Categorization and Identification of *Acacia* Trees Based on Species in *El Ain* Natural Forest Reserve by Using Multi-Temporal Landsat Imagery and Spectral Angel Mapper Classification

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ABSTRACT

Identification and classification of *Acacia* trees cover based on their species in arid and semi-arid areas through remotely sensed images involves various considerations, processes and techniques. Efforts to remotely sense arid land vegetation are often hindered by high reflectance of the soil background, mixtures of green and senescent grasses, and the occurrence of shrubs in grasslands. Elain forest reserve area, in North Kordofan state, Sudan, endures intensive different heterogeneity of *Acacia* trees cover and is highly sensitive to climate fluctuations and human intervention. Mapping of tree based on their species in these areas needs more input of high advance techniques under condition of appropriate forest management strategies. The main objective of current paper was to determine the applicability of the spatial and spectral resolution of Landsat imagery and sup pixel classification in combination with ancillary data and field sampling to distinguish and discriminate Acacia species distribution at Elain Forest Reserve in North Kordofan State. The multi-temporal landsat imagery (1987,1994 and 2016) , Minimum Noise Fraction (MNF) and Pixel Purity Index (PPI) were applied to extract different spectral signatures of *Acacia* trees in the study area. The Spectral Angel Mapper Classification (SAM)- was applied using selected endmmbers from PPI results . The paper provides a reliable comparable method of performing Multispectral Processing of landsat data using ENVI for Hyperspectral classification and mapping *Acacia t*rees based on their species in arid regions .

Keywords: arid lands, Elain forest reserve , multi-temporal landsat imagery , MNF- , PPI and SAM- classification

1. INTRODUCTION

In recent decades, a major effort has been made in classifying, mapping and monitoring forest cover in drylands using different satellite multispectral sensors such as SPOT, IKONOS, MODIS, QuickBird, Landsat and ALOS AVNIR (Han et al., 2004; Wang et al., 2004; Coop et al., 2009; Avelar et al., 2009; Chen et al., 2009; Bagan et al., 2010; Mustapha et al., 2010). Moreover, development of advanced image processing techniques under, remote sensing technology has rapidly expanded to allow estimation of forest cover in heterogeneous landscapes and estimation of tree density, species identification and assessment of temporal changes in individual tree growth. Great progress in image classification has been achieved, including (1) the development of advanced classification algorithms (e.g. neural network, decision tree, support vector machine, object-based algorithms, and sub-pixel based algorithms) (Tso and Mather 2001,Franklin and Wulder 2002, Lu and Weng 2007, Rogan *et al.* 2008, Blaschke 2010), (2) the use of multi-source data in a classification process, such as integration of different spatial resolution or sensor images (Solberg *et al.* 1996, Pohl and Van Genderen 1998, Ali *et al.* 2009, Ehlers *et al.* 2010, Zhang 2010) and the integration of remote sensing and ancillary data (Harris and Ventura 1995, Williams 2001, Li 2010), and (3) the development of techniques for modifying classified images by the use of expert knowledge (Stefanov *et al.* 2001, Hodgson *et al*, 2003, Zhang *et al*. 2010). Mapping of plant species with remote sensing linked to understanding that species have unique spectral signatures associated with characteristic biochemical and biophysical properties (Asner &Martin 2009;Ch et al., 2010; Clark et al., 2005). Trees cover classification by using remote-sensing presents unique challenges due to the spectral heterogeneity of vegetation and tree cover in arid region and makes it extremely difficult to identify the features interest in observed reflectance. Although different tree species often have unique spectral signatures, mapping based on spectral reflectance properties alone is often a large problem, since the spectral signature is hampered by soil background, a variable mixture of green and senescent grasses, multiple scattering due to open canopies and bright soils, and the prevalence of shrubs in grasslands (Okin and Roberts, 2004). In practice, broadband multispectral and multi-temporal data Landsat imagery are still the most common data source for land cover classification, in arid regions due to its suitable spectral and spatial resolutions and long term data availability since the 1970s. Landsat-TM images represent valuable and continuous records of the earth's surface during the last 3 decades (USGS, 2014). Although much research related to tree-cover classification has been conducted, a comprehensive analysis of the selection of spectral signatures and classification algorithms has not fully investigated. Identification and classification of tree cover in arid and semi-arid areas are very important since there lack of global coverage and availability of detailed ground survey due to expensive ground data collection are still the limitations of using remote sensing in a large extent. Monitoring of trees species in such areas needs more input of high advance techniques under condition of appropriate digital image analysis combined with conventional geographical methods and details field surveying (Khiry, 2007). *Elain* natural forest reserve area is a region located in North Kordofan State and it is characterized by a fragile ecosystem having considerable contribution to gum arabic production in the country. The greater part of the area is semi-arid with a small portion of rainfall ranges between 75-300 mm annually. *Elain* forest endures intensive different heterogeneity of *Acacias* trees cover and is highly sensitive to climate fluctuations and human intervention. Additionally, *Elain* Forest contribute positively to environmental stability and sustainability through conservation of ecological processes that link the continuity of life and humans, and conservation of biodiversity and genetic sources which both animal and agricultural production. . The study area endures intensive land use pressures, and the tree cover is more heterogeneity and is highly sensitive to climate fluctuations. This spatial complexity and heterogeneous as well as limitation of spatial resolution of the data reduce reliability of traditional remote sensing approaches to produce accurate results of identification and mapping .It is argued that due to the economic, social and environmental value of this area, spatial and temporal analysis of forest cover and it relation to desertification processes is recommended. Thus, this paper aims to determine the applicability of the spatial and spectral resolution of Landsat imagery and sup pixel classification in combination with ancillary data and field sampling to distinguish and discriminate *Acacias* species distribution at *Elain* Forest Reserve in North Kordofan State. The main objectives of this paper are: 1)To examine the capability of multi-spectral landsat imagery for categorizing and discriminating tree species in *Elain* forest area. 2) To investigate the utility of using multi-spectral processing tools and sub-pixel classification for identifying and mapping *Acacias* species. 3) To produce species diversity maps generated from the classified images corroborated with conventional knowledge on species diversity in the study area

