Mapping Croplands under Rainfed Agriculture in Mubi South Local Government Area, Adamawa State, Nigeria

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Abstract

Improving agricultural output is a priority of the present government in Nigeria for the purpose of achieving self-sufficiency in food production and diversification of the economy away from a mono-economy. Mapping, estimating and monitoring croplands becomes a major priority for stakeholders in planning and policy formulation. In recent years, there has been a growing popularity of the use of remote sensing applications in mapping croplands especially the use of multispectral and hyper spectral images. This paper describes an integrated method using LandSat 8 scene of September 2016 and existing farm land records from the Adamawa State Agricultural Development Programme (AADP) in mapping croplands under rainfed agriculture in Mubi North Local Government Area. The resultant map shows maize as the major crop covering an area of 11,089.31 hectares (24.13% of the total land area) followed by cowpea (4,988.52 hectares or 10.85% of total land area) and groundnuts (4,576.59 hectares or 9.96% of the total land area). Overall, the area covered by crops under rainfed agriculture constitute 46.12% of the total land area (21,196.59 hectares), followed by natural vegetation (18,427.22 hectares or 40.10% of the total land area). Based on the supervised classification technique used in producing the cropland map of the study area, an overall accuracy of 71% and a Kappa index of 0.52 were obtained signifying that the classified map was good. Similarly, margins between the total vegetation area of the classified map and another map produced using the Normalised Difference Vegetation Index (NDVI) was small. It is recommended that the technique used in this paper and similar remote sensing techniques be applied by stakeholders in mapping croplands and monitoring agricultural production.

Keywords: Mapping, Croplands, LandSat Image, Rainfed Agriculture.

1. INTRODUCTION

Accurate cropland information and location of major crop types is important in policy formulation, investment considerations and monitoring of agricultural production (Waldner et al., 2015). Furthermore, cropland information is important in other fields of research. For instance, crop cover information is useful for climate change research, land use/land cover change analysis (Waldner et al., 2015) and hydrological modelling.

According to the Federal Ministry of Agriculture and Rural Development (FMARD), Nigeria is facing 2 major gaps in the agricultural sector: deficit in domestic supply and inability to export quality agricultural products (FMARD, 2016). The present Agricultural Transformation Agenda (ATA) of the Nigerian Government is aimed at addressing these deficits. While, bridging the deficit on domestic supply is meant to ensure national food security, improving the quality of agricultural products for export is for the purpose of diversifying the economy and moving away from over dependence on a single export commodity.

A database on agricultural production (crop type, nature of land, crop pattern, etc.) can support decision-making and prioritization efforts towards ameliorating vulnerable parts of agricultural systems. The value of Satellite Earth Observation (EO) data in agricultural monitoring is well recognized and a variety of methods have been developed in recent years to provide agricultural production related statistics (Ozdogan, 2008). However, spatially explicit monitoring of agricultural production requires routinely updated information on the total surface under cultivation, crop types and sometimes the spatial distribution of crops as input (Ozdogan, 2008). This underlines the need for developing accurate and effective methods to map and classify the distribution of agricultural lands and crop types (crop mapping).

Balancing the inputs and outputs on a farm is fundamental to its success and profitability. The ability of Geographic Information System (GIS) to analyze and visualize agricultural environments and workflows has proved to be very beneficial to those involved in the farming industry. From mobile GIS in the field to the scientific analysis of production data in a farm manager's office, GIS is playing an increasing role in agriculture production throughout the world by helping farmers increase production, reduce costs, and manage their land more efficiently (Nelliset et al., 2009). Natural inputs in farming can be better managed with GIS applications such as crop yield estimates, soil amendment analyses, and...
erosion identification and remediation (Setegn et al., 2009).

The development of remote sensing satellite systems provide an opportunity for data derived from such systems to be widely used to map crop areas in different temporal and spatial scales. It is possible to derive information about crop type, crop density and crop area with the availability of different satellite imagery and developments in image processing and interpretation systems (Bannari, 2006). Crop productivity information, which is a combination of two parameters namely the information about crop type and the information about spatial coverage of that crop, is very important for accurate crop yield estimation (Verbeiren, 2008). Crop productivity can be expressed in terms of vegetation health and biomass density that can be derived from spectral reflectance differences of different bands in satellite image (Masoud, 2006). Spatial coverage of the crop area can be interpreted by aerial properties such as shape and specific texture also derived from satellite imagery. Therefore, remotely sensed data can be used to produce this information via specific analyses and results of these analyses can be used to create crop maps.

