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Research Paper

Spectral mixture analysis (SMA) and change vector analysis (CVA) methods for monitoring and mapping land degradation/desertification in arid and semiarid areas (Sudan), using Landsat imagery

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ABSTRACT

The severe Sahel catastrophe in 1968–1974 as well as repeated famines and food shortage that have hit many African countries during the 1970s have highlighted the need for further research concerning land degradation and environmental monitoring in arid and semi-arid areas. Land degradation, and desertification processes in arid and semi-arid environment were increased in the last four decades, especially in the developing countries like Sudan. To test to what extent remote sensing and geographical information science (GIS) methodologies and techniques could be used for monitoring changes in arid and semi-arid regions and environment, these methodologies have long been suggested as a time and cost-efficient method. In this frame, spectral Mixture Analysis (SMA), Object-based oriented classification (Segmentation), and Change Vector Analysis are recently much recommended as a most suitable method for monitoring and mapping land cover changes in arid and semi-arid environment. Therefor the aim of this study is to use these methods and techniques for environmental monitoring with emphasis on desertification and to find model that can describe and map the status and rate of desertification processes and land cover changes in semi-arid areas in White Nile State (Sudan) by using multi-temporal imagery of the Landsat satellite TM (1987), TM (2000), and ETM+ (2014) respectively. The paper also discusses and evaluates the efficiency of the adapted methodologies in monitoring the land degradation processes and changes in the arid and semi-arid regions.

1. Introduction

The increasing impact of land use and cover changes on the environment has been an issue of concern in the developing countries with consequential effects on sustainable development and long term impact on the agricultural sectors.

With the land use and land cover changes having a significant influence on the ecosystem with impact on biotic diversity, soil degradation, ability of biological systems to support human needs and the venerability of places and people to climatic, economic and sociopolitical perturbation, understanding these surface processes and predicting the impact on the environment and food production system is necessary for militating against the continuous negative impact of these changes.

Deforestation, floods, drought, desertification and land degradation have been issues of environmental concern in Sudan with increasing incidence of aridity in the region and changes in the climatic conditions of the region (Kibreab, 1996). With livestock raising, logging/deforestation and crop production dominant activities in the region, the consideration for the sustainable use of the environmental resources and long term sustainability of the environment is important and reducing the incidence of desertification and soil degradation in the region.

In the last 10 years, the issue of desertification has not only become more widely recognized, both internationally and regionally, but the social and political framework has changed dramatically in a way that makes a change in the research approach crucial (Geeson, 2002). It is very difficult to select one definition of desertification which can be treated as the generally accepted one. There are almost as many definitions as there are authors

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writing about desertification (Olsson, 1985). However most of the definitions have two principles in common:

1) Desertification is, at least partly, caused or accelerated by human activities.
2) The result of desertification is declining productivity of the land in one way or another.

The UNEP (United Nations Environment Programme) definition of desertification as "land degradation in arid, semi-arid and dry sub-humid areas resulting from various factors including climatic variations and human activities" (UNEP, 1992). Land means the terrestrial bioproductive system that comprises soil, vegetation, other biota and ecological and hydrological processes that operate within the system, the definition is particularly relevant. "Land degradation" means reduction and loss of the biological and economic productivity caused by land use change, or by a physical process or a combination of the two. Several factors and processes contribute to land degradation and desertification in White Nile State. This problem decreases land productivity.

The aim of this study is to investigate the possible use of different remote sensing methods to monitoring, mapping and assessing land degradation and desertification in arid and semiarid environment in White Nile State (Sudan) using Landsat satellite imagery.

One of the most effective tools for desertification assessment is remote sensing. It has long been suggested as a time and cost efficient method for observing dry land ecosystem environments (Hassan and Luscombe, 1990), monitoring land cover degradation as well as characterizing the dynamism of sand dunes (Collado et al., 2002). The important of remote sensing in monitoring and mapping of activities in the land cover is widely recognized and well introduced. Developments in satellite technologies and remotely sensed image acquisition and analysis offer an effective opportunity for increasing the reliability of monitoring and mapping land use and land cover change over wide areas. White Nile State is located in semi central of Sudan has semi-arid climate characterized by a fragile ecosystem which makes the regions more vulnerable to land degradation and desertification processes and risk. The region is highly sensitive to climate fluctuations, where various types of impact such as changes or removal of vegetation cover, change in land use system, accumulation of sand due to rainfall fluctuation and over-grazing cases of land degradation and desertification. Therefore, monitoring and mapping of land cover change in the region is needed and highly recommended.