2. METHODOLOGY

In the current paper a multi- thematic approach of research methodologies combining remote sensing data to ancillary data as well as field data was applied. In order to assess forest cover and identify the different *Acacias* tree species, Minimum Noise Fraction (MNF) , Purity Pixel Index (PPI) and Spectral Angel Mapper (SAM) classification was applied.

Selection of El Ain forest reserve as a site study:

North Kordofan state is located at latitudes 12º 16' North and longitudes 27º 32' East. The State is considered as representative of the gum arabic belt in western Sudan . *El Ain* forest is located in 26 km south of El Obeid town in North Kordofan (Fig 1), an area of natural woodland covering 11,850 hectares. *El Ain* Natural Forest Management Project is located within this area and lies 32 km south of El Obied town at latitudes 13º 11' North and longitudes 30º 12' East. The forest type in the study area is of the semi-arid type which is divided into five sub-divisions namely, *Acacia nilotica – Maerua crassifolia* Desert Scrub, Semi-Desert Grassland on Sand, *Acacia millifera – commiphora* Desert Scrub, Low Rainfall Savanna on sand and other species found in depression. *Adansonia digitata* is often found together with *Acacia nubica*. The dominant grasses are *Aristida, Pallida* species, *Eragrostis tremula* and *Cenchrus bifloruas.*The study area is located in the semi-arid region with unpredictable rainfall. The semi-arid areas are known as non-equilibrium environments where annual rainfall and other external events (drought, diseases) are the most important factors that determine the production potential of resources such as vegetation, particularly annual grasses and livestock. It is consider as very high intensive and diversity of trees as well as economical and tourism area in the state.

