African Journal of Agricultural Research Vol. 5(13), pp. 1609-1615, 4 July, 2010
Available online at http://www.academicjournals.org/AJAR
DOI: 10.5897/AJAR09.078
ISSN 1991-637X ©2010 Academic Journals

Full Length Research Paper

Expansion of mechanised rain-fed agriculture and land-use/land-cover change in Southern Gadarif, Sudan

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Accepted 20 April, 2010

This study was an effort to produce synthetic knowledge on the rapid land-use/land-cover (LULC) changes and on the integrating rates of change with fundamental patterns in southern Gadarif region, Sudan, for the period 1972 - 2003 using remote sensing imagery. The area is known for its sorghum and sesame production. Comparisons of LULC changes showed that the land-cover of the southern Gadarif region has changed drastically since the introduction of mechanized rain-fed agriculture in the area. The agricultural expansion was on the expenses of the natural vegetation cover. The average natural vegetation clearing rate was around 0.8% per year, and the most rapid clearing occurred during the seventies when conversion rates increased to about 4.5% per year. The average rate of vegetation clearing in the region exceeded the national average of deforestation. Recently, the conversion of natural vegetation to agricultural land has slowed because almost no land was left for further expansion. In the period 1999 - 2003 significant natural re-vegetation on abandoned land was detected. Being the most important rain-fed agricultural region in the country, information about patterns of LULC changes through time provides a better understanding of land utilization aspects and also plays a crucial role in the formulation of policies and program required for sustainable development of the region.

Key words: Mechanised agriculture, change detection, vegetation clearance, remote sensing, Gadarif, Sudan.

INTRODUCTION

Timely and accurate change detection of earth surface features is extremely important to understand relationships and interactions between human and natural phenomena in order to promote better decision making (Lu et al., 2004). Thus remotely sensed data represents a viable source of land-use/land-cover (LULC) information which can be efficiently and cheaply extracted in order to assess and monitor these changes effectively, because of repetitive coverage in short intervals and consistent image quality (Mas, 1999). Traditional methods for land-cover change monitoring rely on field-data and aerial photography. They can, however, be costly and time-consuming for large areas (Peterson et al., 2004). LCLU change detection provides fundamental input for planning, management and environmental studies, such as landscape dynamics or natural risks and impacts (Serra et al., 2003). Due to its temporal resolution, remotely sensed data provides an excellent historical framework for estimating the spatial extent of LCLU changes. In this respect remotely sensed data represents the sole source of such information in many parts of the world, especially in developing countries. It involves the application of multi-temporal datasets to quantitatively analyse the temporal effects of the phenomenon. Due to the advantages of repetitive data acquisition, its synoptic view, and digital format suitable for computer processing, remotely sensed data have become the major data source for different change detection applications during past decades (Singh, 1989). A proper change detection research should provide the following information: area change and change rate; spatial distribution of changed types; change trajectories of land-cover types; and accuracy assessment of change detection results (Lu et al., 2004). In a variety of studies, the post-classification change detection method was found to be the most suitable one for detecting LULC

Abbreviation: LULC, land-use/land-cover.

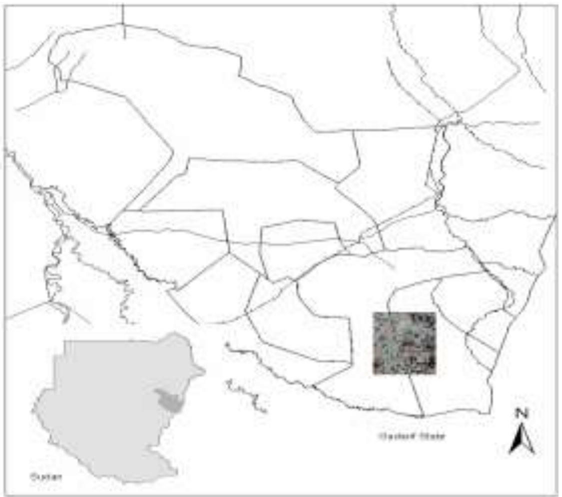

Figure 1. Location of the study area in Southern Gadarif.

change (Howarth and Wickware, 1981; Mas, 1999; Serra et al., 2003; Peterson et al., 2004).