Results of different studies that focused on crop area identification with remotely sensed data has pointed out that, determination of different crop types in their growing stages cannot be performed efficiently with single dated images. Within this context, classification of multitemporal images gives identifiable results with added phenologic information (Masoud, 2006). Thus in this paper we follow the method applied by Maxwell et al. (1996), Ozdarici-Ok et al. (2015) and Patill et al. (2015) in integrating remote sense image, crop area information and ground based data to map cropland area in Mubi South Local Government Area.

In the following sections, the materials and methods used in delineating cropland areas is explained then followed by the discussion on the results and lastly recommendations are provided based on the findings.

2. MATERIALS AND METHODS

The study area is Mubi South Local Government Area in the northern part of Adamawa State. It is located between latitudes 10° 18’ 00” and 10° 03’ 00” North of the Equator and between longitudes 13°30’ 00” and 13° 10’ 00” East of the Greenwich Meridian. To the north and west, the area is bounded by Mubi North Local government Area. Towards the south, it shares a boundary with Maiha Local Government Area of Adamawa State (Figure 1). It shares an international boundary with the Republic of Cameroun to the east. Three wards in Mubi Town fall under Mubi South Local Government Area. Mubi Town is a vibrant economic hub with a very large international cattle market. The climate of the area falls under KoppenAw clatic classification (Adebayo, 2004) characterized by tropical dry winters and warm summer rainfall. Most parts of the study area cover part of the Mandara Mountain range including the Hudu Hills; the source of the Yadzeram River, a major river in the area that flows northwards into the Lake Chad (Adebayo and Dayya, 2004).

Data types used includes LandSat 8 ETM image scene of September 2016, cropland data of the study area from the Adamawa State Development Programme (AADP), political map of Adamawa State showing all the 21 local government areas, onsite field observations and GPS measurements. Procedure for the processing of the 2016 LandSat image is shown in Figure 2. During the groundtruthing process, the dominant crop types in each area is identified and then compared with the AADP data from the State ministry of Agriculture. The records include data on; crop type, crop yield, crop location and crop quality. In areas covered by a particular crop, the dominant spectral signature within the red and near infrared bands is assigned to that crop coverclass. The study made use of the LandSat 8 bands 2 (blue), 3 (green), 4 (red) and 5 (NIR) extensively for visual identification and classification. The bands 4 and 5 are part of the electromagnetic spectrum that are most useful for ecological and vegetation studies. The maximum likelihood algorithm (Belward and de Hoyos, 1987) in Erdas Imagine 2010 was used in the supervised classification technique. The algorithm is as follows:

\[ \frac{g_k(x)}{p(C_k)} = \ln p(C_k) - \frac{1}{2} \ln |\Sigma_k| - \frac{1}{2} (x - y_k)^T \Sigma_k^{-1} (x - y_k) \]

where:
- \( C_k \) = land cover class k;
- \( x \) = spectral signature vector of a image pixel;
- \( p(C_k) \) = probability that the correct class is \( C_k \);
- \( \Sigma_k \) = determinant of the covariance matrix of the data in class \( C_k \);
- \( \Sigma_k^{-1} \) = inverse of the covariance matrix;
- \( y_k \) = spectral signature vector of class k.
Eight land cover types were adopted for the supervised classification, these include three non-vegetative and five vegetative land cover classes. The three non-vegetative classes include rocks, bare land and built up area. The vegetative land cover classes can be further grouped into two distinctive groups; agricultural land cover comprising of predominantly cowpea, corn, soya beans or groundnut cover; and the second predominantly non-agricultural (natural) vegetation cover grouped together. The supervised land cover map was subjected to accuracy assessment for producer's, user's, total accuracy and Kappa index ($K$) in order to determine the degree of accuracy of the classification (Plourde and Congalton, 2003). The equation for the Kappa index is as follows:

$$
K = \frac{N \sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_{i+} x_{+i})}{N^2 - \sum_{i=1}^{r} (x_{i+} x_{+i})}
$$

Where, $\hat{K}$ is the Kappa hat index, $N$ is the total number of pixels (observed), $r$ is the number of rows in the matrix, $x_{ii}$ is the number observations in row $i$ and column $i$, $x_{i+}$ and $x_{+i}$ are marginal totals of row $i$ and column $i$, respectively (Congalton, 1991; Hashemian, 2004).

