73.0***
Bare ground /dirt road	132	5,829	110	0	53	3	269	288	254	9	0	6,947	***83.9***
Fallow/ Grassland	387	138	10,512	1,860	1,239	46	365	336	28	3	0	14,914	***70.5***
Forest	33	0	173	225,812	214	26	0	2	0	0	0	226,260	***99.8***
Matured Cassava	426	256	8,012	39	15,261	0	81	28	11	0	0	24,114	***63.3***
Major River	0	0	0	0	0	4,858	0	0	0	0	1	4,859	***100.0***
Matured Maize	0	227	2,205	4	225	1	10,667	498	179	0	0	14,006	***76.2***
Very young Cassava	1	404	781	846	36	0	617	1,574	162	0	0	4,421	***35.6***
Young Cassava	6	504	82	6	85	0	481	694	1,968	1	0	3,827	***51.4***
Built up	0	0	0	0	0	0	0	0	0	1,803	1	1,804	***99.9***
Tarred Road	0	0	0	0	0	0	0	0	0	7	826	833	***99.2***
Total	15,190	7,360	23,558	230,758	18,492	4,942	12,480	3,420	2,603	1,823	828	321,454	
Producer accuracy (%)	***93.5***	***79.2***	***44.6***	***97.9***	***82.5***	***98.3***	***85.5***	***46.0***	***75.6***	***98.9***	***99.8***		

Overall accuracy = 91.25% Kappa coefficient = 0.8182

identified this with a producer accuracy of 62% and user accuracy of 64%. While MLC classifier confused matured cassava with degraded forest and Fallow/Grassland, both NNC and SVM confused matured cassava with Fallow/grassland category. These results imply that only between 40-50% of the places classified as matured cassava is truly matured cassava on the ground. Spectral similarity between matured cassava and fallow/grassland is expected since both are perennial mixtures of shrubs and grasses. Our results in identifying matured cassava is similar to what Yang et al 2007 obtained in using Quick Bird imagery to classify grain sorghum and Sugar cane in South Texas, USA. They also observed that high commission errors with sugar cane and cotton were due to mixtures with herbaceous species. The producer accuracy for matured maize ranged between 82 -85% while the user accuracy ranged between 74 to 76% for the three classifiers with MLC giving the best accuracy. These accuracies are slightly higher than those obtained for the matured cassava category. The commission and omission errors with matured maize category are mainly from fallow/grassland and bare ground/dirt road for both NNC and SVM classifiers while the confusions came from very young cassava and young cassava categories under MLC classifiers. These observations confirm the assertion of Murmu and Biswas 2015 that classification of crops is a complex activity which includes complexity of the landscape, selected remotely sensed data, and image-processing and classification approaches. 0 and 0 present the classification accuracy of the three classifiers using two LANDSAT8 Operation Land imager (OLI) scenes taken December 14, 2014 and January 15, 2015. The overall accuracies for both LANDSAT8 scenes ranged from 82 - 94%. For both LANDSAT8 dates, MLC performed best with 95% and 92% overall accuracies for December 14, 2014 and January 15, 2015 images respectively. The overall performance of SVM and NNC was close in both image scenes though SVM was always in the lead. The kappa coefficients for the two LANDSAT8 images were also high ranging from 0.72 to 0.92. Comparing overall accuracies and kappa coefficients between classifications based on WorldView-3 and LANDSAT8, it is clear from Tables 4-8 that the general accuracies suggest that both image products are useful in classifying crops and landcover types in the humid ecology of the south western Nigeria.

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Table 3: Confusion matrixes for land cover classification of the WorldView-3 using the Neural Net classifier.