Post-classification is a term describing the comparative analysis of spectral classifications for different dates produced independently (Singh, 1989). The technique compares, on a pixel-by-pixel basis, multiple maps created from remotely sensed data collected at different times (Peterson et al., 2004). It identifies not only areas of change, but also provides directional information of the observed change (Jensen, 1996). In the Gadarif region, Sudan, destruction of the natural vegetation for agricultural expansion is one of the major causes for the degradation of renewable resources and the environment (Sulieman and Buchroithner, 2009). Therefore, it is essential to assess the impact of this introduction on the natural resources, namely natural vegetation, so as to have a clear vision of sustainable management and utilization of this vital resource for its present use and future perspectives. Analysis of the recent history of LULC offers a present-day baseline for assessing future landscape patterns and their consequences (Zheng et al., 1997). Recently, remote sensing has significantly improved the capability to monitor processes of deforestation and secondary succession processes, particularly in the tropics (Westman et al., 1989). Within this context, the objectives of the study are to identify changes in the spatial and temporal pattern of the LULC due to the expansion of mechanized rain-fed agriculture and to quantify rates of changes for the period 1972 - 2003.

STUDY AREA

The study area, located in the Southern Gadarif region (Sudan), is approximately 55 x 40 km^2 (Figure 1). The area is known for its production of sorghum and sesame. Agriculture is the main economic activities in the area. Introduction of large-scale mechanized farming in the area started in the 1950s. The topographical features of the study area are undulating relief with several major drainage systems. Dominant soil type is dark heavy cracking vertisol. A well-defined rainy season lasts from June to September. The annual average precipitation is 670 mm and the annual average temperature is 29°C. Vegetation cover is woodland savannah (Sulieman, 2008).

METHODOLOGY

Data sets

Cloud-free Landsat Multi-spectral Scanner (MSS) and Enhanced Thematic Mapper (ETM) imagery have been utilized for the multi-temporal change detection (Table 1). Due to the unavailability of other sources of data Landsat imagery represents the only available data source for detecting historical LULC changes in the study area. Moreover, its consistency of acquisition over the last four decades and reasonable spatial resolution make it an indispensable means for LULC classification world-wide. Except the Landsat MSS 1989 -12 -12 the rest was freely downloaded from the Global Land Cover Facilities (http://www.landcover.org/index.shtml).

Data processing

Even for the new generation of space sensor systems image pre-processing remains an essential initial step for any remote sensing application. Image corrections are also necessary for the current study for many reasons. Multi-sensor imagery (four different sensors) will be utilized, namely Landsat 1, 3, 4 and 7. Moreover, the temporal range of the imagery set is about 30 years (1972 to 2003) using scenes from five dates. For sure, during this relatively long period, many factors (e.g. radiometric and geometric artifacts) have changed (Markham and Barker, 1987).

Geometric corrections are critical to enable accurate multi-temporal imagery analysis and vegetation mapping. Scene to scene registration to sub-pixel accuracy is required for multi-temporal analysis. Image co-registration was based on 7 to 20 GCPs for the 55 x 40 km^2 study area which were manually placed or automatically matched using image-to-image registration technique in ERDAS Imagine. Landsat ETM+ March 2003, the most recent in the image set, was taken as reference image for the co-registration. The reference image rectification is achieved using 1:100 000 topographic map dated to 1983. However, during this time lag of 30 years the area underwent significant changes. Therefore, it was hard to fulfil the recommended accuracy of less than one pixel for the rectification process due to the recent changes in the area and lack of man-made features. However, the geometric lines of the farm boundary which can easily be detected in the raw images are also changing every short period if not from season to season due to agricultural practices or abandonment. To improve the accuracy, ground control points (GCPs) were collected using a handheld GPS which provides 15 m real-time accuracy. This also implies another source of error.

