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Impact of Biofuel Production on Land-Use Change: Case of Jatropha Farming, Kisarawe District, Tanzania

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Abstract: Globally, agricultural sector is the major driver for land use change (LUC), in East Africa where savannas, grassland and shrubland are dominant, land previously occupied by forests is the major source of new agricultural land. The use of agricultural-based biofuels has been expanding worldwide, biofuel farming associated with LUC should be measured as the direct land use change (dLUC); when a biofuel feedstock (e.g., jatropha) directly displaces another land use. The indirect land use change (iLUC); when a productive land use displaced by a biofuel feedstock propels the conversion of native vegetation elsewhere. Few studies have been carried out in Tanzania to investigate the effect of agriculture-based biofuel on LUC, the objective of this study was to investigate the LUC resulting from jatropha production introduced in year 2009 by Sunbiofuel Company in villages within Kisarawe District, Coast Region. Remote sensing and geographical information system (GIS) techniques on Landsat multidate satellite imagery and secondary data were used to establish patterns of direct and indirect LUC. Multidate satellite images were classified and analyzed to study the LUC at three epochs; before cultivation (year 1985), immediately after starting production (year 2010) and year 2011. The study revealed a significant increase in cultivated land, a decrease in forested land and encroachment into forest reserve. It was concluded that the conversion of land used for crop production into jatropha farming caused direct and indirect LUC in the area. The outputs from the study can be used as inputs to the models and methodologies for quantifying LUC effects due to introduction/expansion of biofuels production within a district.

Key words: biofuels, land use change (LUC), classification, remote sensing, GIS

1. Introduction

Globally, agricultural sector is the major driver for land use change (LUC), Ramankutty et al. (2002) [1] estimated for the year 2000 1.5 billion ha were cropland; out of which 47 percent were converted from forest, 38 percent converted from savanna/grassland and 13 percent converted from shrub. The distribution of cropland and pastures over the different biomes is not homogeneous worldwide; in Europe there is a strong concentration on land which were previously used for forest while in Africa, lands previously occupied by savannas/grasslands are more relevant. The historical expansion of the agricultural sector over time justifies that it was responsible for significant conversion of native vegetation land. Studies by Gibbs (2010) [2] of regions in which the agricultural sector has been growing steadily show that forests were the primary source of new agricultural land in the 1980s and 1990s. In Central Africa, West Africa and South Asia, more than 90 percent of new agricultural land occupied and disturbed forestland. Even in South America and East Africa where savannas, grassland and shrub land are more relevant, land previously occupied by forests is still the major source of new agricultural land [3]. The use of agricultural-based biofuels has been expanding globally, with the assumption that they can be used as a source for decreasing green house gas (GHG) emissions. But, the

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actual effectiveness of biofuels in targeting GHG emissions when considering land-use changes is still doubtful. Discussions on how to assess GHG emissions from biofuel policies, specifically on non-observed LUC effects involve the limitations on the existing methodologies, and how to isolate the effects of biofuels. Biofuel GHG emissions associated with LUC should be measured as the direct conversion; when a biofuel feedstock (e.g., jatropha) directly displaces another land use. The indirect conversion occurs when a productive land use displaced by a biofuel feedstock propels the conversion of native vegetation elsewhere[4]. In global analyses, both the direct and indirect effects can be measured through models. Different models and methodologies are available for quantifying LUC effects owing to the expansion of biofuels. The methodologies roles are to establish patterns of LUCs based on observable historical data, the patterns are used to define direct and indirect contributions of individual agricultural uses within a boundary. Few studies have been carried in Africa to investigate the effect of agriculture-based biofuel on LUC.

The objective of this study is to investigate the LUC resulting from biofuel production carried out by Sunbiofuel Company in villages within Kisarawe District, Coast Region. Landsat multidate satellite imagery and secondary data were used to establish patterns of direct and indirect LUC. The outputs from the study can be used as inputs to the models and methodologies for quantifying LUC effects due to introduction/expansion of biofuels production within a district.

2. Biofuel Project in Kisarawe

Kisarawe district acreage is 353,500 ha, of which 309,000 ha are arable and 83,645 ha are under cultivation [5]. The district is ideal for food production, also attractive to jatropha investors; since not all land is arable there is a competitions for land to grow food and jatropha within Kisarawe. Under the Agricultural Sector Development Plan (ASDP), the Kisarawe local government is aiming to boost its economy by introducing a new cash crop — jatropha. It was envisaged that a multinational company, in the name of *Sun Biofuels* in the area will empower the local community to improve road and water systems infrastructures, and modernize the agriculture sector. In pursuit to get cheap biofuels onto the European markets fast, many European companies made commitments to local communities in the south of how they will use their land for biofuels production with provision of many benefits. The Sun Biofuels is a British company, based in United Kingdom (UK), registered with the *Tanzania Investment Centre* (TIC) to produce biofuel in the country with its operations in Kisarawe District (Coast Region). The company acquired 9,000 ha of land within 11 villages at Malumbo in Kisarawe for its operations; the company endevour was to extract oil from jatropha for export. The company began land clearance in 2009 to establish more than 8,000 ha biofuel plantation, by mid 2011 about 2,000 ha were cleared and replanted with jatropha.