Spectral mixture analysis (SMA) is a sub-pixel classification technique which could be used to unmixed the soil-plant canopy measurements into the respective soil, vegetation and non-photosynthetic vegetation (Smith et al., 1990a,b). SMA depends on the spectral response of land cover components. Sub pixel classifier is an advanced image method used to detect material that are smaller than an image pixel, using multispectral imagery. It is also useful for detecting materials that cover larger areas but are mixed with other materials that complicate accurate classification. It is a powerful, low cost alternative to ground surveys, field sampling, and high-resolution imagery (ERDAS Imagine, 2013).It addresses the "mixed pixel problem" by successfully identifying a specific material when materials other than the one you are looking for are combined in a pixel. It discriminates between spectrally similar materials, such as individual plant species, specific water types, or distinctive man-made materials. It allows you to develop spectral signatures that are scene to scene transferable. Some advantages of using subpixel classifier or linear spectral unmixing over other traditional classification methods is that (1) Classification objects that are smaller than the spatial resolution of the sensor, (2) Identifies specific materials in mixed pixels, (3) create pure spectral signatures, (4) can be used for many types of applications, (5) Develops scene to scene transferable spectral signatures, even at different time of the day and year, and (6) Enables searches over wide geographic areas.

Multi-temporal imaging enables assessment of changes in the type or condition of surface features. This is one of the most important of all analyses in remote sensing, typically called *change detection*. Many of these analyses use images acquired at two points in time, known as *bitemporal change detection* (Campbell, 2011). Change detection methods are commonly used in monitoring land degradation. Change can be identified either as change in the number of environmental components or as a change in percentages of the components (Adams et al., 1995). Visual interpretation and direct measurement using map-algebra are widely used in change detection. Change Vector Analysis (CVA) is a techniques where multiple image bands can be analyzed simultaneously. As its name suggests, CVA does not only function as a change detection method, but also helps analyzing and classifying the change. In CVA, pixel values are vectors of spectral bands. Change vectors (CV) are calculated by subtracting vectors pixelwise as in image differencing. The magnitude and direction of the change vectors are used for change analysis. The change vector magnitude can indicate the degree of change. Thus, it can be used for change and no-change classification (Singh, 1989).

Sudan is a developing country where desertification is widespread. UNEP considers that three compounding desertification processes are underway (UNEP, 2007): climate-based conversion of land types from semi-desert to desert, mainly due to a reduction in annual rainfall; degradation of existing desert environment, including Wadis and oases, principally caused by deforestation, overgrazing and erosion; conversion of land types from semi-desert to desert by human activates (deforestation, overgrazing and cultivation) even if rainfall may still be sufficient to support semi-desert vegetation cover. These processes are relatively difficult to distinguish, separate and quantify on the ground (Diouf and Lambin, 2001).

Specific studies are therefore necessary to define the driving forces (variables) affecting the processes and adopt efficient site-specific strategies to combat desertification (Dawelbait and Morari, 2008). Since lack of data, funds, and governments support, gives remote sensing data priority to be reliable tool to study desertification (Khiry, 2007) in the selected study area.

According to that evolution, the overall objective of this paper is to test the application of Object-Oriented and SMA pixels based to Landsat images as a tool to study the desertification processes, and driving variables influencing land degradation and vegetation cover in the study site which located within White Nile State, Sudan during different years.

2. Material and methods

2.1. Study site

The study site I have chosen is located in the North of White Nile State, Sudan, between latitude 12 56 35 and 13 3 49 N and longitude 31 051 and 31 58 51 E, as shown in (Fig. 1). The climate is semi-desert with summer rain warm winter, average annual rainfall ranging from 100–225 mm, which falls mainly in the months of (May–September), with a peak in August (Fig. 2) Mean maximum temperature of the hottest month (May or June) is 40–42 °C, and the mean minimum temperature of the coldest month (January is 13–16 °C). There is summer grazing in Wadis and some extensive cultivation of rainfed sorghum or "Dukhn" on water receiving. The soil is mostly rather sandy soil with high infiltration rates and inherent low fertility. Sand sheet and sand dunes stabilized by vegetation.