A separate map of 3 clustered land cover classes was produced using the unsupervised classification technique based on the K-means algorithm. This land cover map was produced for comparison with the map produced using supervised classification technique. To study the similarities of areas classified as vegetation in both maps, data on predominant crops in different parts of the study area was obtained from AADP (Table 1), and this was followed by on sight field observations. Among the 6 crops listed by the AADP, 4 were selected because of the extent of their cultivation. The 4 selected crops formed part of the agricultural land cover types listed earlier.

<table>
<thead>
<tr>
<th>Crop</th>
<th>Location</th>
<th>Maize/corn</th>
<th>G/com</th>
<th>Cowpea</th>
<th>G/nut</th>
<th>Potatoes</th>
<th>Soya beans</th>
</tr>
</thead>
<tbody>
<tr>
<td>Location</td>
<td></td>
<td>All around</td>
<td>Lamurde and Mugulvu</td>
<td>All around</td>
<td>Gella, Chaba, Lamorde</td>
<td>Kwaja</td>
<td>Madanya, Sahuda</td>
</tr>
<tr>
<td>No of ground plots</td>
<td>56</td>
<td>47</td>
<td>63</td>
<td>52</td>
<td>41</td>
<td>50</td>
<td></td>
</tr>
</tbody>
</table>

Figure 1: Map of Adamawa State showing the 21 local governments including the study area. The inset at the top left is the map of Nigeria showing the location of Adamawa State.
3. RESULTS AND DISCUSSION

Based on the findings (as shown in Figure 3 and Table 2), natural vegetation represented the largest estimated land cover class at just over 40% of the study area with about 18,427.22 hectares; and maize has the largest crop cover at 11,089.31 hectares or 24.13% of the total land cover. The second largest crop is cowpea (4,988.52 hectares or 10.85% of the total land cover), followed by groundnuts (4,576.59 hectares or 9.96% of the total land cover), and the smaller crop in terms of total area coverage is soyabeans with 542.17 hectares (1.18% of the total land cover). Maize is a stable food in the study area mostly grown in small to medium size plots in combination with cowpea or groundnuts. While, harvest is mostly stored for consumption surplus is sold out to generate extra income. Intercropping maize with leguminous crops like cowpea and groundnuts is for the purpose of improving soil fertility and increasing the yield of the cereal. Cowpea, soya beans and groundnuts are mostly produced as cash crops. While, most of the harvest of cash crops is sold out, a small proportion is reserved for consumption.

The total area of the 4 crop cover types is 21,196.59 hectares (46.12%), making land area put under rain fed agriculture the largest. This implies that close to half of the total land area in the local government area is being put under agricultural production.

The land cover classes of the map generated from three clustered categories based on the unsupervised classification technique applied to the LandSat ETM 2016 Image were identified as vegetation, rock outcrops and other non-vegetation, respectively. The estimated area of vegetation inclusive of croplands based on the unsupervised classification is slightly higher than what was obtained based on the supervised classification. The total vegetation area based on this classification is 39,130.88 hectares (85.15%), non-vegetation cover is 3,336.88 hectares (7.26%) of the total land cover area and rock outcrop is 3,489.45 hectares or 7.59% (Table 3 and Figure 4). The possible explanation for this is that the unsupervised classification was able to cluster vegetation and is more efficient in discriminating vegetation than the supervised classification technique that requires human training of the software and is, therefore, susceptible to human error.

The paper identified several classification errors with the supervised classification map. Amongst these are the classification of guinea corn farm plots under maize crop type and the classification of farm plots under mixed cropping especially maize intercropped with either cowpea or groundnuts as maize.
Figure 3: Land cover types in the study area based on supervised classification technique
Figure 4: Three (3) Class Land Cover Map of the study area based on Unsupervised Classification Technique

Table 2: Estimated area of 8 land cover classes in the study area based on the supervised classification technique

