A comparison of pixel-based and object-based approaches for land use land cover classification in semi-arid areas, Sudan

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Abstract. This paper deals with the comparison between application of pixel-based and object-based approaches in land use land cover classification in semi-arid areas in Sudan. The second aim is to assess the accuracy of classification for each approach. The study was conducted in the gum arabic belt in North Kordofan State, which is affected by modifications in conditions and composition of vegetation cover trends. The study used ASTER L1B registered radiance at the sensor image acquired on (19.10.2010). The image was radiometrically corrected by using ENVI-FLAASH software. Subset with an area of (40880) ha was created. The image classification (pixel-based and object-based) and accuracy assessment were conducted. Total number of (47) GCPs were surveyed and used in accuracy assessment using ERDAS 9.1. Image segmentation process was implemented using Definiens eCognition 7.1 software. Segmentation level 4 of scale parameter 25 was selected for classification based on colour and form homogeneity. Land use land cover classes were derived by classification using the nearest neighbor classifier with membership functions (fuzzy logic) for each class. The land use land cover distribution in the area for forest dominated by Acacia senegal is (20%) and for residential area is (1.50%) for the two methods of classification. While for bare and farm land, grass and bush land and mixed woodland classes are (6.69% and 1.63%), (18.62% and 15.16%) and (53% and 61%) for pixel based and object based methods, respectively. The overall accuracy and Kappa statistic of the classification produced by the pixel-based and object-based were (72.92%, and 54.17%) and (0.6259 and 0.3810), respectively. The pixel based approach performed slightly better than the object-based approach in land use land cover classification in the semi-arid land in gum Arabic belt.

1. Introduction

Land cover refers to the surface cover on the ground, whether vegetation, urban infrastructure, water, bare soil or other. Identifying, delineating and mapping of land cover are important for global monitoring studies, resource management and planning activities [2] and [12]. Remote sensing techniques help in developing areas in studying the changes in vegetation cover. Also geographic information system (GIS) is very powerful tool when applied to earth sciences and land use studies [5]. Land use land cover classification of vast areas using traditional methods is a time consuming and expensive process. Remote sensing offers a quick and efficient approach to the classification and mapping of land use land cover in a basis for future planning. Hard classification methods assume that
each pixel represents a homogeneous area on the ground and showing only one land cover type [19]. But in fact, the spatial structure and variation of land cover can cause numerous ‘mixed pixels’ in remotely sensed imagery also in semi-arid areas (e.g. gum arabic belt). The soft classification methods like sub-pixel and fuzzy classification are an alternative to the standard ‘hard’ classifier and providing the user with a measure of the degree (termed membership grade) to which the given pixel belongs to some or all of the candidate classes [12] and [20]. Object based image analysis is observed and used in the past few years. Its application has been extended in various fields, especially for forest mapping and Land use land cover classification [15] and [17]. Object-based, has emerged, and has generally had better success with narrow band and high spatial resolution data [26]. An object based image analysis (OBIA) approach has been proposed as an alternative analysis framework that can mitigate the deficiency associated with the pixel-based approach [6]. OBIA approaches for analyzing remotely sensed data have been established and investigated since the 1970s [6]. The classification process, in this case, begins with a segmentation of neighboring pixels into homogenous units or objects [3]. Object-oriented methods of image classification have become more popular in recent years due to the availability of software (eCognition®).

The gum arabic belt contains large areas of land with little land resources information. The belt is dominated with *Acacia senegal* trees (*Hashab*). [9] reviewed many studies conducted in Sudan using various types of satellite imageries to identify the features of land use land cover changes. In Sudan most land use land cover classifications were derived from remotely sensed data using pixel based methods of classification mainly by maximum likelihood classification (hard classification) as the commonly used technique for classification. Therefore, the study aims to compare classification of land use land cover using pixel based and object based approaches in semi arid areas in Sudan, which can be performed and provides the ground cover information for future land management in the gum arabic belt in Kordofan region. Secondly, to achieve accuracy assessment for the two classification approaches.

2. Material and methods

2.1. Study area

The selected study area is located in North Kordofan State, which is one of the most vulnerable areas in the country concerned with desertification processes. It is located in central Sudan between latitudes 9° 30’ and 16° 24’ N and longitudes 27° to 32° E. Kordofan, which lies largely within the arid zone (figure 1). The area is located in gum arabic belt in North Kordofan State. The rainfall in the state is concentrated during a few summer months (high seasonality) and to relatively few occasions (high intensity). The mean annual temperature varies between 28° and 30°C.