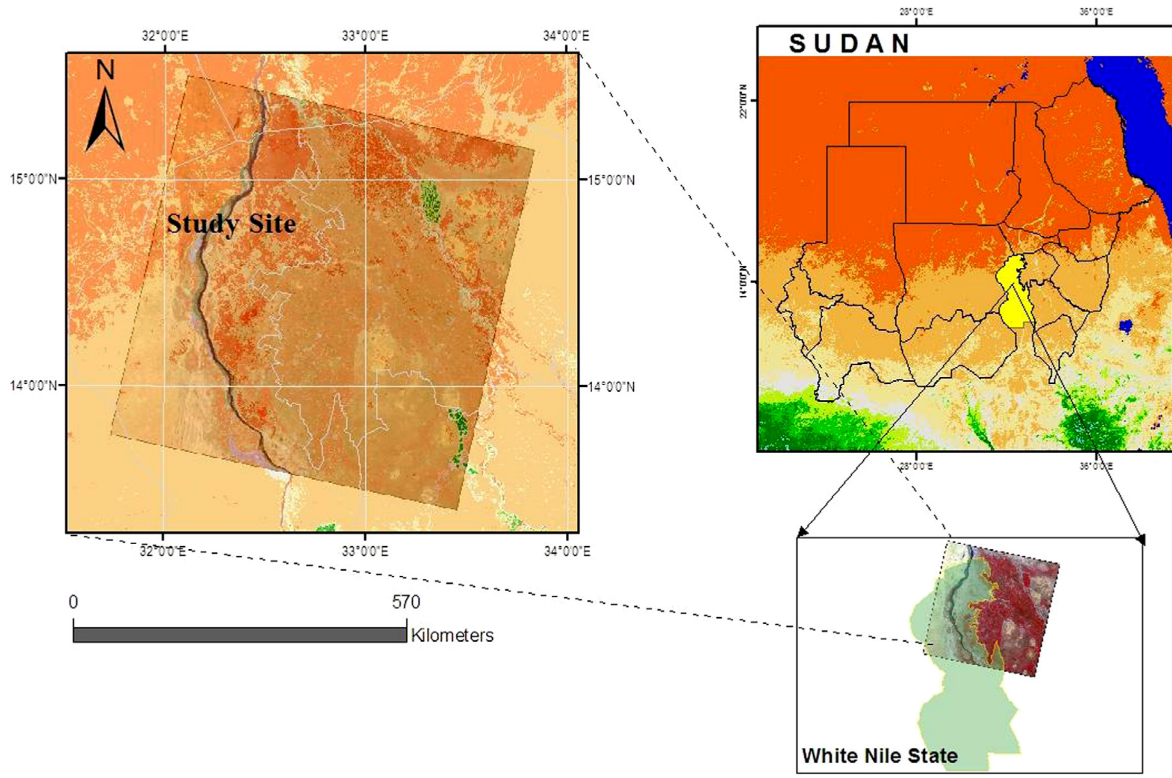

Fig. 1. Location of the study site in White Nile State, Sudan.

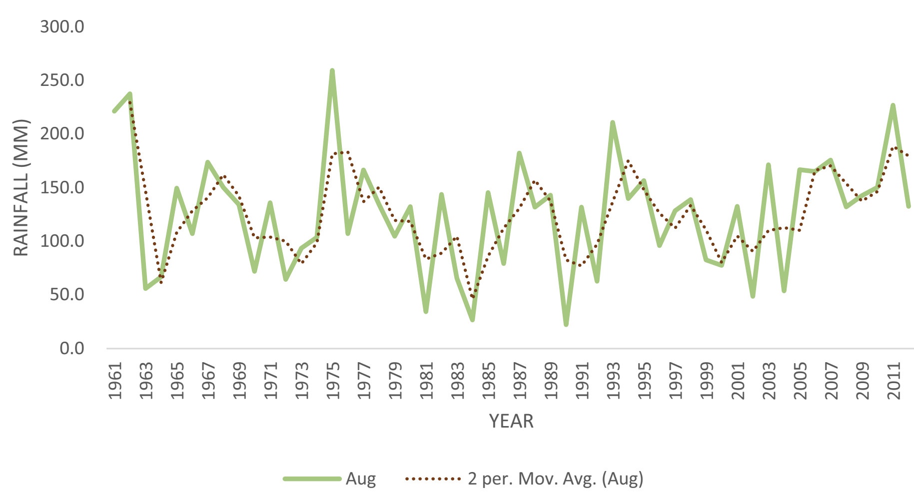

Fig. 2. August rainfall in the study area 1961–2012.

Natural vegetation consists of tress (Acacia app), hushes and grass. Rangeland and rainfed croplands are the most important land use systems which affected by sand encroachment. (Figs. 3and 4) respectively. The main crops are sorghum (*Sorghum Vulgare Pers*), millet (*Panicum miliaceum* L.), sesame (*Sesamum indicum* L.), and water melon (*Citrullus lanatus*) (Field survey, 2013). The rainy season usually leads to a short growing period (rainfed agriculture), and this season followed by a very long dry season with a reduction in agricultural productivity. Degraded land increased in the most of the part of the state by the creep of sand, and that lead to accumulation of sand dunes on the agricultural land, which lead to reduction of productivity. The reason of creeping of sand, is the winter win that comes from the (south/west) direction.

2.2. Data acquisition

Three Landsat satellites imagery were selected and analyzed in this study:

- One Landsat-1 TM scene from January 29, 1990. Path/Row 186 /050, pixel size 56 × 79 meters, sun elevation 53.65°, and sun azimuth 130.57°.
- One Landsat-5 TM scene from November 24, 1986. Path/Row 173/050, pixel size 56 × 79 meters, sun elevation 42°, and sun azimuth 125°.
- One Landsat-8 ETM+ scene from November 05, 2014. Path/Row 173/050, pixel size 30 × 30 meters, sun elevation 53.7°, and sun azimuth 145°.

Fig. 3. Rainfed croplands (during rainy season) southern part of the study.

Fig. 4. Sand encroachment on Natural vegetation consists of tress (Acacia app) during (dry season) northern part.