3. Study Area

The study area covers about 105,870 ha, geographically it spans from Longitude 38°41′02″E to 38°41′03″E and Latitude 6°51′07″S to 7°11′39″S in Kisarawe District. Kisarawe is one of the districts of the Coast (Pwani) Region in Tanzania’s east coast; approximately 20 km from Dar es Salaam City. The population of the Kisarawe district is 95,614 with average population growth rate of 2.1% [5]. The Coast region, has the average temperature of about 28°C. The region experiences average annual rainfall ranging between 800 and 1,000 mm. The long rains are mainly received for about 120 days on average between March and June. The short rains are received for about 60 days between October and December.

Kisarawe District farmers work on a90% subsistence level and the district has the least off-farm income among coastal regions [5]. The district has a good road

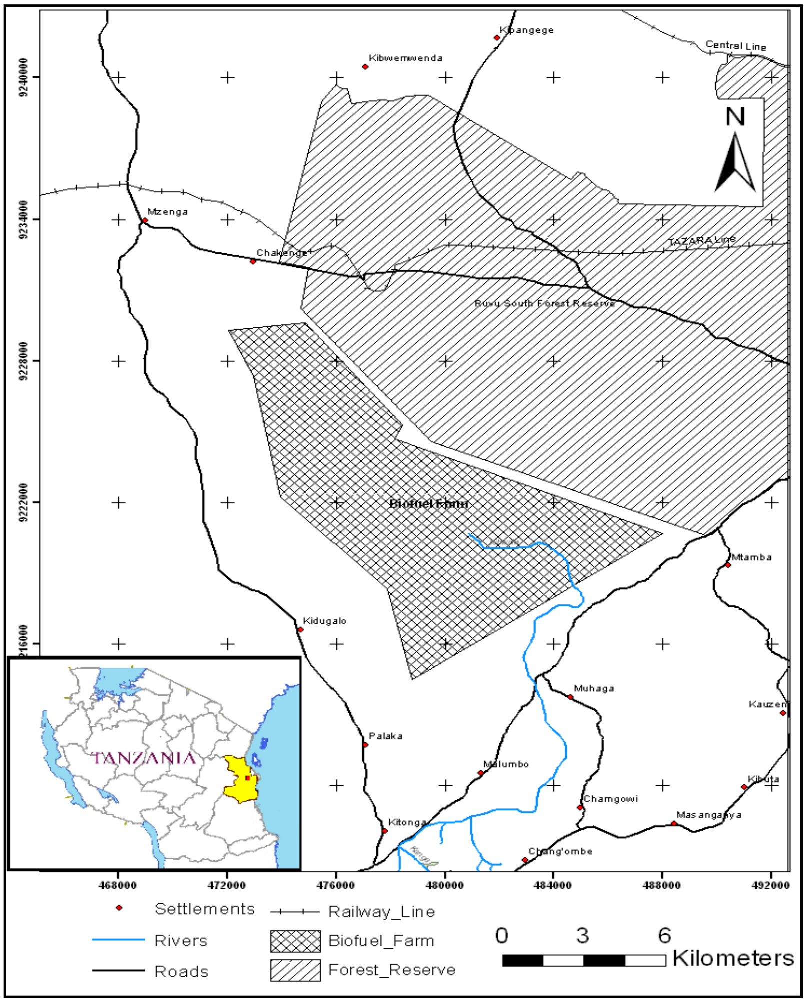

Fig. 1 Study area location showing biofuel production area.

connection to the Central railway line and TAZARA railway line, these makes Kisarawe to be ideal for agroindustry development. Three rivers, namely, Ruvu, Wami, and Rufiji are in the district. Within the district there are Kazimzumbwi, Pugu and Ruvu South Forest Reserves, which are the lowland coastal forests, which were gazetted as protective and productive forest in 1957 [6, 7]. Ecologically, Kisarawe is suitable for such crops as maize, rice, cashew, sorghum, cowpea, sweet potato, cotton, passion fruit, simsim, and millet; the annual crop yields are relatively low.

4. Data and Pre-processing

4.1 Landsat Data

The satellite data used in this study, Landsat imagery of path 166 and row 65 (p166r065), were multidate Landsat *Thematic Mapper* (TM) for the years 1985, 2010 and 2011. These images were of 30m resolution of July 1985, 2010 and 2011.