Land-use/land-cover types

There exist no recent maps and records concerning the land use

Table 1. Satellite imagery used for the multi-temporal change detection.

Satellite	Sensor	Path/row	Acquisition date	Spatial resolution (m)
Landsat 1	MSS	184/51	1972-12-11	60*
Landsat 3	MSS	184/51	1979-11-23	60*
Landsat 4	MSS	171/51	1989-12-12	60
Landsat 7	ETM	171/51	1999-11-06	30
Landsat 7	ETM	171/51	2003-03-22	30

*Resampled resolution.

activities for the study area. Therefore, the determination of LULC classes was based on field survey, interviews with farmers and visual comparison of the original images. Thus, the major LULC classes were bare land, natural forest, cultivated agricultural land, abandoned agricultural land and secondary forest on abandoned agricultural land. However, the last two classes only appeared after the seventies.

Supervised classification

The major step in a straightforward supervised classification is the selection of training pixels. Prior to the identification of training pixels, field surveys (March and April 2005) were carried out and historical land-use information was collected from pioneer farmers who were among the first group to invest in mechanized farming in the area. The second group interviewed was the staff of the Forest National Corporation.

Accuracy assessment

Unfortunately, neither aerial photographs nor ground data could be used to conduct an accuracy assessment of the 1972 and 1979 imagery. Due to drastic changes of the LULC in the study area the 1:100 000 topographic map from 1983 was not valid. Instead, the accuracy of the classified image was assessed by visually interpreting the unclassified satellite images. Random samples of 320 points were obtained across each scene. Identification of LULC types of the sampling points for each scene was based on image interpretation and was then recorded for comparison with the results obtained from the classified maps (ERDAS, 2003).

Training data evaluation

The selection of signatures that accurately represent the classes was carried out using a contingency matrix. Contingency matrices perform a quick classification of the pixels in a set of training samples. This allows getting an impression of considering what percentages of the sample pixels are actually classified as expected. In order to obtain an appropriate level of classification accuracy, contingency of training data were tested prior to the classification using the ERDAS Imagine signature evaluation tools. The contingency matrix utility allows the evaluation of signatures created from different areas of interest in the image. The output of the contingency matrix utility is a matrix of percentages and/or pixel numbers that allow seeing how many pixels in each training area were assigned to each class (ERDAS, 2003). A perfect set of training data which resulted in a contingency only along the diagonal is depicted in the appendices.

RESULTS AND DISCUSSION

Maximum likelihood classification

Based on the comparison with 320 points, overall classification accuracies were estimated to be 88.50, 85.19, 89.90, 92.12 and 90.71% for 1972, 1979, 1989, 1999 and 2003 imagery respectively. Standard errors obtained from the accuracy assessment performed were ranged between 1.4% for bare land and 6.8% for abandoned agricultural land. While the purpose of this study was to detect major changes in land cover over the last thirty years rather than to develop a detailed classification of the LULC, the accuracy gained and its standard deviation seem to be sufficient. Zheng et al. (1997) performed a comparison with 345 visually interpreted points from each image; the overall classification accuracies were estimated to be 81.9 and 91.8% on the 1988 and 1972 land-cover maps in Changbai Mountain area of China and North Korea, respectively. It was observed that it was not always like this that the higher resolution imagery has grater classification accuracy. Though containing more detailed ground information, the images of finer spatial resolution do not necessarily achieve higher classification accuracy (Hsieh and Lee, 2000; Huiping et al., 2003).