Category	Degraded forest	Bare ground/ dirt road	Fallow/ Grassland	Forest	Matured Cassava	Major River	Matured Maize	Very young Cassava	Young Cassava	Built up	Tarred Road	Total	User accuracy (%)
Degraded forest	11,622	0	69	107	97	0	0	0	0	0	0	11,895	**97.7**
Bare ground /dirt road	0	5,922	17	0	7	0	612	880	813	2	0	8,253	**71.76**
Fallow/ Grassland	1,818	155	16,830	756	5,032	45	1,309	394	27	0	0	26,366	**63.83**
Forest	1,098	0	761	229,879	351	23	0	28	0	0	0	232,140	**99.03**
Matured Cassava	642	378	4,913	4	12,922	0	236	86	58	0	0	19,239	**67.17**
Major River	4	0	0	0	0	4,872	0	0	0	0	0	4,876	**99.92**
Matured Maize	0	790	953	10	70	2	10,239	1,327	464	0	0	13,855	**73.9**
Very young Cassava	4	28	12	2	7	0	39	250	27	3	0	372	**67.2**
Young Cassava	2	87	3	0	4	0	45	455	1,214	0	0	1810	**67.07**
Built up	0	0	0	0	2	0	0	0	0	1,811	21	1834	**98.75**
Tarred Road	0	0	0	0	0	0	0	0	0	7	807	814	**99.14**
Total	15,190	7,360	23,558	230,758	18,492	4,942	12,480	3,420	2,603	1,823	828	321,454	
Producer accuracy (%)	**76.51**	**80.46**	**71.44**	**99.62**	**69.88**	**98.58**	**82.04**	**7.31**	**46.64**	**99.34**	**97.46**		

Overall Accuracy = 92.196 Kappa coefficient = 0.833

Table 4: Confusion matrixes for land cover classification of the WorldView-3 using Support Vector Machine classifier.

Landcover category	Degraded forest	Bare ground/ dirt road	Fallow/ Grassland	Forest	Matured Cassava	Major River	Matured Maize	Very young Cassava	Young Cassava	Built up	Tarred Road	Total	User accuracy (%)
Degraded forest	13,471	2	859	920	702	1	0	4	0	0	0	15,959	**84.4**
Bare ground/ dirt road	1	5,814	14	0	9	0	705	1,042	803	4	3	8,395	**69.3**
Fallow/ Grassland	652	110	15,763	707	5,934	25	1,216	456	40	0	0	24,903	**63.3**
Forest	350	0	546	229,096	229	6	0	5	0	0	0	230,232	**99.5**
Matured Cassava	709	337	5,144	23	11,436	0	66	66	32	0	0	17,813	**64.2**
Major River	3	0	4	0	0	4,909	0	0	0	0	1	4,917	**99.8**
Matured Maize	0	824	1,202	12	154	1	10,310	968	371	2	0	13,844	**74.5**
Very young Cassava	1	217	12	0	4	0	119	420	187	0	0	960	**43.8**
Young Cassava	3	56	14	0	24	0	64	459	1,170	1	0	1,791	**65.3**
Built up	0	0	0	0	0	0	0	0	0	1,796	18	1,814	**99.0**
Tarred Road	0	0	0	0	0	0	0	0	0	20	806	826	**97.6**
Total	15,190	7,360	23,558	230,758	18,492	4,942	12,480	3,420	2,603	1,823	828	321,454	
Producer accuracy (%)	**88.7**	**79.0**	**66.9**	**99.3**	**61.8**	**99.3**	**82.6**	**12.3**	**45.0**	**98.5**	**97.3**		

