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Accuracy Assessment of the Area of Hashab Tree (*Acacia senegal*) Defoliated by Tree Locust

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Abstract

This paper tends to depict the accuracy assessment of the area of *Acacia senegal* defoliated by tree locust in the study area. Multi-temporal satellite imagery covering the study area includes: Landsat7 (ETM+) 2007 and Spot5 (2008, 2009) were acquired. Radiometric and geometric correction, image enhancement and supervised classification were done with the help of ERDAS 9.3. Accuracy assessment was calculated based on the confusion matrix and Kappa coefficient. The results of the area of *A. senegal* defoliated by tree locust for Landsat7 (ETM+) 2007 showed overall classification accuracy 80%, the producer accuracy was 100, 100, 35 and 100% for non-defoliated, light defoliated moderate defoliated and high defoliated *A. senegal* respectively, the user accuracy was 100, 100, 55, and 95% for non-defoliated, light defoliated moderate defoliated and high defoliated *A. senegal* respectively. The overall Kappa Statistics = 0.75. The same accuracy assessment was also scrod for supervised classification of the area of *A. senegal* defoliated by tree locust for Spot5 (2008 and 2009). The results revealed, the overall classification accuracy 86.67%, the producer accuracy was 70, 100, 100 and 65%for non-defoliated, light defoliated moderate defoliated and high defoliated *A. senegal* respectively, and the user accuracy was 100, 90, 100, 100% for non-defoliated, light defoliated moderate defoliated and high defoliated *A. senegal* respectively. The overall Kappa Statistics = 0.82. However the results of accuracy assessment of supervised classification of *A. senegal* defoliated by tree locust classes in all years showed excellent classification for the majority of classes. The study concluded that aaccuracy assessment is one of the most important tools for quantifying how accurate the classification product is, more over confusion error matrix and Kappa coefficient were very efficient in the calculation of accuracy assessment.

Keywords

Acacia Senegal, Tree Locust, Defoliation, Accuracy Assessment

1. Introduction

Image classification is defined as the process of creating thematic maps from satellite imagery (process of sorting pixels into a finite number of individual classes, or categories of data based on their data file values. The result of a classification is that all pixels in an image are assigned to particular classes or themes, resulting in a classified image that is essentially a thematic map of the original image. The purpose of image classification is to match the spectral classes in the data to the information classes of interest. Generally, digital classification techniques may be categorized by the training process into supervised or unsupervised classification [3, 8 and 19].

Supervised classification techniques use prior knowledge about the field, which is very much helpful in getting better classification [19, 14]. Supervised classification used to classify image pixels by specifying various training areas representing land cover present in a scene. It is mostly preferred because it generally gives more accurate class definitions and higher accuracy than unsupervised approaches [3]. On other hand unsupervised classification is based on the fact that similar classes cluster in the feature space. Clustering is done by applying suitable algorithms on the bases of spectral signature, generating 'spectral classes', each spectral class is assigned to a class on the ground. There are a number of statistical techniques for clustering [19].

Accuracy assessment is important tool for determining the quality of the map created from remotely sensed data and quantifying how accurate the classification product is. The term accuracy means the level of agreement between labels assigned by the classifier and class allocations based on ground data collected by the user, known as test data [16]. Accuracy assessment can be qualitative or quantitative, expensive or inexpensive, quick or time consuming, well designed and efficient or haphazard. It is usually done by comparing the classification product with some reference data that is believed to reflect the true land cover accurately. Accuracy assessment is presented by a confusion error matrix by Kappa coefficient as a common and typical method [7]. There are two types of map accuracy assessment; Positional and thematic. Positional accuracy deals with the location of map features and measures how far a spatial feature on the map is from its true or reference location on the ground [4]. Thematic accuracy deals with the labels or attributes of the features of the map, and measures whether mapped feature labels are different from the true feature labels. The accuracy of any map or spatial data set is a function of both positional accuracy and thematic accuracy. Thematic accuracy is more difficult than positional accuracy. The classification is incomplete until its accuracy has been assessed.