![Figure 1. Location of the study area.](image-url)
2.2. Material and methods
An image of ASTER L1B registered radiance at the sensor on acquired on (19.10.2010) was used in
the study. ASTER image was geo-referenced to the WGS84 datum and Universal Transverse Mercator
(UTM) projection [1]. The image was radiometrically corrected by using ENVI-FLAASH software
(Fast Line-of-sight- Atmospheric Analysis of Spectral Hypercube) module in ENVI 4.5. Then a subset
covering an area of (40880 ha) was created from ASTER image. Field data was carried for the
investigation of ground control points (GCPs). The coordinates for each point were recorded using
hand-held GARMIN eTrex Venture HC Global Positioning System (GPS). Information on land use
and cover was recorded. Total number of (47) GCPs were surveyed and used in accuracy assessment
using the calculation of a confusion matrix [8]. The segmentation and classification were conducted on
three levels to be incorporated into the hierarchical image object network. Classification accuracy was
assessed by comparing the automated technique with the field inventory data using Kappa coefficient.
The image classification (pixel-based and object-based) and accuracy assessment were conducted
(figure 2). Image segmentation process was implemented using Definiens eCognition 7.1 software.
The process involved multi-resolution segmentation and classification. The pixel-based classification
using maximum likelihood method was applied for the same subset image. The comparison and
analysis of these two classification approaches used three spectral bands of visible/near Infrared
(VNIR).

![Flowchart](image)

**Figure 2.** Flowchart for image processing and classification using object-based and pixel-based approaches.
3. Results
The comparison of both techniques was based on a visual analysis of the respective thematic maps outputs and on evaluation of the corresponding accuracy assessment measures (overall, producer’s and user’s accuracies, kappa coefficient). The classification of the land use land cover classes are indentified into five classes, which are bare and farm land, grass and bush land, forest dominated by Hashab, mixed woodland and residential areas.

3.1. Object-based classification
The multi-resolution segmentation technique was used to build up a hierarchical network of image objects that allowed the definition of relations between neighboring objects of different size [4]. Multi-resolution segmentation is a bottom-up segmentation strategy assembling objects to create larger objects and is based on the chosen scale, colour and shape parameters. Each parameter was weighted from 0 to 1. The scale parameter is the most important determining factor of multi-resolution segmentation [24].

Four levels of scales (200, 100, 50 and 25) combined with shape factor 0.7 and compactness 0.7 was tested and one optimum set of scale parameter was selected for the study (table 1). Within each segmentation level, an image object is not only linked to its neighbours, but also to its super-object and its sub-object providing useful context information for classification analysis [14]. In this study, segmentation level 4 of scale parameter 25 was selected for classification as it gave the best result in visualization of land use land cover classes based on colour and form homogeneity. The segmentation parameter 25 produced homogeneous segments for the optimal separation compared with the other levels.

| Segmentation level | Scale parameter | Shape factor | Compactness | Number of objects |
|--------------------|-----------------|--------------|-------------|-------------------|
| Level 1            | 200             | 0.2          | 0.7         | 1311              |
| Level 2            | 100             | 0.2          | 0.7         | 4935              |
| Level 3            | 50              | 0.2          | 0.7         | 18917             |
| Level 4            | 25              | 0.7          | 0.7         | 79614             |

For each individual image object, more than 150 object properties are created, which are also known as object features are provided [10]. Each object class has characteristic features enabling it to be separated from other object. The appropriate application of object features in OBIA for class description is based on previous user experience and knowledge or it can utilize feature reduction algorithms [25].

| Type                | Feature                                      |
|---------------------|----------------------------------------------|
| Customized          | NDVI, SAVI, RVI, Ratio (IR/R), (IR-G), (IR-R), (R-G) |
| Layer Value         | Brightness, Max. Diff., Mean (L1, L2, L3), Stddev (L1, L2, L3) |
| Texture After Haralick | GLCM* Homogeneity (all dir.) (L1, L2, L3, all dir) |
|                     | GLCM Mean (all dir.) (L1, L2, L3, all dir)    |
|                     | GLCM Contrast (all dir.) (L1, L2, L3, all dir) |
|                     | GLCM Dissimilarity (all dir.) (L1, L2, L3, all dir) |

* Gray Level Co-occurrence Matrix
Stddev = Standard deviation
The feature extraction and analysis were applied based on 32 selected features to identify the characteristics of each feature of the objects determining gland use land cover classes, and to find the suitable threshold values for class separation and distinguishing among the given classes (table 2). To achieve this measurement and to identify the characteristic features for the individual object classes for the classification, separability and threshold calculation were used [22], [7] and [21].

[7] used the Bhattacharyya distance ($B$) for calculating class separability and feature selection (equation 1) for mapping urban areas. [22] developed a tool called SEaTH (Separability and Thresholds), designed to determine suitable features and their threshold values in the Definiens software.