The dates coincided after the rainy season for monitoring the potential long-term processes of desertification. All satellites imagery are free clouds. Landsat images were selected because of they are free of charge, with high monitoring frequency every 16-days revisit time, and cover large are 185 × 185 km.

2.3. Image pre-processing

One satellite image classification method were used in this study including; (1) Spectral mixture analysis or sup-pixel classification method (SMA). Application of a classification based on an object oriented approach has several advantage instead of the pixel-driven approach. Image objects, besides the spectral information, contain additional attribute (e.g., shape, texture, relational and contextual information) that can be used for classification purposes (Baatz and Schape, 2000; Blaschke and Strobl, 2001; Laliberte et al., 2004). The classification process, in this case, begin with a segmentation of neighboring pixel into homogenous units or objects (Baatze et al., 2008). Object-oriented methods of image classification have become more popular in recent years due to the availability of software (eCognition, IDRISI, ERDAS IMAGINE and ENVI).

The Landsat TM and ETM+ scenes covering the study site were radiometrically and atmospherically calibrated and converted from digital number (DN) into at-satellite radiance, and reflectance values, by using ENVI software tools (FLAASH). For each of TM and ETM+ bands conversion from absolutely calibrated digital numbers on CCT to spectral radiance (Lλ) was accomplished.

Conversion from spectral radiance to effective at-satellite reflectance (Ppλ) for Landsat TM and ETM+ was accomplished.

2.4. Spectral mixture analysis and end-members

In remote sensing images of arid and semiarid environments, the material and features are smaller than an image pixel, where the one pixel contains mixture spectral information due to the high variability in the distribution of land cover components, using multispectral imagery. Subpixel classification method for instance object-oriented based classification (segmentation), and spectral mixture analysis which based on collection of en-members from the satellite imagery, considered as very useful methods for detecting mixture features in one pixel, and also materials that cover larger areas but are mixed with other materials that complicate accurate classification. It is a powerful, low cost, and alternative to ground survey, field sampling, and high-resolution imagery (ENVI, 2002). It addresses the "mixed pixel problem" by successfully identifying a specific material when materials other than the one you are looking for are combined in a pixel. It discriminates between spectrally similar materials, such as individual plant species, specific water types, or distinctive man-made materials in rural areas. It allows you to develop spectral signatures that are scene to scene transferable.

SMA transforms radiation or reflectance data into fractions of a few dominant endmembers, which are fundamental physical components of the scene and not themselves a mixture of other components (Elmore et al., 2000). Fraction images represent the mixing proportions of these endmembers spectra (Smith et al., 1985; Adams et al., 1986). SMA generally involves three steps (Huete, 2004): a) assessment of dimensionality or number of unique reflecting materials in a landscape to obtain the endmembers; b) identification of the physical nature of each endmembers within a pixel; c) determination of the amounts of each endmember in each pixel.

The basic and general mathematic model of the Linear Mixing Model LMM can be expresses as:

$$Rp(\lambda) = \sum_{k}^{n} EM_{ik} f_{ik+\varepsilon_i} \quad (1)$$

$$\sum_{k}^{n} f_{ik=1} \quad (2)$$

Where:

$Rp(\lambda)$ = is the apparent surface reflectance of a pixel in an image or band.
EM_{ik} = relative radiance in band i for each endmembers.
f_{ik} = fraction of each image endmember k calculated band by band.
K = each of n endmembers.
ε_i = reminder between measured and modelled DN (band residuals).

Since the pixel compositions are assumed to be percentages, the mixing proportions are assumed to sum to one.

2.5. Material of Interest (MOI) or endmembers

The selection of MOIs or endmembers is the most critical step in SMA to provide a physically meaningful of information fraction (Tompkins et al., 1997). Some SMA approaches use MOI or endmember spectra derived from (Library endmember), which are produced from reflectance measurement using (spectrometer device) in a laboratory (Smith et al., 1990a,b). But in this study we employed the (image endmember) to derive and provide the endmember spectra by using PCA method. Bateson and Curtiss (1996) and Bateson et al. (2000) generated SMA models using PCA to explore image data in multiple dimensions. Fig. 5 shown the all procedures of the adopted method.

The multispectral or vector character of most remote sensing image data renders it amenable to spectral transformations that generate new sets of image components or bands. These components then represent an alternative description of the data, in which the new components of a pixel vector are related to its old brightness values in the original set of spectral bands via a linear operation. The transformed image may make evident features not discernable in the original data or alternatively it might be possible to preserve the essential information content of the image (for a given application) with a reduced number of the transformed dimensions. The last point has significance for displaying data in the three dimensions available on a colour monitor or in colour hardcopy, and for transmission and storage of data (Richards et al., 2006). According the literatures, the most important information will be available at PC1, PC2, and PC3.