The results of the maximum likelihood classification are shown in Table 2, while Figure 2 depicts the visual display. During the seventies the LULC consisted of three classes: bare land, natural forest and cultivated agricultural land. Later in the eighties abandoned agricultural land and secondary forest on abandoned agricultural land appeared. The area under cultivation was drastically expanded at the expenses of the natural vegetation cover. During 1980s, however, farmers began to abandon their land. Land abandonment was detected in many areas, even in the newly cultivated land in the southern part of the study area which could be due to the problem of accessibility. Land abandonment is a common practice in Gadarif due to poor soil fertility and weed invasion as a result of mal-agricultural practices (Sulieman and Buchroithner, 2009). Moreover, some areas in the southern part of the study along the border with Ethiopia is partially inaccessible due to problems of insecurity. Therefore most of these areas are now covered by

Table 2. Area (ha) and percentage of LULC classes during the study period 1972 - 2003.

Class	1972		1979		1989		1999		2003	
	Area	**(%)**	**Area**	**(%)**	**Area**	**(%)**	**Area**	**(%)**	**Area**	**(%)**
1	8235.40	04.51	13052.62	07.14	8163.92	04.44	2027.05	01.11	13874.44	07.61
2	107101.80	58.67	49345.59	27.03	26303.50	14.31	46243.36	25.36	56630.79	31.05
3	67239.31	36.83	120178.30	65.82	113824.0	61.94	73609.46	40.37	69054.73	37.85
4	NE*		NE		35472.49	19.30	38250.93	20.98	21548.25	11.82
5	NE		NE		NE		22222.26	12.18	21317.60	11.69

Where 1: Bare land, 2: Natural forest, 3: Cultivated agricultural land, 4: Abandoned agricultural land and 5: Secondary forest on abandoned agricultural land. *NE: LULC class not existed.

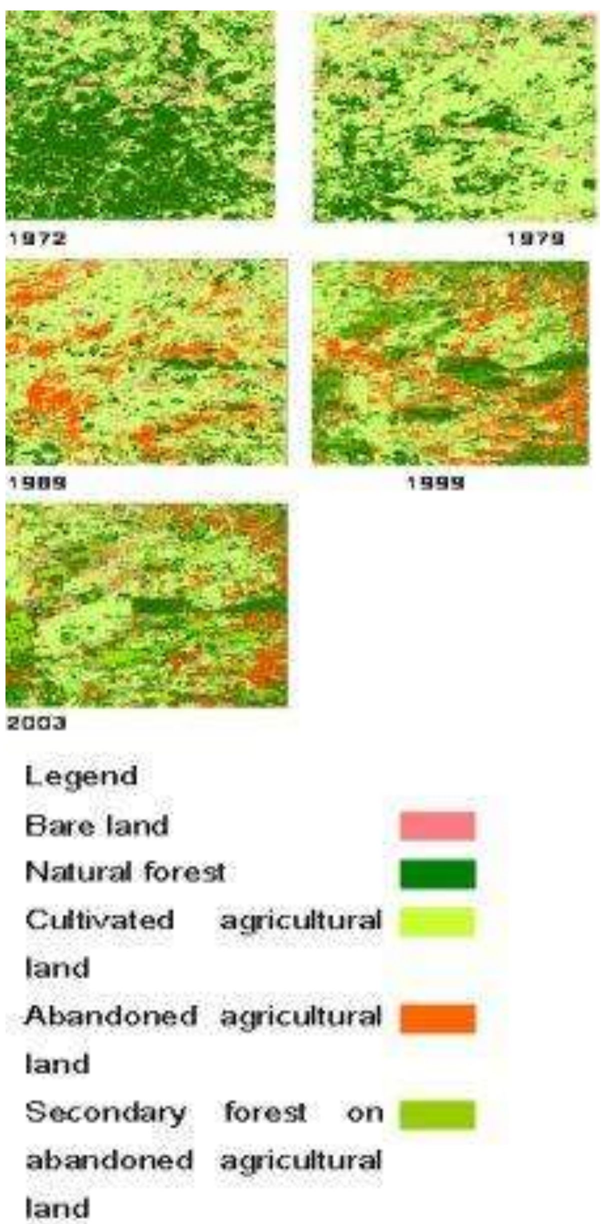

Figure 2. Maximum likelihood classification showing LULC through the period 1972 - 2003.

secondary forest. In this context, accessibility has to be considered as one of the most important driving factors of LULC change (Geist and Lambin, 2002). According to Verburg et al. (2004) the possibility for people to reach desired locations, such as a market or forest land, can influence both the extent and the location of land-use conversions.