On the basis of these representative training data for each land use land cover class, the probability distribution for each class was estimated and used to calculate the separability between two land use land cover classes. The study distinguished between the two classes $C_1$ and $C_2$ followed by using a threshold of separation ($T$). The thresholds were determined by Bayes’ rule as following equations using [21]:

$$B = \frac{1}{8} (m_1 - m_2)^2 \frac{2}{s_1^2 + s_2^2} + \frac{1}{2} \ln \left[ \frac{s_1^2 + s_2^2}{2s_1s_2} \right]$$

$$J = \left[ 2(1 - e^{-B}) \right]^{1/2}$$

$$T = \frac{1}{\sigma_{c_1}^2 - \sigma_{c_2}^2} \left[ m_{c_2} - m_{c_1} \pm \sigma_{c_1} \sqrt{(m_{c_1} - m_{c_2})^2 + 2A(\sigma_{c_1}^2 - \sigma_{c_2}^2)} \right]$$

Where $m_{i}$ and $\sigma_{i}^2$, $i = 1, 2$, are the mean and the variance, respectively, for the two feature distributions.

The Jeffries–Matusita ($J$) distance between a pair of probability functions is the measure of the average distance between the two class density functions [23]. The range of ($B$) falls in half-closed interval $[0, \infty]$. This range is transformed into the closed interval $[0, 2]$ by using a simple transformation of Jeffries Matusita distance measure ($J$). When calculating the separability between the two classes, the features which have high Jeffries-Matusita value ($J = 2$), is the optimum features for separation between the two classes.

The results of all possible combinations for the separation of the land use land cover classes are presented in table (3). Separation between two land use land cover classes, only two features were selected when the value of ($J$) is greater than 1.7, otherwise more than two features were selected when the ($J$) value is less than 1.7 in order to increase the classification quality and permit best separation between these two classes. Therefore all objects in bare and farm land class could easily to be separated from those in the forest dominated by Hashab trees when the ($J$) value for feature brightness is 1.91 and 1.85 for mean layer 1. In other words, all objects with thresholds ($T$) for feature brightness greater than 1.91653 should be assigned to bare and farm land class, and all objects with thresholds ($T$) for feature mean layer 1 greater than 1.85754 also should be assigned to bare and farm land class. All other combinations between the other are land use land cover classes (table 3).

Finally the land use land cover classes were derived by classification using the nearest neighbor classifier with the defined membership functions (fuzzy logic) for each class. Each class was classified separately. Firstly bare and farm land class was separated using two features then forest dominated by Hashab (using three features), grass and bush land (using four features), mixed woodland (using one feature) and the residential areas (using one feature) were classified (table 4).
3.2. Pixel-based classification
Digital pixel-based methods aim to offer objective and repeatable procedures for identifying land use land cover classes. This approach is referred to pixel-based methods given that each pixel is compared from one date to another independently from its' neighbours. The maximum likelihood technique was selected for supervised classification and for comparison with the object-based classification. The distribution of the pixel based classification for the bare and farm land, grass and bush land, forest dominated by Hashab, mixed woodland and residential area classes are found as 18.62%, 53.16%, 20.02%, 6.695 and 1.50, respectively (table 4).

Table 3. Object features used for the separation of classes using seperability \((J)\) and threshold \((T)\).

| No. | Classes separation                  | Feature     | Seperability \((J)\) | Direction | Threshold \((T)\) |
|-----|-------------------------------------|-------------|-----------------------|-----------|------------------|
| 1   | Bare and farm land from forest dominated by Hashab | Brightness  | 1.91653               | <         | 3248.64          |
|     |                                     | Mean Layer 1| 1.85754               | <         | 2009.00          |
| 2   | Bare and farm land from grass and bush | Brightness  | 1.91275               | <         | 3251.27          |
|     |                                     | Man Layer 1 | 1.76075               | <         | 2046.27          |
| 3   | Bare and farm land from mixed woodland | Brightness  | 1.9998                | <         | 2997.40          |
|     |                                     | Mean Layer 1| 1.99976               | <         | 1795.90          |
| 4   | Forest dominated by Hashab form grass and bush | Brightness  | 1.6921                | >         | 1325.10          |
|     |                                     | Ratio       | 1.0404                | <         | 1.6442           |
|     |                                     | Mean Layer 1| 0.85241               | >         | 1321.12          |
|     |                                     | Mean Layer 2| 0.75248               | >         | 1423.1           |
| 5   | Forest dominated by Hashab from mixed woodland | Brightness  | 1.16844               | <         | 2411.30          |
|     |                                     | Ratio       | 0.82175               | <         | 0.31251          |
|     |                                     | Mean Layer 1| 1.0000                | >         | 1470.99          |
|     |                                     | Mean Layer 2| 0.95889               | >         | 2066.00          |
| 6   | Grass and farm from mixed woodland  | NDVI        | 0.97539               | >         | 0.24453          |

Table 4. Land use land cover classes derived from pixel-based and object- based classification.

| Class name                              | Area (ha) | %    | Area (ha) | %    |
|-----------------------------------------|-----------|------|-----------|------|
| Bare and farm land                      | 7611.8    | 18.62| 6197.6    | 15.16|
| Grass and bush land                     | 21731.8   | 53.16| 24970.0   | 61.08|
| Forest dominated by Hashab              | 8183.9    | 20.02| 8428.5    | 20.60|
| Mixed woodland                          | 2736.4    | 6.69 | 667.5     | 1.63 |
| Residential area                         | 615.2     | 1.50 | 615.2     | 1.50 |

1 Maximum likelihood classification
2 Object-based classification
The visual interpretation and comparison of results of mixed-based versus object-based classification of the respective image revealed some differences between the land use land cover classes (figure 3).