The approach here is to detect and classification of materials that occupy as little as 20% of a pixel. To select the MOI in this paper, the method is based on PCA application using ENVI application to identify the individual endmembers of multiple surface components. The spectral mixing feature space as represented as orthogonal scatterplots of the first three PC bands were generated and the vertices of these plots were selected as endmember (MOI) after visualization in the original images. Endmember spectra were applied to SMA in order to produce the fraction images with associated the RMSE images within the ENVI 5.1 remote sensing image analysis environment software.

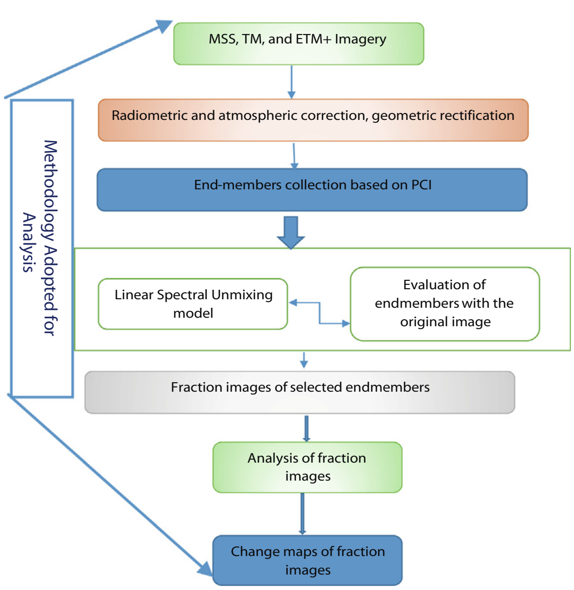

Fig. 5. The Methodology Adobated for Data Analysis.

2.6. Change detection repeated imaging

Multi-temporal imaging enables assessment of changes in the type or condition of surface features. This is one of the most important of all analyses in remote sensing, typically called change detection. Many of these analyses use images acquired at two points in time, known as bitemporal change detection. Comparing images subsequent to classifying each is called post- classification change detection. Post-classification change detection consists only of comparing the "from" class and "to" class for each pixel or segment. The approach considered in this study is Change Vector Analysis (CVA). With change vector analysis, difference images are created for each of the corresponding bands. These difference images are then squared and added. The square root of the result represents the magnitude of the change vector. When only two bands (for each of the two dates) are involved, it is also possible to create a direction image (indicating the direction of change in bands apace)(Pontius, 2000). The module CVA calculates both magnitude and direction images for 2-band image pairs. Figs. 6 and 7 illustrates these calculations. The magnitude image is in the same units as the input bands and is the distance (Euclidean distance) between the Date 1 and Date 2 positions. The direction images is in azimuths measured clockwise from a vertical line extending up from the Date 2 position. Four classes of magnitude were represented for either degradation or re-growing according to (Kuzera et al., 2005).

$$R = \sqrt{(\beta\sigma_{1-}\beta\sigma_2)^2(\beta\rho_{1+}\beta\rho_2)^2} \tag{3}$$

Where:

R = the magnitude of the vector change.
$\beta\sigma^1$ = Fraction in time 1.
$\beta\sigma^2$ = fraction in time 2.
$\beta^{\rho 1}$ = fraction cover in time 1 and.
$\beta^{\rho 2}$ = fraction cover in time 2.

Angles measured between 0 and 90° and 180–270° indicated either increase or decrease in both vegetation and sand consequently persistence in the condition (Figs. 6 and 7) (Khiry, 2007).

3. Results and discussion

3.1. The SMA analysis results

3.1.1. Endmember (Material of Interest (MOI)) Spectra and SMA Applications

Fig. 8 (a, b, and c) respectively illustrates the PCs analysis of the MSS, TM and ETM+ and their scatter plots. Where the PC1 and PC2 are very useful for material of interest (endmembers) collection, which reduction the dimension of Imagery and explained over

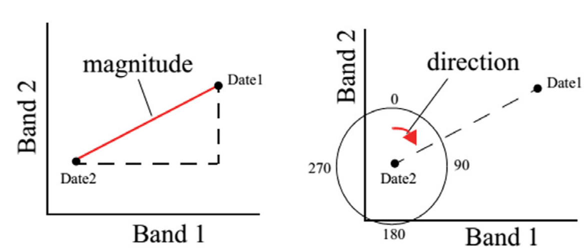

Fig. 6. The direction and magnitude of change (Source: ENVI, 2002) User Manual.

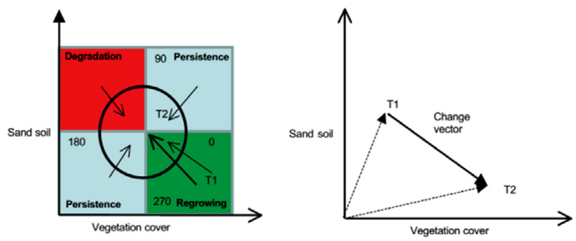

Fig. 7. Change vector analyses diagrams.