Accuracy assessment of land use and land cover interpretation is complex, and errors can occur in the classification and identification of land cover categories. [13], when dealing with classification errors, pointed out that land use classification categories are discrete variables and that each pixel is either correctly classified or incorrectly classified. [12] proposed a five-question checklist in determining land cover map accuracy. To answer the five questions [12] proposed using an error matrix. The rows and columns reflect the number of sample units assigned to a category (from image classification) in relation to how many of those sample units actually belong to that category on the ground. Observations from the ground can then be compared with classifications from the imagery. Cells in the diagonal represent all correctly classified sample units. The matrix can then be used to determine the overall accuracy and correct predictions for each category and to determine whether a category is over- or underestimated. Overall accuracy can be determined by summing the total correct samples and dividing that by the total number of samples. The proportion of sample sites correctly predicted for each category relative to ground truth data, which is also known as the producer's accuracy, can be determined, indicating what level of omission error there is in the final map. The user's accuracy, which is the proportion of the land cover map per category that has been classified correctly relative to land cover map categories, determines what level of commission error there is in the final map product. By measuring the producer's and user's accuracies, a determination can be made asto which categories have been overemphasized or underemphasized [7, 5, 22]. [21] Provide a review of accuracy assessment of satellite-derived land cover data, whereas [26] state that the usefulness of a land cover map is dependent on sound accuracy assessment of the land cover classification.

Many problems are often encountered when evaluating an image classification, these problems such as interrelated problems that limit the quantification of classification [11]. However, classifying remotely sensed data into a thematic map 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 [9].

2. Materials and Methods

2.1. Study Area

Laboratory work was conducted in the Gum Arabic Research Centre (GARC) at Elobeid. Field work was conducted during three successive seasons, 2007/2008, 2008/2009 and 2009/2010 at Acacia Agricultural Scheme (Nawa and Elrahad locations), 37 Km south east Elobeid, Sheikan locality, North Kordofan State. The total area of the project is approximately 27000 feddans which was planted with hashab trees in 1997. The inter-row spacing is 3m and the intra-row spacing is 5m. Hashab trees were evenly grown, approximately about 280 hashab tree/ feddan (Acacia Agricultural Scheme Reports, 2007). Hashab plantations were more or less stunted possibly due to soil compaction [24]. The soil is hard crust; generally flat, non-cracking clay mixed with Aeolian sand and with low infiltration rates locally named *Gardud* [10]. The climate is semi-arid with annual rainfall ranging from less than 200 mm in the north to about 350 mm in the south; the temperature is highest during July ranging 30 - 40°C [1].

2.2. Data Acquisition and Analyses

Different satellite imageries covering the study area were acquired and employed. These were Multi-temporal satellite imagery Landsat7 (ETM+) 2007 and Spot5 (2008 and 2009). Radiometric and geometric correction, image enhancement were done, then the study area was classified into different classes depending on level of defoliation using supervised image classification with the help of ERDAS 9.3. The area of *Acacia senegal* defoliated by tree locust map was generated using ARC GIS version 9.3 and finally accuracy assessment was done depending on confusion matrix and Kappa coefficient.

Table 1. *Characteristics of Landsat7 satellite imagery used in the study.*

Satellite	Sensor ID	Bands	Spectral band (um)	Path/Row	Ground Resolution	Acquisition date
Landsat7	ETM+	7	*	174/51	15 m**	Aug. 2007

* band widths (band1; 0.45-0.52 (blue), band2; 0.52.0.60 (green), band3; 0.63-0.69 (red), band 4; 0.76-0.90 (near-infrared), band5; 1.55-1.75 (mid-infrared), band 6; 10-4-12.5 (thermal), band7; 2.08- 2.35 (mid-infrared), Path / row No was 174/51 and Dynamic range was 8 bit
** The spatial resolution was 15m (after merging panchromatic with multispectral bands)

Table 2. *Characteristics of Spot satellite imagery used in the study.*

Satellite	Sensor ID	Bands	Spectral band (um)	Ground Resolution	Acquisition date
Spot	XS	4	*	2.5 m	Aug. 2008/2009

* The sensor provided data in green (0.50–0.59 µm), red (0.61–0.68 µm), near-infrared (NIR; 0.78–0.89 µm), and short-wave infrared (SWIR; 1.58–1.75 µm) wavelengths at 2.5m resolution. Dynamic range was 8 bit.