3.3. Accuracy assessment
The overall accuracy of the classification produced by the pixel-based method was 72.92%, with Kappa statistic of 0.6259, whereas the overall accuracy and Kappa statistic of the classification produced by the object-based method were 54.17% and 0.3810, respectively (table 5 and table 6).

| Table 5. Classification accuracy assessment of pixel-based approach. |
|---------------------------------------------------------------|
| Class name                                      | Reference totals | Classified totals | Number correct | Producers Accuracy (%) | Users Accuracy (%) |
| Bare and farm land                                 | 14              | 11               | 10             | 71.43                  | 90.91            |
| Grass and bush land                                | 15              | 24               | 14             | 93.33                  | 58.33            |
| Forest dominated by Hashab                         | 13              | 8                | 6              | 46.15                  | 75.00            |
| Mixed woodland                                     | 2               | 1                | 1              | 50.00                  | 100.00           |
| Residential area                                   | 4               | 4                | 4              | 100.00                 | 100.00           |
| Total                                            | 48              | 48               | 35             |                        |                  |

Overall classification accuracy = 72.92%
Overall Kappa Statistics = 0.6259

| Table 6. Classification accuracy assessment of object-based approach. |
|---------------------------------------------------------------------|
| Class name                                      | Reference totals | Classified totals | Number correct | Producers Accuracy (%) | Users Accuracy (%) |
| Bare and farm land                                 | 14              | 11               | 10             | 71.43                  | 90.91            |
| Grass and bush land                                | 15              | 5                | 1              | 96.67                  | 20.00            |
| Forest dominated by Hashab                         | 13              | 27               | 10             | 76.92                  | 37.04            |
| Mixed woodland                                     | 2               | 1                | 1              | 50.00                  | 100.00           |
| Residential area                                   | 4               | 4                | 4              | 100.00                 | 100.00           |
| Total                                            | 48              | 48               | 25             |                        |                  |

Overall classification accuracy = 54.17%
Overall Kappa Statistics = 0.3810

4. Discussion
Quantitative results from this study give a good overview for understanding the differences in performance of the two approaches for the same data. Considerable variability in the performance of these methods was observed. The pixel-based approach creates individual pixels or group of pixels while the object-based approach creates multi-pixel features. The bare and farm land as well as grass and bush land classes are more or less classified with the same area of coverage by the two approaches. The discrimination of mixed woodland class is confused with other classes in object-
based classification due to the similarly of pixel-based spectral information between the classes. The most significant misclassification between the two classification approaches occurred in the mixed woodland and grass and bush land classes. The mixed woodland class seems to be underestimated while the grass and bush land class seems to be overestimated in object-based classification compared with the pixel-based approach. This is due to medium resolution of the multi-spectral bands of the ASTER image (i.e. 15 m) which is not be sufficient for classification of heterogeneous nature of the land use land cover classes in the study area (mixed pixels problem).

![Figure 3. Results of land use land cover classification for (A) pixel-based and (B) object-based approaches.](image)

Grouping of pixels to objects in the object-oriented classification method decreases the variance within the same land cover type by averaging the pixels within the objects, which prevents the significant salt and pepper effect in pixel-based classification [18]. Therefore, the object-oriented classification approach is becoming more suitable for the needs of mapping when dealing with the high resolution imagery.

The object-based method misclassifies pixels especially in spectrally heterogeneous classes like mixed woodland and Hashab forests. However, the pixel-based approach generally performs better since most of the land use land cover classes selected for classification is highly homogeneous. Object based largely depends on the experimental objects used, which the successful results attributed to the careful selection of training objects [27].
The pixel-based approach is still efficient when used for land cover classification in semi-arid areas based on medium resolution imagery. Unlike pixel-based classification, the object-oriented approaches produce an output which is composed of segments that can be easily exported to GIS for creating and updating the information [13]. In addition to that object-based analysis combines spectral and spatial information as well as the texture and context information in the image [11]. The mixed pixel problem associated with conventional medium spatial and spectral resolution satellite imagery of semi-arid lands can be overcome by moving from conventional crisp per-pixel classification to soft spectral object-based approaches when using very high resolution.

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