99% of the variation. About 2 to 3 endmembers were selected manually using PCI analysis scatter plots (e.g., Shifting Sand, Green vegetation, and crop) in each satellite imagery.

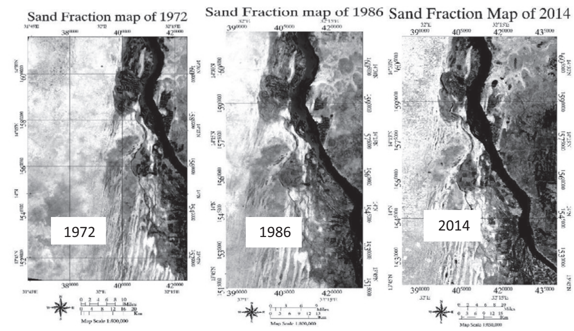

Fig. 9. Images of sand Fraction for the three images respectively (Brightness illustrate very high fraction).

3.1.2. Fractions of shifting sand

The fractions of shifting sand of the three Landsat satellite imagery and spectral reflectance of sand endmember are presented in Fig. 9. The visual interpretation of the resulting shifting sand fraction images indicates that shifting sand fractions increased from 1972 to 2014. According to El-toum (1974), the wind movement in the winter season start from the north east direction, which is dry wind coming from the Sahara desert.

This is mainly attributed to the fact that shifting sand (sand encroachment) increased following the wind direction from south-west to the north-east toward the study area. According to the statistical calculation, the increases percentage of sand fraction was 50.18% in year 1972, 38% in year 1986, and 41.5% in 2014. The source of this sand movement is Qos Ab-Dulue which located in north kordofan state. According to El-Tom (1996), in summer and winter season the wind direction is under change from the north-east to the south west. Therefore the south-west wind is responsible for the shifting sand (sand encroachment) in the study site. This indicate that the study area had been subjected to desertification processes with sand encroachment into cropped area in the first two years.

Fig. 10 (a, b, and c) respectively with subset area, shows the fraction of green vegetation (Rainfed agriculture) at the three years of images (i.e., 1972, 1982, and 2014) respectively. The visual interpretation of Rainfed agricultural fractions shows significant increase by 16.4% in 2014, while in 1972 occupied about less than 2%. That mean the study area has been subjected to recovery in the vegetation cover.

The changes in fractions of the three years was indicated by sub-areas (Fig. 11) in each of the fraction images as illustrated in Fig. 10. It clear that the area covered by sand in 1972 was increased from 1972 to 1986 with very slight vegetation cover in 1986. While the vegetation cover was showed grate recovery over 2014. The reason of that recovery is the trees plantation along the study site boundary.