The confusion matrix was created by comparing error values for each class that was classified with its respective value in the ground truth data. The ground truth points used for the accuracy assessment for the three classified thematic maps in the study area are (270) points. The table has the same number of columns and rows which equal to the number of classes. The area non-defoliated and defoliated classes in the ground-truth image head the rows, while the same classes for the classified image head the columns [25]. Kappa coefficient is a statistic which measures inter-rater agreement for qualitative (categorical) items. It is generally thought to be a more robust measure than simple percent agreement calculation, since $\hat{K}$ takes into account the possibility of the agreement occurring by chance. The Kappa coefficient ($\hat{K}$) is then computed using the following equation:

$$\mathrm{K}\hat{} = \frac{N\sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r} X_i + X_{+i}}{N^2 - \sum_{i=1}^{r} X_i + X_{+i}} \quad (1)$$

Where:
r: Number of rows/columns in confusion matrix
Xii: Number of observation in row i and column i
Xi+: Total number of row i
X+i: Total number of column i
N: Number of observations

The Kappa statistics provides a statistically valid assessment of the quality of classification was used to assess overall class accuracy. According to Pontius [18], a Kappa value higher than 0.5 can be considered as satisfactory for modelling of land use change. While [15] characterized agreement for the Kappa coefficients as follows: values > 0.79 are excellent, values between 0.6 and 0.79 are substantial and values of 0.59 or less indicate moderate or poor agreement.

The overall classification accuracy is the percentage of correctly classified samples of an error matrix. It is computed by dividing the total number of correctly classified samples by the total number of reference samples. It can be expressed by the following equation:

$$\text{Overall accuracy} = \frac{1}{N}\sum_{k-1}^{n} a_{kk} \quad (2)$$

Where:
A: Individual cell values
k +a: Row total
k a+: Column total
n: Total number of classes
N: Total number of samples

The mapping accuracy of each class of non-defoliated and defoliated area was derived from the calculated producer's accuracy and user's accuracy [23 and 6] using the following equations:

$$\text{Producer s accuracy} = \frac{aii}{\sum_{i-1}^{n} a_{+i}} \quad (3)$$

$$\text{User accuracy} = \frac{aii}{\sum_{i-1}^{n} a_{+i}} \quad (4)$$

Where:
a ii: Number of samples correctly classified
a i+: Column total for class i
a +i: Row total for class i

The confusion matrix, the producer's and the user's accuracy are calculated for each class, as well as the overall accuracy and the accuracy estimate that removes the effect of random change on accuracy, referred to as the Kappa statistic [20].

3. Results and Discussion

Remote sensing data were used for supervised classification of the defoliated and non-defoliated area in the study area resulted into four classes namely, non-defoliated, light defoliated, moderately defoliated and heavily defoliated area (Table 3).

Table 3. *Supervised classification of defoliated and non-defoliated area of Acacia senegal.*

Class	Area of *Acacia senegal*			Percentages %		
	2007	2008	2009	2007	2008	2009
Non-defoliated	2855.4	3343.8	4227	10.62	12.43	15.7
Light defoliated	8566.4	8115.8	9903	31.84	30.17	36.8
Moderately defoliated	11599.8	8463.4	9247.6	43.13	31.5	34.4
Heavily defoliated	3876.4	6975	3520.4	14.41	25.9	13.1
Total	26898	26898	26898	100	100	100