Post-classification comparisons (Land-use/land-cover change rates)

Post-classification comparisons provides "from-to" information. Actual change can be obtained by a direct comparison between classified images from one date with that from the other date. Temporal changes that have occurred between the two dates can be measured by performing a change matrix (Table 3). The principal advantage of post-classification lies in the fact that the two dates of imagery are separately classified; thereby minimizing the problem of radiometric calibration between dates (Coppin et al., 2004).

The period 1972 to 1979 shows an intensive clearance of natural vegetation due to a dramatic expansion of mechanized rain-fed agriculture. It reached up to 4.52% per year and the total area under the plough represent 65.9% (120178.30 ha). According to the information collected from the farmers, the seventies were the golden time of the rain-fed mechanized agriculture in the region, and the high initial profitability encouraged many farmers to clear new areas from its natural vegetation. Moreover, opening new areas has double benefit, gaining a new fertile agricultural land and at the same time selling the harvested wood at local market as fire wood and or building materials. Woody materials are still the main building material in the region. Abandoned agricultural land was not detected during this period. The LULC changes for the period 1979 - 1989 show also a decrease of the natural vegetation and the abandoned agricultural land appeared during this period (represent 10.8%). It is clear that the agricultural expansion reached its culmination during this period, and farmers started to abandon parts of their land due to drops in crop yield or

Table 3. LULC change matrices (ha) during the period 1972 - 2003.

	1972	**1979**			**Total 1972**
	Class	**1**	**2**	**3**	
Matrix 1	1	847.10	1589.55	5798.75	8235.40
	2	5900.98	34064.27	67136.54	107101.80
	3	6304.54	13691.77	47243.00	67239.31
	Total 1979	13052.62	49345.59	120178.30	

	1979	**1989**				**Total 1979**
	Class	1	2	3	4	
Matrix 2	1	1158.46	1543.65	8828.63	1600.97	13131.71
	2	1710.75	9042.31	27891.15	11023.80	49668.01
	3	5294.70	15717.54	77104.22	22847.72	120964.20
	4	0.00	0.00	0.00	0.00	0.00
	Total 1989	8163.92	26303.50	113824.00	35472.49	

	1989	**1999**					**Total 1989**
	Class	1	2	3	4	5	
Matrix 3	1	256.52	2495.08	1726.13	1420.04	2203.48	8101.25
	2	321.85	9389.06	8105.40	4898.79	3386.45	26101.55
	3	1174.25	28745.28	45422.83	22565.51	15042.24	35200.16
	4	274.43	5613.94	18355.11	9366.59	1590.09	112950.10
	5	0.00	0.00	0.00	0.00	0.00	0.00
	Total 1999	2027.05	46243.36	73609.46	38250.93	22222.26	

	1999	**2003**					**Total 1999**
	Class	1	2	3	4	5	
Matrix 4	1	319.51	628.28	428.58	297.57	353.11	2027.05
	2	3493.44	18496.58	10767.71	5055.90	8429.73	46243.36
	3	4470.88	18644.83	37979.18	8597.10	37979.18	107671.20
	4	1869.28	12353.97	14953.09	6215.73	2858.86	38250.93
	5	3725.68	6493.84	4879.74	1372.21	5750.79	22222.26
	Total 2003	13878.79	56617.50	69008.30	21538.50	55371.68	

Where 1: Bare land, 2: Natural forest, 3: Cultivated agricultural land, 4: Abandoned agricultural land and 5: Secondary forest on abandoned agricultural land.