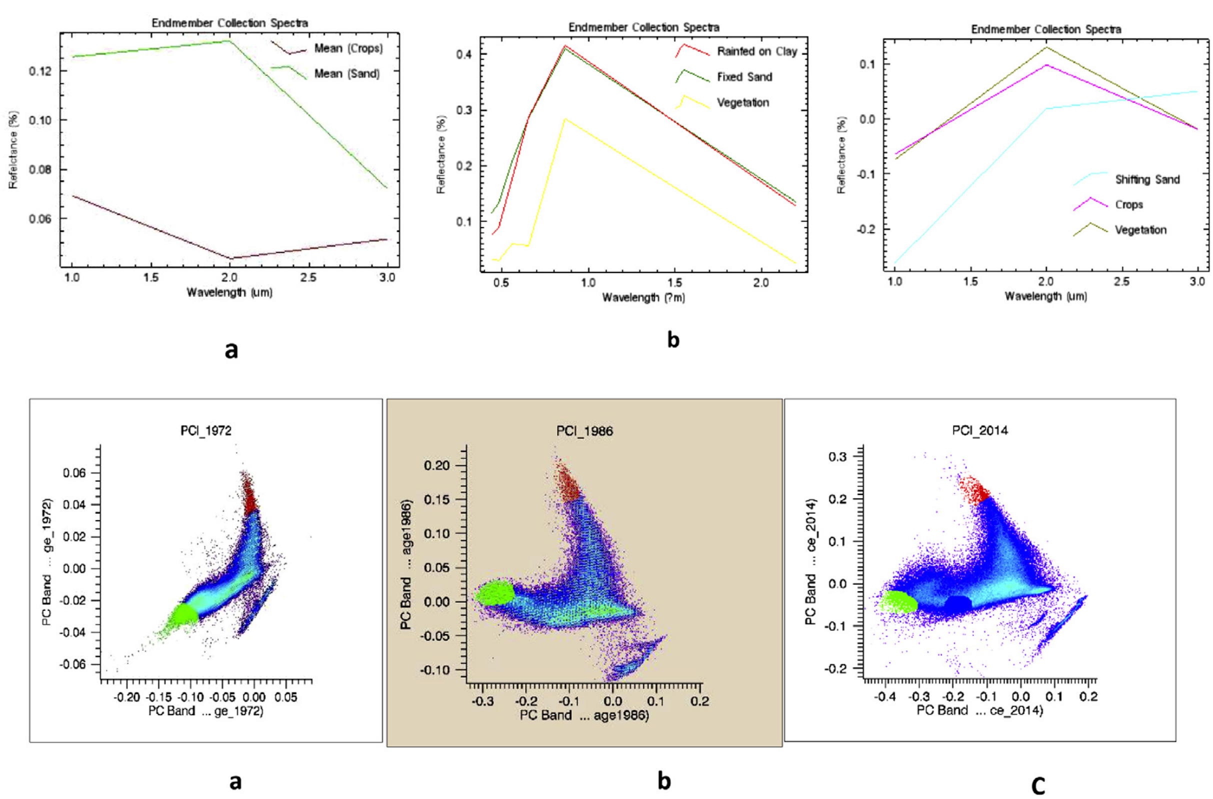

Fig. 8. Endmember fraction of (Shifting sand, Vegetation, and Crop) of the years 1972, 1986 and 2014 respectively and the scatter plot of the three endmembers.

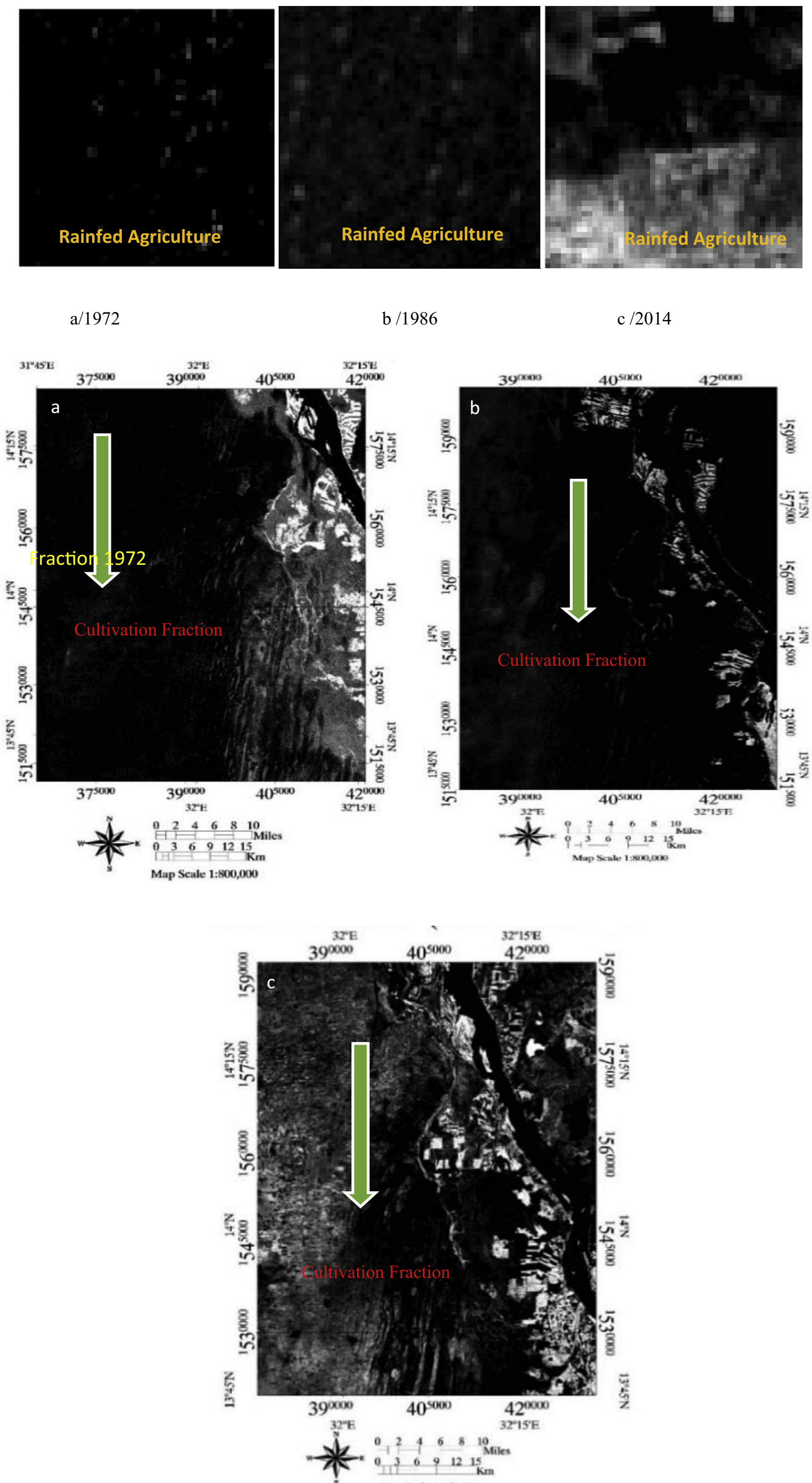

Fig. 10. Increasing of cropped area over the different years (1972, 1986, and 2014) which indicated by the letters (a, b, and c) respectively, where the white colour mean areas cropped areas, while the black colour means areas without crops.