Overall Accuracy = 91.7677% Kappa coefficient = 0.8256

However, a detailed look at the results reveals also that the different crops and land cover types were classified at varying degrees of accuracies. Producer and user accuracies for the following land cover types; Forest, Major River, Tarred Road and Built up; were always very high greater than 90% for all the three classifiers for both LANDSAT8 and WorldView-3 multi-spectral products indicating the usefulness of this products in identifying them. On the other hand, the producer and user accuracy for the crop classes are always lower. Cassava classes were identified at different levels of accuracy by all classification techniques. The producer and user accuracy for matured cassava under MLC classifier was 88% and 81% respectively indicating that 88% of the matured cassava area were correctly identified and that 81% of those classified as matured cassava in the classification map are actually matured cassava on the ground. Hence we define the ground accuracy as the product of producer and user accuracy because this is true percentage of pixels that belong to each class on the ground. For instance, the matured cassava has a ground accuracy of 72% under MLC classifier. Major confusion with matured cassava came from fallow/grassland for all three classifier indicating discriminating fallow/grassland from matured cassava is the major setback. MLC classifier performed best in classifying matured cassava for both LANDSAT OLI scenes followed by SVM. Our result is slightly lower than what Phongaksorn et al., 2012 obtained for classifying biofuel cassava using LANDSAT 5 in Thailand where they obtained a producer and user accuracy of 98% and 99% respectively. Their results were probably better due to better industrial farm management for biofuel crops. Young cassava and very young cassava were identified at lower producer and user accuracy than matured cassava using the two LANDSAT scenes although MLC ranked first among the three classifiers.

Table 5: Classification accuracy for LANDSAT8 OLI acquired January 15, 2015.

	Maximum Likelihood			Neural Net classifier			Support Vector Machine		
Category	Producer accuracy (%)	User accuracy (%)	Ground Accuracy (%)	Producer accuracy (%)	User accurac y (%)	Ground Accuracy (%)	Producer accuracy (%)	User accuracy (%)	Ground Accurac y (%)
Degraded forest	89.0	78.2	69.6	68.81	62.5	43.0	73.4	81.6	59.9
Bareground/dirt road	70.6	81.4	57.4	50	80.95	40.5	51.5	50.7	26.1
Fallow/Bush/Grassland	78.6	88.3	69.4	74.57	82.69	61.7	78.6	71.2	56.0
Forest	98.6	99.7	98.2	95.58	97.09	92.8	99.1	98.0	97.2
Matured Cassava	88.2	81.8	72.2	81.37	79.05	64.3	60.8	79.5	48.3
Major River	95.6	97.7	93.4	80	97.3	77.8	93.3	100.0	93.3
Matured Maize	89.7	86.1	77.2	88.03	61.31	54.0	76.9	58.1	44.7
Very young Cassava	83.0	68.4	56.8	63.83	40.54	25.9	53.2	75.8	40.3
Young Cassava	77.8	75.0	58.3	44.44	80	35.6	50.0	64.3	32.1
Builtup	95.7	100.0	95.7	78.26	94.74	74.1	87.0	100.0	87.0
Tarred Road	100.0	100.0	100.0	91.67	84.62	77.6	100.0	100.0	100.0
Overall accuracy Kappa coefficient	92.21% 0.8847			85.08% 0.7793			85.87% 0.7875		

Table 6: Classification accuracy for LANDSAT8 OLI acquired December 14, 2014.

	Maximum Likelihood			Neural Net classifier			Support Vector Machine		
Category	Producer accuracy (%)	User accuracy (%)	Ground accuracy (%)	Producer accuracy (%)	User accuracy (%)	Ground accuracy (%)	Producer accuracy (%)	User accuracy (%)	Ground accuracy (%)
Degraded forest	90.8	87.6	79.6	48.62	71.62	34.8	73.4	81.6	59.9
Bareground/dirt road	88.2	88.2	77.9	48.53	55.93	27.1	51.5	50.7	26.1
Fallow/Bush/Grassland	86.7	88.8	77.0	65.32	64.57	42.2	78.6	71.2	56.0
Forest	98.7	99.9	98.6	98.23	94.48	92.8	99.1	98.0	97.2
Matured Cassava	98.0	95.2	93.4	47.06	47.52	22.4	60.8	79.5	48.3
Major River	97.8	97.8	95.6	88.89	100	88.9	93.3	100.0	93.3
Matured Maize	83.8	80.3	67.3	79.49	57.41	45.6	76.9	58.1	44.7
Very young Cassava	89.4	91.3	81.6	59.57	66.67	39.7	53.2	75.8	40.3
Young Cassava	88.9	81.4	72.3	46.3	86.21	39.9	50.0	64.3	32.1
Builtup	95.7	100.0	95.7	82.61	100	82.6	87.0	100.0	87.0
Tarred Road	100.0	100.0	100.0	100	92.31	92.3	100.0	100.0	100.0
Overall accuracy Kappa coefficient	94.75% 0.92			81.76% 0.7239			86.17 0.793		