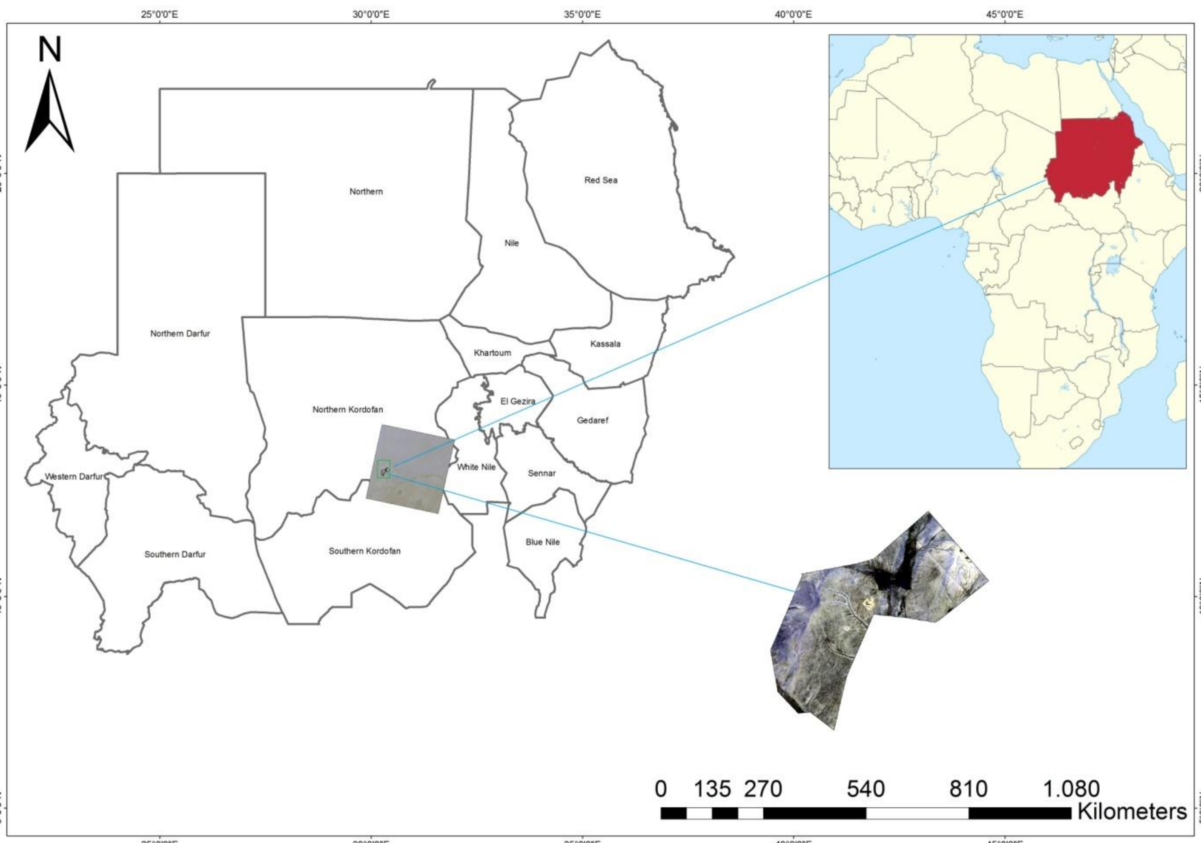


Figure 1: Location of *Elain* Forest Area (North Kordofan State)

Data acquisition and preprocessing of landsat imagry

Multi-temporal Landsat data for period (1987 , 1994 and 2016) were collected for analysis (Table 1). Imagery were collected in wet, early dry and mid dry season of the region. They pre-processed and radiometric calibration of DN into reflectance radiance was applied to each landsat image . The software employed for this work was the ENVI version 5.5 and Arc map version 10.2. Historical working plan and forest survey reports prepared by Forest National Co-operation for *Elain* Forest was studied. The analysis of historical and current working plan maps of *Elain* forest before and after the drought period in Sudan were prepared to offer a background information and historical database for the forest cover and vegetation in the study area.The study used bands 1,2,3,4,5 for landsat 1987 , bands 1,2,3,4,5,,7,for landsat 1994 and bands 1,2,3,4,5,6,7,8.for landsat 2016. The thermal bands was excluding during analysis.

Minimum Noise Fraction (MNF)

MNF Transformation is a method which was applied to landsat data to segregate noise in the data, determine inherent data dimensionality, and reduce computational requirements for subsequent processing (Green etal., 1988; Boardman and Kruse, 1995). The MNF divides data space into two parts; one with large eigenvalues and coherent eigenimages and the second with near-unity eigenvalues and noise-dominated images. Applied the MNF transform to the subset *land sat* data and viewed MNF eigenvalue plots to determine break-in-slop and MNF cut-off between "signal" and "noise" and bands with high eigenvalue were selected (Figure 3).

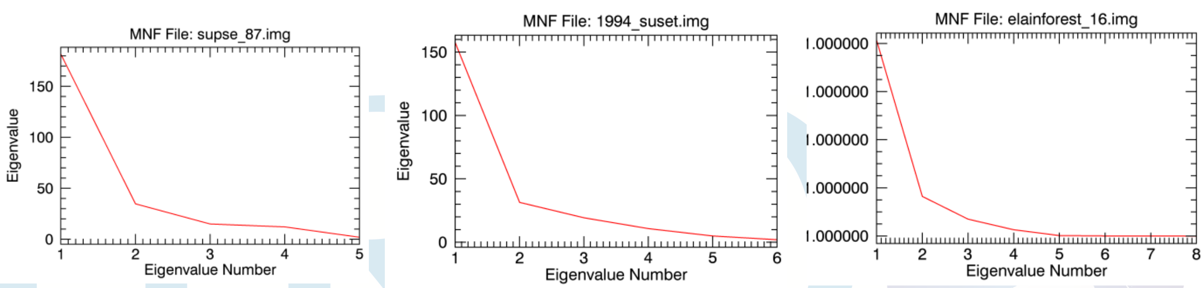


Figure 3: MNF Eigenvalue Plot for landsat images (1987. 1994 & 2016)