Between 1986 and 2014, the cropped areas (rainfed agriculture) was increased by 9% in 2014 as showed in Fig. 11 b. But still affected by sand encroachment, which cover about 41%.

The cropped area was increased by rainfed agriculture in 2014. The cropped area was illustrated and indicated by the very high brightness which increased in 2014, compared to 1986 (Fig. 11).

3.2. Change vector analysis (CVA)

The sand and rain fed cultivated area fractions from SMA were used as an input for Change Vector Analysis (CVA) to stratify and analyze desertification processes in the period of 1972 to 2014. The resulting image of CVA display magnitude and directions of the changes. The change detection image was generated from the

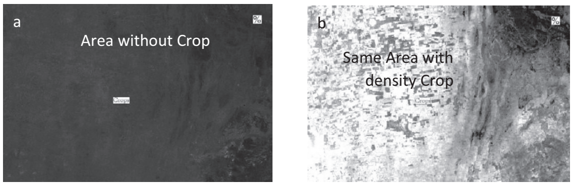

Fig. 11. Zomed – Subset image of SMA analyses results (a/b), showing the temporal dynamic change of crop area in 1986 compared to 2014 (High fraction of crop illustrated by brightness colour).

colour composite of the magnitude and the angle of change direction in vegetation fraction (Table 1).The desertified areas in CVA are characterized by an increase of sand fraction and decrease in vegetation fraction. This is measured by a positive angle of sand fraction and a negative angle of vegetation fraction. The re-growth class was characterized by an increase of vegetation cover and decrease of sand soil. While the persistence areas was indicated by increase or decrease in both sand and vegetation fractions. The change classes as an example are presented in Fig. 12, between 1972 and 2014.

The result of the CVA image highlights intensive dynamics related to the different classes during the periods of 1972 and 2014, which characterized by the increase of (green vegetation) cropped are in the study area. The change image shows that desertification class cover about 25.6% of the total area. Meanwhile the r-growth and persistence classes cover 45.9% and 28.004% respectively. This indicates the trend of the increasing and decreasing sand encroachment in the study area during year 1972–2014.

Generally speaking, we can say that, there are good grounds to stress that desertification/land degradation is the one main cause for the food shortage and poverty of the people. This is based on three arguments:

Table 1
Possible change classes from both input and related types of change.

Class name	Sand fraction	G.Vegetation Fraction
Desertified	+	–
Re-growth	–	+
Persistence	+–	+–

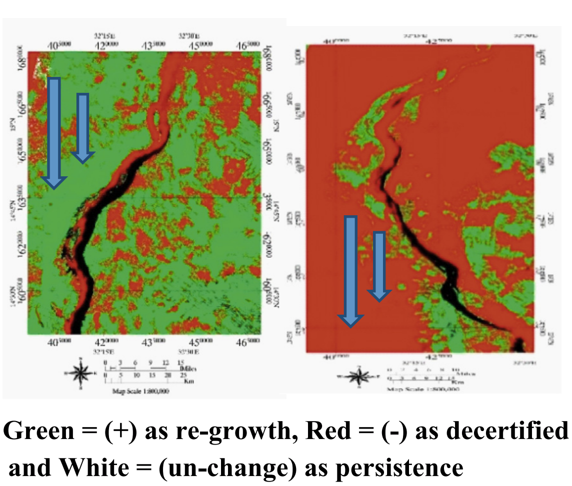

Fig. 12. The changed in Vegetation fraction during the 1972–2014 years (Left and right).

i. Low productivity of crops.
ii. Perception of the people.
iii. Reduction or disappearance of plant cover in some areas.

The most important consequences of desertification have been referred to. These can be summarized in the following: (1) Marked low productivity of crops, (2) Significant degradation in the vegetation cover despite of the rains recovery, (3) sharp decline in the animal wealth, (4) drop in soil fertility, and reduction in the natural vegetation cover (rangelands).

4. Conclusion

The paper provide that SMA technique is powerful for characterization and mapping of land degradation in the study area by providing direct measure of different land cover. SMA provides an invaluable tool for detecting and mapping land cover changes by offering more detailed information at sub-pixel level. Application of operational multi-temporal remote sensing data (Landsat TM and ETM±) in the present study demonstrate that it is possible to apply SMA efficiently in efforts to optimize the detection and analysis of regional and local land cover/land use changes in the Arid and semiarid environment. The study proved that sand encroachment threatens agricultural and pastoral areas in the study area, which led in some parts of the study area to disrupt agricultural operations. The study also proves that remotely sensed image, Change detection vector (CVA) and spectral Mixture Analysis (SMA) techniques provide detailed results which should be further exploited in similar studies.

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