6 CONCLUSIONS

Our results demonstrate that WorldView-3 satellite image product has good potentials in identifying tropical crops such as cassava and maize at different stages of growth. Moreover it identifies with high accuracy other landcover types such as forest, fallow/grassland and built up. However there is need for more research in the use of this product for crop identification especially during the main crop growing season when cloud cover is most prevalent. Results obtained using LANDSAT8 OLI multispectral products also suggest that it can be used for assessment of cropland at regional scale with good reliability.

REFERENCES

Brewster, C.C., Allen, J.C. and Kopp, D.D., 1999. IPM from space: using satellite imagery to construct regional crop maps for studying crop insect interaction. American. Entomologist, 45, 105–117.

Buechel, S.W., Philipson, W.R. and Philpot, W.D., 1989. The effects of a complex environment on crop separability with Landsat TM. Remote Sensing of Environment, 27, 261–272.

Campbell, J.B., 1996. *Introduction to Remote Sensing, 2nd Edition*. Guilford Press; 2nd edition, 622 pp.

Carfagna, E., Gallego, J.F., 2005. Using remote sensing for agricultural statistics. Int. Stat. Rev. 2005,73, 389–404.

Duda, R.O, Hart, P.E., 1973. *Pattern classification and scene analysis*. New York, NY: Wiley.

Ehrlich, D., Estes, J.E., Scepan, J. and McGwire, K.C., 1994. Crop area monitoring with an advanced agricultural information system. Geocarto International, 9, 31–42.

Fauquet C., Fargette D., 1990. "African Cassava Mosaic Virus: Etiology, Epidemiology, and Control" (PDF). Plant Disease 74 (6): 404–11. doi:10.1094/pd-74-0404.

Foley, J.A., Ramankutty, N., Brauman, K.A, Cassidy, E.S., Gerber, J.S., Johnston, M., Mueller, N.D., O'Connell, C., Ray, D.K., West, P.C., 2011. Solutions for a cultivated planet. Nature 2011, 478, 337–342.

Foody G.M, Mathur A. 2004. A relative evaluation of multiclass image classification by support vector machines. IEEE Transactions on Geoscience and Remote Sensing. 42: 1335–1343.

Hanna, R., Allah, M., Berry, A. and Sharobeem, Y., 2004. Crop estimation using satellite based and ground-based surveys (comparative study). In Proc. *ASAE Annual International Meeting, (St. Joseph, Michigan: American Society of Agricultural Engineers)*.

Hsu, C. W., Chang, C. C., Lin, C. J., 2010. A practical guide to support vector classification. Department of Computer Science National Taiwan University, Taipei 106, Taiwan http://www.csie.ntu.edu.tw/~cjlin.

Jia, K, Wu, B.F., Li Q.Z. 2013. Crop classification using HJ satellite multispectral data in the North China Plain. Journal of Applied Remote Sensing. 7: 073576.

Jia, K., We, X., Gu, X., Yao, Y., Xie, X., Li, B., 2014. Land cover classification using LANDSAT8 Operational Land Imager data in Beijing, China. Geocarto International. Taylor & Francis. Vol. 29 No. 8, 941–951, http://dx.doi.org/10.1080/10106049.2014.894586.

Lippmann, R.P., 1987. An introduction to computing with neural nets. ASSP Magazine, IEEE 4 (2), 4-22.

Low, F., and Duveiller, G., 2014. Defining the Spatial Resolution Requirements for Crop identification Using Optical Remote Sensing; Remote Sens. 2014, 6, 9034-9063; doi: 10.3390/rs6099034.

Lulla K, Duane Nellis M, Rundquist B. 2013. The LANDSAT8 is ready for geospatial science and technology researchers and practitioners. Geocarto International. 28: 191–191.