PPI to Find Endmembers

The Pixel Purity Index (PPI) was used to find the most most "spectrally pure" or extreme, pixels in a multispectral land sat images .Separating pure from more mixed pixels reduces the number of pixels to be analyzed for endmember determination and makes separation and identification of endmembers easier. The most spectrally pure pixels typically correspond to endmembers.Pure image pixels are identified by n-dimensional data cloud (n-dimensional scatter plots) onto a random unit vector.The extreme pixels in each projection are recorded and the total number of times each pixel is marked as extreme is noted. A PPI image is created in which the digital number (DN) of each pixel corresponds to the number of times that pixel was recorded as extreme. PPI analysis was applied to the MNF output by using the first three bands .The number of iteration was set to 10,000 and the number of iteration per block was 250 to ensure that some vegetation pixels were picked. Since there are few pure vegetation pixels, the 'tolerance factor", the threshold factor in standard deviation was set to 2.5. (Figure 4

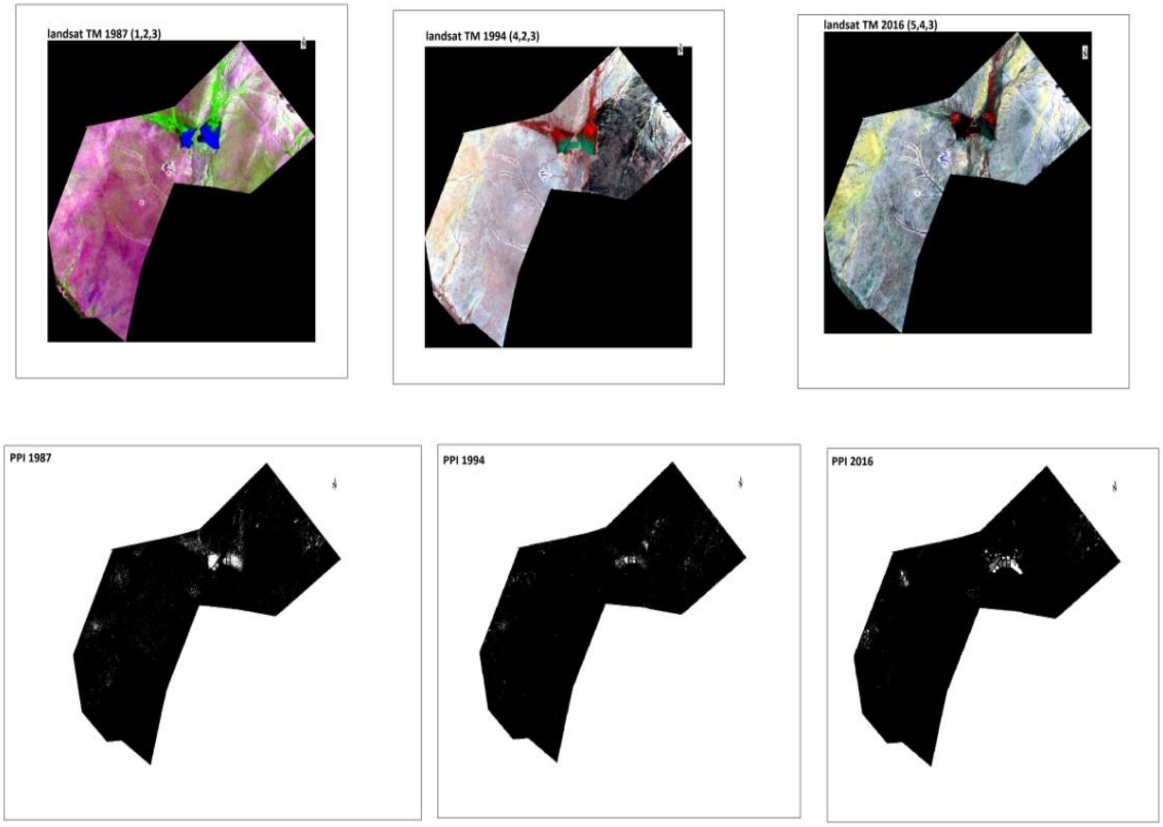
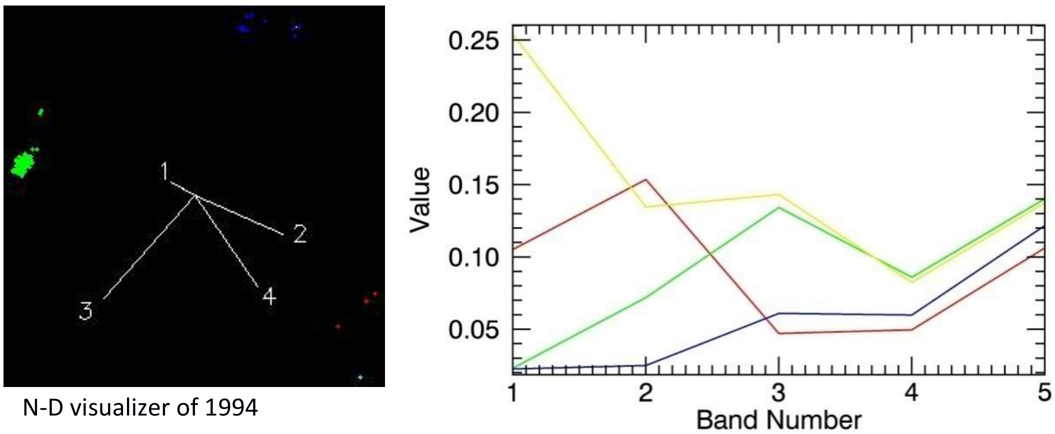