The results of supervised classification of the area of *A. senegal* defoliated by tree locust for the (Landsat ETM+ image 2007 showed overall classification accuracy 80%, the producer accuracy was 100, 100, 35 and 100% for non-defoliated, light defoliated moderate defoliated and high defoliated *A. senegal* respectively, the user accuracy was 100, 100, 55, and 95% for non-defoliated, light defoliated moderate defoliated and high defoliated *A. senegal* respectively. The overall Kappa Statistics = 0.75 which proves that the classification was within the excellent range which was arranged by [18]. In case of Spot5 2008 and 2009 images, The results revealed, the overall classification accuracy 86.67%, the producer accuracy was 70, 100, 100 and 65% for non-defoliated, light defoliated moderate defoliated and high defoliated *A. senegal* respectively, and the user accuracy was 100, 90, 100, 100% for non-defoliated, light defoliated moderate defoliated and high defoliated *A. senegal* respectively. The overall Kappa Statistics = 0.82. However the results of accuracy assessment of supervised classification of *A. senegal* defoliated by tree locust classes in all years showed excellent classification for the majority of classes (Table 4).

Table 4. *Summary of accuracy assessment of defoliated area of Acacia senegal.*

Classified image	Overall Kappa (K^) statistics	Overallaccuracy
Landsat7 ETM+ 2007	0.75	80%
Spot 5 image 2008	0.82	86.67%
Spot 5 image2009	0.82	86.67%

The results of accuracy assessment of supervised classification of defoliated area covered by *Acacia senegal* in all years showed excellent classification for all classes, with exception the class of Moderate defoliated area of *Acacia senegal* in the image Landsat7 ETM+ 2007 which showed poor classification (Table 5). The low level of classification accuracy for these classes could be attributed to such complexity of the landscape in a study area, selected remotely sensed data, season, and image-processing and classification approaches, which agrees with [9 and 17]. [2] examine the accuracy assessment of land use land cover classification using Google Earth in the case of Kilite Awulalo, Tigray State, Ethiopia for the year 2014. The result shows that total overall accuracy of land use and land cover for the year 2014 Landsat8 image is 82.00% and Kappa (K) is 77.02% which is acceptable in both accuracy total (overall) and Kappa accuracy.

Table 5. *Summary of Kappa (K^) statistics of defoliated area of Acacia senegal.*

Class name	Kappa (K^) 2007	Kappa (K^) 2008	Kappa (K^) 2009
Non-defoliated area of *Acacia senegal*	1.0	1.00	1.00
Light defoliated area of *Acacia senegal*	1.0	0.88	0.88
Moderate defoliated area of *Acacia senegal*	0.5	1.00	1.00
High defoliated area of *Acacia senegal*	0.9	1.00	1.00

Concerning the overall producer and user accuracy for the classified imagery classes during the study periods, the result revealed excellent user accuracy for near all classes in all years; however some classes recorded satisfactory user accuracy e.g. The class of Moderate defoliated area of *Acacia Senegal* in the image Landsat7 ETM+ 2007 (Table 6).

Table 6. *Summary Producer and User Accuracy assessment for supervised classification of defoliated area of Acacia senegal.*

Year	2007		2008		2009	
Class name	Producers Accuracy	Users Accuracy	Producers Accuracy	Users Accuracy	Producers Accuracy	Users Accuracy
Non-defoliated area of *Acacia senegal*	100%	100%	66.7%	100.0%	66.7%	100.0%
Light defoliated area of *Acacia senegal*	100%	100%	100.0%	90.0%	100.0%	90.0%
Moderate defoliated area of *Acacia senegal*	35%	55%	100.0%	100.0%	100.0%	100.0%
High defoliated area of *Acacia senegal*	100%	90%	65.0%	100.0%	65.0%	100.0%

4. Conclusion

The study concluded that; accuracy assessment is one of the most important tools for quantifying how accurate the classification product is, more over confusion error matrix and Kappa coefficient were very efficient in the calculation of accuracy assessment. Finally, it can be concluded that GIS and RS provide massive advantage when examining cover data spatially and quantitatively within this specific site.

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