Murmu S., Biswas S., 2015. Application of Fuzzy logic and Neural Network in Crop Classification: A Review. International conference on water resources, coastal and ocean engineering (ICWRCOE 2015). Aquatic Procedia 4 (2015) 1203 – 1210, Available online at www.sciencedirect.com.

Omkar S.N., Senthilnath J., Mudigere D., and Kumar M.M., 2008, Crop Classification using Biologically-inspired Techniques with High Resolution Satellite Image, Journal of Indian Society of Remote Sensing, (36) 175-182.

Ozdarici-Ok, A.; Ok, A.O.; Schindler, K., 2015. Mapping of Agricultural Crops from Single High-Resolution Multispectral Images—Data-Driven Smoothing vs Parcel-Based Smoothing. Remote Sens. 2015, 7, 5611-5638; doi: 10.3390/rs70505611.

Pal, M., Mather, P.M., 2005. Support vector machines for classification in remote sensing. Int. J. Remote Sensing. 2005, 26, 1007–1011.

Phongaksorn N., Tripathi, N. K., Kumar, S., Soni, P., 2012. Inter-Sensor Comparison between THEOS and LANDSAT 5 TM Data in a Study of Two Crops Related to Biofuel in Thailand. Remote Sens. 2012, 4, 354-376; doi: 10.3390/rs4020354.

Richards, J. A., Jia, X., 2006. Remote Sensing Digital Image Analysis, An Introduction, Springer, Fourth Edition.

Rodriguez, J.R., Miranda, D. and Alvarez, C.J., 2006. Application of satellite images to locate and inventory vineyards in the designation of origin ''Bierzo'' in Spain. Transactions of the ASABE, 49(1), 277–290.

Sandoval, G., Roberto A., Vazquez, P. G., and Jose A., 2014. Crop Classification Using Different Color Spaces and RBF Neural Networks. Intelligent Systems Group, Faculty of Engineering, La Salle University Benjamin Franklin 47, Condesa, Mexico, DF, 06140. L. Rutkowski et al. (Eds.): ICAISC 2014, Part I, LNAI 8467, pp. 598–609, 2014. Springer International Publishing Switzerland 2014.

Sonneveld B.G. J.S., 2005. Compilation of a soil map of Nigeria: A nation-wide soil resource and landform inventory. Nig. J. Soil Res. Vol. 6: 2005 71 – 83.

Srestasathiern P .and Rakwatin, P., 2014. Oil Palm Tree Detection with High Resolution Multi-Spectral Satellite Imagery. Remote Sens. 2014, 6(10), 9749-9774; doi:10.3390/rs6109749.

Vapnik, V., 1979. Estimation of Dependences Based on Empirical Data. Nauka, Moscow, pp. 5165–5184, 27 (in Russian) (English translation: Springer Verlag, New York, 1982).

Vassilev V., 2013 Crop investigation using high-resolution worldview-1 and quickbird-2 satellite images on a test site in Bulgaria. Bulgarian Academy of Sciences. Space Research and Technology Institute. Aerospace Research in Bulgaria. 25, 2013, Sofia.

Xavier, B., Vanhalleb, L., and Defournya, P., 2005. Efficiency of crop identification based on optical and SAR image time series. Remote Sensing of Environment, 96, 352–365.

Yang C., James H. E., Reginald S. F., Dale, M., 2007. Using high resolution QuickBird imagery for crop identification and area estimation. Geocarto International Vol. 22, No. 3, September 2007, 219–233.

Yuan H., Van Der Wiele C. F., Khorram, S., 2009. An Automated Artificial Neural Network System for Land Use/Land Cover Classification from LANDSAT TM Imagery. Remote Sens. 2009, 1, 243-265; doi: 10.3390/rs1030243.

Zhu, G., Blumberg, D.G., 2002. Classification using ASTER data and SVM algorithms; The case study of Beer Sheva, Israel. Remote Sensing of Environment 80 (2), 233–240.

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