Figure 4: PPI images for landsat imagery (*The brightness areas represent the pure pixel)*

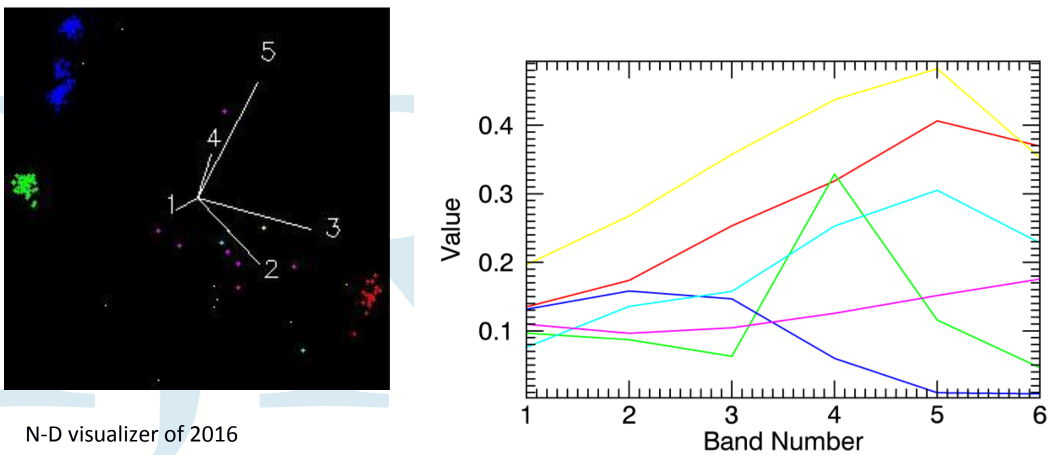
Dimensional Visualizer

N-Dimensional Visualizerprovides an interactive tool for selecting the endmembers in n-space where n is the number of bands of interest. The most important pixels, those best suggest the endmember materials, are the purest pixels, previously selected using PPI threshold. Those bands encompass almost all the signal variability and limiting the number of bands will improve the interactive visualization performance. The study used n-D Visualizer to separate the pure pixels into a set of endmembers. Five bands (TM 1987), six bands (TM 1994) and eight bands (TM 2016) from the each MNF data were used and the spectral signatures of purest pixel were selected (Figure 6)