<table>
<thead>
<tr>
<th>Class/ Crop Type</th>
<th>Area (Hectares)</th>
<th>Percentage (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Bare Land</td>
<td>1,105.81</td>
<td>2.41</td>
</tr>
<tr>
<td>2 Cowpea</td>
<td>4,988.52</td>
<td>10.85</td>
</tr>
<tr>
<td>3 Built Up Area</td>
<td>1,847.24</td>
<td>4.02</td>
</tr>
<tr>
<td>4 Corn/ Maize</td>
<td>11,089.31</td>
<td>24.13</td>
</tr>
<tr>
<td>5 G’Nut</td>
<td>4,576.59</td>
<td>9.96</td>
</tr>
<tr>
<td>6 Rocks</td>
<td>3,380.12</td>
<td>7.35</td>
</tr>
<tr>
<td>7 Soya Beans</td>
<td>542.17</td>
<td>1.18</td>
</tr>
<tr>
<td>8 Vegetation</td>
<td>18,427.22</td>
<td>40.10</td>
</tr>
<tr>
<td>Total</td>
<td>45,957.00</td>
<td>100.00</td>
</tr>
</tbody>
</table>

Table 3: Estimated area of 3 land cover classes in the study area based on the unsupervised classification technique

<table>
<thead>
<tr>
<th>Class/ Crop Type</th>
<th>Area (Hectares)</th>
<th>Percentage (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Vegetation</td>
<td>39,130.67</td>
<td>85.15</td>
</tr>
<tr>
<td>2 Non-Vegetation</td>
<td>3,336.88</td>
<td>7.26</td>
</tr>
<tr>
<td>3 Rocks</td>
<td>3,489.45</td>
<td>7.59</td>
</tr>
<tr>
<td>Total</td>
<td>45,957.00</td>
<td>100.00</td>
</tr>
</tbody>
</table>

However, the overall accuracy of 71% and a kappa index of 0.52 suggest that the classified map is good (Table 4) and the supervised classification process that produced the 8 class land cover map was satisfactory.

Table 4: Accuracy of supervised classification based on 8 land cover classes

<table>
<thead>
<tr>
<th>Land cover Class type</th>
<th>Producer’s Accuracy (%)</th>
<th>User’s Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Bare Land</td>
<td>92.81</td>
<td>68.36</td>
</tr>
<tr>
<td>2 Cowpea</td>
<td>61.39</td>
<td>74.91</td>
</tr>
<tr>
<td>3 Built up Area</td>
<td>23.77</td>
<td>20.19</td>
</tr>
<tr>
<td>4 Corn</td>
<td>64.74</td>
<td>70.86</td>
</tr>
<tr>
<td>5 Ground Nuts</td>
<td>51.2</td>
<td>59.5</td>
</tr>
<tr>
<td>6 Rock</td>
<td>80.28</td>
<td>71.94</td>
</tr>
<tr>
<td>7 Soya Beans</td>
<td>46.26</td>
<td>65.71</td>
</tr>
<tr>
<td>8 Vegetation</td>
<td>99.2</td>
<td>99.71</td>
</tr>
</tbody>
</table>

4. CONCLUSION AND RECOMMENDATION

In this paper, an attempt was made to integrate LandSat 8 ETM image scene of 2016, records of croplands and field observations in mapping cropland area in Mubi South Local Government Area. The area was classified into 8 land cover classes including 3 non-vegetative, 4 crop classes and a natural vegetation class. Based on this method, natural vegetation has the largest land cover area but combined cropland area under rain fed agriculture surpasses the area covered by natural vegetation accounting for close to half of the total area of the local government. Maize is the largest crop cover followed by cowpea and groundnuts.

In the course of the investigation, errors were identified accruing from classifying areas under mixed cropping; bare land and built-up areas; cowpea and groundnuts grown on shallow soils. Despite errors resulting from the classification process, results of an accuracy assessment indicate that the supervised classification process was overall good. This outcome is further supported by the slight differences between the total vegetation area obtained from the unsupervised classification and the map obtained using the supervised classification technique.

Based on the findings in this paper, the following recommendations are proposed:

1. For future monitoring and mapping of cropland, the methodology used in this research work could be adopted because of its simple approach and good results.
2. Government should take advantage of the benefits of modern technology and encourage research that will develop the agricultural sector, improve yield, thereby providing raw materials that will attract the establishment of agricultural related industries.
3. Close to 50% of the study area is under cultivation, this may have a very serious implication on the natural vegetation and stability of natural systems. Stakeholders should adopt agricultural practices that will increase productivity without expanding lands, while maintaining environmental quality, and also considering policies for the protection of forest and natural vegetation.

4. Farmers should be encouraged to grow cash crops so as to enhance their income, since majority of them depend directly on what is grown on their farmlands.

REFERENCES