weed invasion (Sulieman and Buchroithner, 2009). Later, during the period 1989 -1999, the conversion of natural vegetation to agricultural land has slowed down and abandoned land increases. Therefore, about 40% of the area was under cultivation, whilst the natural vegetation (the already existing one and the parts which could naturally re-establish) covers up about a quarter of the area. However, the abandoned agricultural land could be managed as natural restoration sites. Following appropriate silvicultural strategies this could enhance the productivity of abandoned areas for producing firewood or building materials, whilst maintaining or enhancing habitat and conservation benefits of the natural re-growth could serve as one of the attractive options for farmers. During the field visit it was observed that firewood or building represent a major source of income for significant group of farmers. Asefa et al. (2003) mentioned that land abandonment is the common conservation strategies to promote restoration of biodiversity in degraded agricultural and grazing lands in Northern Ethiopia. The average natural vegetation clearing rate during the study period was around 0.79 ha per year. The average and largest rate of deforestation exceeded the average rate of deforestation for the entire country (FRA, 2005). Land-use change patterns in the study area have been caused by two different contradicting agents in different periods: vegetation clearing for mechanized rain fed expansion in one period and abandonment in the succeeding period.

Conclusion

Multi-temporal change detection analysis using satellite imagery successfully identified changes in the spatial and temporal pattern of the LULC due to the expansion of mechanized rain-fed agriculture. Adequate temporal and spatial resolution is highly recommended due to high spatial and temporal changes. From a financial point of view such cheap and opened - source of satellite imagery could represent the only source of data for countries like Sudan where there is no budget from purchasing satellite imagery. Generally, forest clearing and vegetation re-growth can be distinguished visually in Landsat data. It is difficult, however, to differentiate land cover types exhibiting vegetation re-growth in its early successional stage. Most of the inaccuracy of the classification was associated with spectral confusion of some re-growth areas that were classified as agricultural land.

ACKNOWLEDGEMENT

The financial support of the German Academic Exchange Service (DAAD) is duly acknowledged.

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APPENDIX

Appendix 1. Contingency of error matrix for maximum likelihood classification of training data.

	Classified data	Reference data (%)			Total pixel
		1	2	3	
1972	1	100	0.00	0.52	1733
	2	0.00	99.55	0.78	11739
	3	0.00	0.45	98.70	6264
	Total pixel	1700	11743	6293	19736

	Classified data	Reference data (%)			Total pixel
		1	2	3	
1979	1	100.00	0.02	0.19	1388
	2	0.00	93.51	1.41	16076
	3	0.00	6.46	98.39	11204
	Total pixel	1364	17036	10268	28668

	Classified data	Reference data (%)				Total pixel
		1	2	3	4	
1989	1	99.97	0.03	0.33	0.00	
	2	0.00	91.58	1.99	0.40	
	3	0.03	6.83	96.58	1.66	
	4	0.00	1.56	1.10	97.94	
	Total pixel	2905	35353	35111	19294	

	Classified data	Reference data (%)					Total pixel
		1	2	3	4	5	
1999	1	99.38	0.01	0.00	0.00	0.34	509
	2	0.00	93.87	2.32	0.24	1.91	23430
	3	0.00	2.87	96.95	0.20	0.03	8146
	4	0.00	0.59	0.56	99.56	0.00	2656
	5	0.62	2.66	0.17	0.00	97.73	7373
	Total pixel	486	24625	7667	2478	6858	42114

	Classified data	Reference data (%)					Total pixel
		1	2	3	4	5	
2003	1	99.82	0.04	2.08	0.00	0.48	2517
	2	0.00	95.63	1.05	2.60	1.48	25548
	3	0.09	2.02	96.71	0.02	0.11	12410
	4	0.00	0.83	0.06	97.38	0.00	4908
	5	0.09	1.48	0.11	0.00	97.92	6672
	Total pixel	2224	26351	12272	4809	6399	52055

Where 1: Bare land, 2: Natural forest, 3: Cultivated agricultural land, 4: Abandoned agricultural land and 5: Secondary forest on abandoned agricultural land.