N-D visualizer of 1987



N-D visualizer of 1994



N-D visualizer of 2016

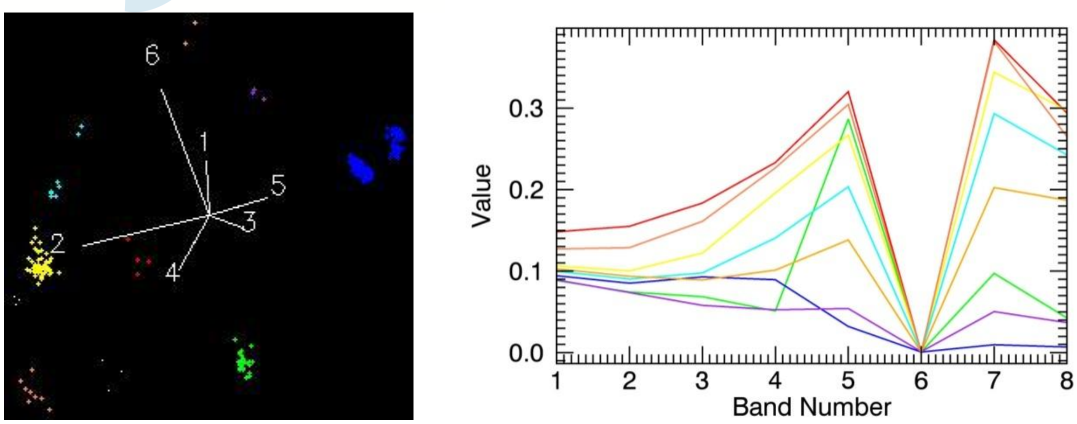


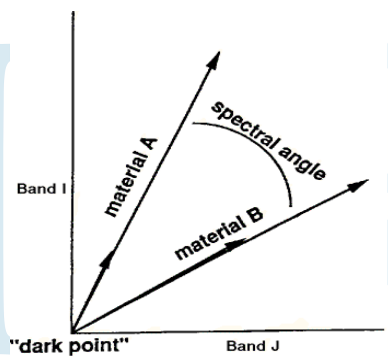
Figure 6: N-D visualizer plots and spectral profiles of selected endmmbers of landsat imagery

Spectral Angle Mapper Classification (SAM)

The Spectral Angle Mapper (SAM) measures the similarity of unknown and reference spectra in n-dimensions. The angle between the spectra treated as vectors in n-space is the "spectral angle", This method assumes that the data have been reduced to apparent reflectance and uses only the "direction" of the spectra, and not their "length". SAM determines the similarity of an unknown spectrum *t* to a reference spectrum *r* , by applying the following equation (CSES, 1992): Equation (1)

$$\alpha = \cos^{-1}\left(\frac{\sum_{i=1}^{nb} t_i r_i}{\left(\sum_{i=1}^{nb} t_i^{2}\right)^{1/2}\left(\sum_{i=1}^{nb} r_i^{2}\right)^{1/2}}\right) \qquad \text{Eqn.1}$$

where nb equals the number of bands in the image.



Eqn.1

For each reference spectrum chosen in the analysis of Landsat imagery, the spectral angle a is determined for every image spectrum (pixel). This value, in radians, is assigned to the corresponding pixel in the output SAM image, one output image for each reference spectrum. The derived spectral angle maps form a new data cube with the number of bands equal to the number of reference spectra used in the mapping .The results of the classification will be a set of rule images corresponding to the number of endmembers you selected and a SAM Classification Image. The SAM was applied to selected endmmbers from landsat sets and the results showed in Figure 7.

RESULTS

Referring to spectral profiles collected from n-d plot visualizer and SAM images of *acacia* trees and soil, mean while the landsat 1994 and 2016 detected 6 and 8 endmmbers, respectively . The limiting of band numbers of TM 5 make it very difficult to distinguish different types of land cover in the study area . Table 2 shows the distribution of different endmembers classes selected for ASM analysis . The results of SAM shows that it is possible to classify the *Acacias* tree and on other hand it was very difficult to separate bare soil from low tree cover(Figure7).

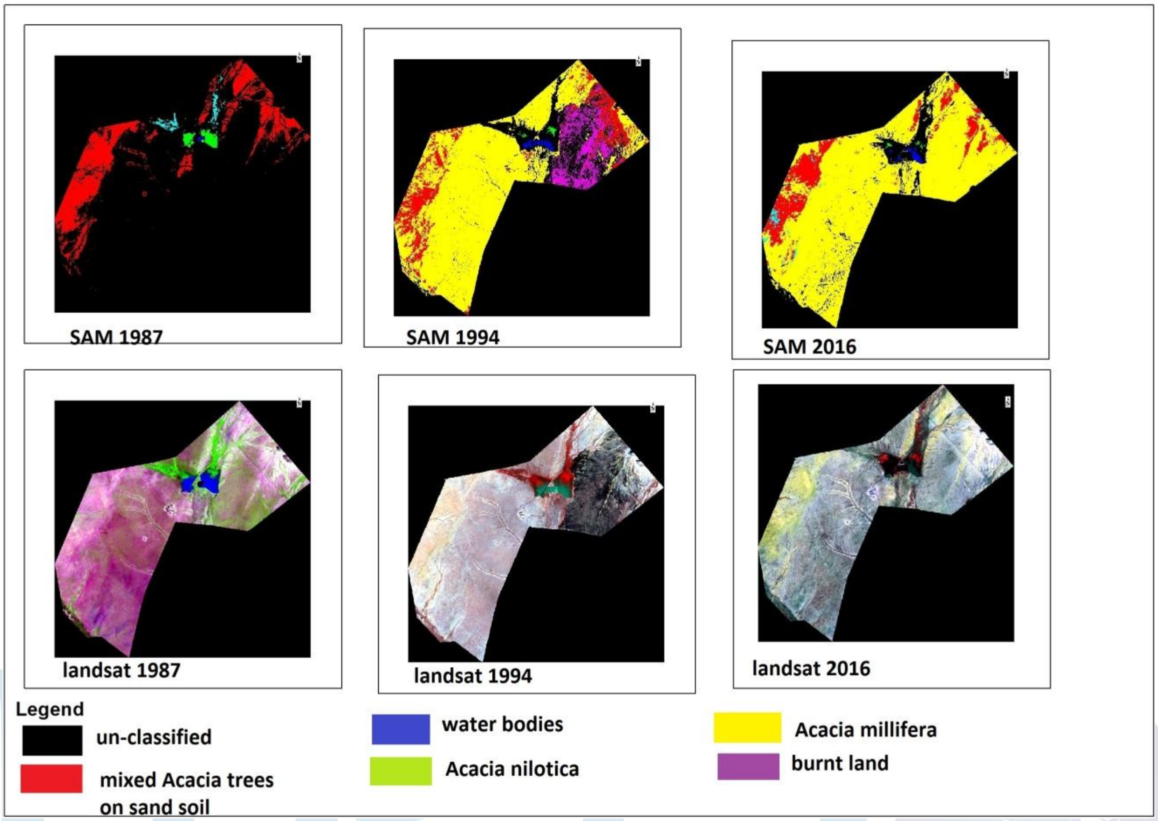


Figure 7: SAM results of landsat imagery

The percentage of each classes have been calculated for the total pure pixel of each Landsat used for SAM analysis . Burnt land class was recognized only with landsat 1994 . Comparing the results of SAM (Figure 7) to detail surveying map of *Elain* forest area (Figure 8) it obvious that the landsat 1987 data showed reliable results in classified water bodies and health vegetation with less detail on mixed *acacia* trees on sand soil and *Acacia millifera*. Meanwhile landsat 1994 and 2016 give more much detail on distributed mixed *acacias* tree and acacia *millifera* as well as burnt land . This could be to advances in Landsat sensors from TM to TM OL1 with two additional spectral bands and narrower band width is an advantage to applications requiring finer narrow bands more so the development of spectral indices for the various applications of Landsat data including agriculture, land-cover mapping, fresh and coastal waters mapping, snow and ice, soil and geology (Roy et al.,2014).

CONCLUSIONS, LIMITATIONS AND FUTURE STUDIES

Analysis of tree cover in arid and semi-arid region is important tool for forest management and planning. Although the heterogeneity of tree cover in such areas make it very difficult to obtain accurate results with available landsat data . The main task of this paper to compare the capability of multi-temporal landsat in classifying and identifying tree cover in *Elain* forest area . This can be accomplished by performing multispectral processing using ENVI hyperspectral classification . The paper come out with some links between theory, methodology and applications. Through this study , it found that it is extremely able to identify tree species by using multi-temporal landsat data and spectral analysis . The spectra of vegetation in such areas is always mixed with soil reflectance, thus the paper emphasize the need of more detail ground data on spatial distribution of tree cover . Finally, It is a great challenge for arid region to identify the tree species using landsat data , however it can be by conducted different classification approaches and data set . It recommended to seek opportunity in constitute modernize research in mapping and classification tree cover in arid and semi arid region by using very high resolution satellites data such as rapid eye imagery and advanced methods such as object based classification.

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Table 1: Characteristics of landsat imagery used in analysis

Sensor type	Landsat 5 TM	Landsat 5 TM	Landsat 8 OL1
Path/raw	174/51	174/51	174/51
Acquisition date	09.15.1987	11.21.1994	01.02.2016
Bandwidth (µm)	1- 0.45-052 (blue) 2- 0.52-0.6 (green) 3- 0.63-0.69 (red) 4- 0.76-0.9 (Near-IR) 5- 1.55-1.75 (Mid-IR) 6- 10.4-12.5 (Thermal-IR) 7- 2.08-2.35 (Mid-IR)	1- 0.45-052 (blue) 2- 0.52-0.6 (green) 3- 0.63-0.69 (red) 4- 0.76-0.9 (Near-IR) 5- 1.55-1.75 (Mid-IR) 6- 10.4-12.5 (Thermal-IR) 7- 2.08-2.35 (Mid-IR)	1- 0.43 – 0.45 (coastal) 2- 0.45 – 0.51(blue) 3- 0.53 – 0.59 (green) 4- 0.63 – 0.67 (red) 5- 0.85 – 0.88 (NIR) 6- 1.57 – 1.65 (SWIR 1) 7- 2.11 – 2.29 (SWIR 2) 8- 0.50 – 0.68 (Pan) 9- 1.36 – 1.38 (Cirrus) 10-10.6 – 11.19 (TIRS 1) 11- 11.5 - 12.51(TIRS 2)
Resolution (m)	30 m	30m thermal IR 120m	30m Panchromatic 15

Table 2: Distribution of endmmbers classes for SAM analysis

Class name	Landsat 1987	Landsat 1994	Landsat 2016
Un-classified	91.25%	66.43%	63.12%
Mixed *Acacia* trees on sand soil	7.86%	4.62%	4.47%
Acacia millifera	0.38%	25.70%	31.79%
Burnt land	-	2.79%	-
Water bodies	0.028%	0.20%	0.15%
Acacia nilotica	0.46%	0.08%	0.04%

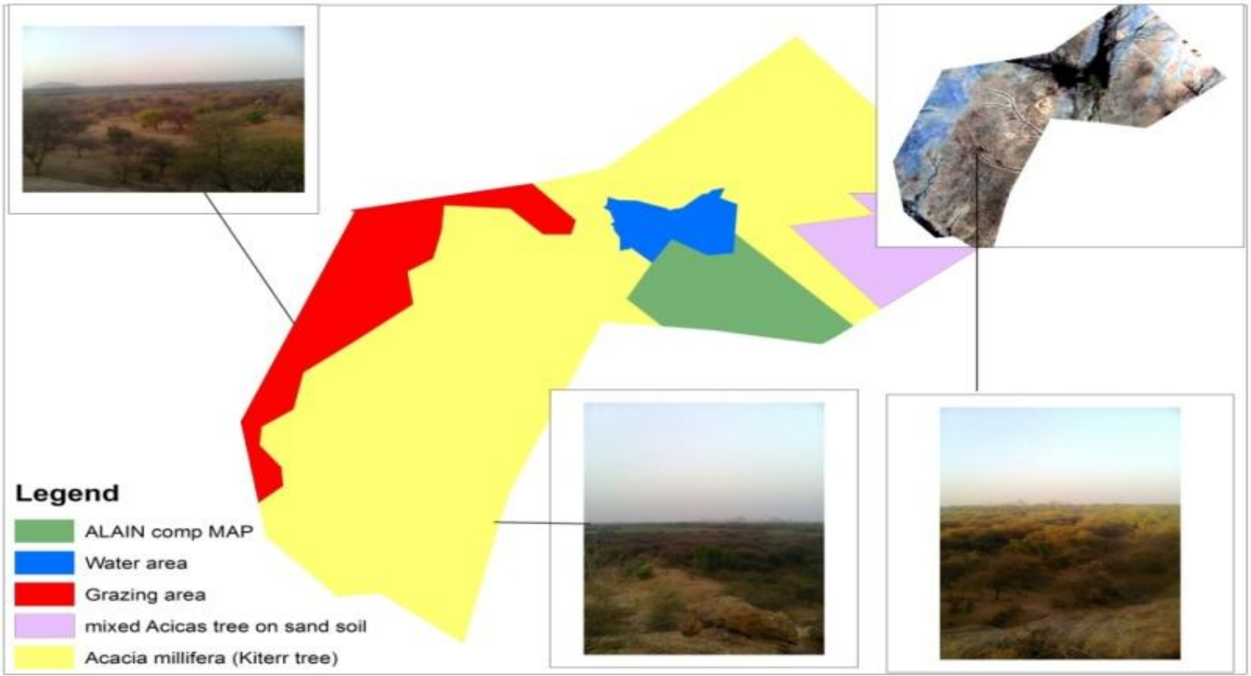

Figure 8: Surveying map of *Elain f*orest