4.2 Reference Data

The reference datasets, for training samples during image classification and in accuracy assessment, were; *Google Earth* imagery of year 2010 (downloaded on July/August 2013), existing Standard Topographical Sheet of Kisarawe (Sheet 186/3) at scale of 1/50,000 and ground reference data obtained from differential and hand-held *global positioning system* (GPS) observations.The characteristics of the data are presented in Table 1.

Table 1 Details of the data used in the study.

SN	Data Type	Description
1.	Landsat TM imagery	Path 166 Row 065 – resolution 30m (i) July 1985 during dry season (ii) July 2010 during dry season (iii) July 2011 during dry season
2.	Topographical sheet	Sheet 186/3 of 1987 at scale of 1:50,000 - Kisarawe standard sheet.
3.	Ground survey	Sunbiofuel farm boundary coordinates from cadastral survey plan, ground truth data from hand-held GPS observations.
4.	Google Earth image	Study area image downloaded on 6th October 2012 and in July/August 2013.

4.3 Data Pre-processing

The data were pre-processed and georeferenced to UTM Zone 37 (WGS84) coordinate system, the study area sub-scene were extracted from the images and topographical sheet using ERDAS Imagine software.

5. Methods

5.1 Image Classification

Yuan (2005) states that, a systematic listing of the classes of interest (classification scheme) for an image classification project has to be exhaustive and mutually exclusive. Also, number of classes has to be optimal since large number of classes may lead to misclassification while too few classes may miss the users information needs. In this research study, three schemes for land-use/cover classification were compared, the classification schemes were; Level I of Anderson et al. (1976) [8] which was developed purposely for use with remote sensing techniques, the Global Land Cover (GLC 2000) (recognized by European nations), and the Good Practice Guidance for Land Use, Land Use Change and Forestry (GPG-LULUCF) which is recognized by United Nations and the Intergovernmental Panel on Climate Change (IPCC).

The classification scheme adopted was modified from Anderson (1976) [8] with three, instead of six, classes Level I. The three classes used were; agriculture-grass, bare land and forest. These classes were picked to suit the study area condition, also since Landsat data are only suitable for Level I land-use/cover mapping [9], the description of these LUC classes are presented in Table 2.

5.2 Classification Accuracy Assessment

Supervised maximum likelihood classification method was used to classify the three epochs imagery separately, ERDAS Imagine accuracy assessment was performed for each classified image. A randomly selected pixels from each classification were used for accuracy assessment, for the classified land use maps of 1985, 2010, and 2011 the number of selected reference pixels were 265, 275 and 266 respectively. The numbers of reference pixels were chosen on basis of Congalton (1991) [10], who stated that more than 250 reference pixels are needed in order to achieve class mean accuracy to the tolerance of 5%.

5.3 Change Detection

Land Change Modeler (LCM) module of IDRISI Selva was used to analyze the landuse/cover changes between classes during the 1985-2010 and 1985-2011epochs. Change detection was performed using tools in the module to evaluate gains and losses, net change and transitions trend on the study area. The images were imported from ERDAS environment to the IDRIS Selva platform by analysis.

6. Results and Discussion

6.1 Classification Accuracy

The accuracy of each class was estimated using producers and users accuracies. The producers

Table 2 Study LUC classification scheme.

S/N	LUC Class	Description
1	Agriculture-Grass land	Crop fields, savanna grassland, cultivated land with young growing crops/nurseries and shrubs
2	Bare land	Quarries, sand, cultivated land without crops, built-up area and gravel pits
3	Forest	Deciduous forest land, evergreen forest land, and mixed forest land

accuracy is a measure for the probability that the classifier has marked an image pixel into specific class, while users accuracy is a measure showing the probability that a pixel is a specific class given that the classifier has named the pixel into that class [10]. Table 3 gives summary of the accuracy assessment results realized from ERDAS accuracy analysis. The classification accuracies were as follows; User's accuracy of individual classes ranged from 82% to 94% for year 1985, 69% to 77 % for year 2010 and 62% to 87% for year 2011 while producer's accuracy ranged from 85%-93%, 71%-77% and 57%-72% for years 1985, 2010 and 2011 respectively.

6.2 Classification and Change Maps

Classification maps were realized for all three years (Fig. 2). For year 1985 agriculture-grass land was approximately 42,491 ha (41.01%), forest 10,281 ha (9.92%) and bare land class was 50,845 ha (49.07%). In year 2010 agriculture-grass land was 1,944 ha (1.88%), forest 40,700 ha (39.28%) and bare land category was 60,974 ha (58.84%). For year 2011 agriculture-grass land was 22,023 ha (21.25%), forest was approximately 27,167 ha (26.22%) and bare land class was 54,428 ha (52.53%).

Table 3 Classification accuracy assessment.

Class Name	Reference	Classified	Number	Producers	Users
	Totals	Totals	Correct	Accuracy	Accuracy
(Year 1985)					
Agriculture – Grassland	133	140	122	93.44%	85.97%
Bare land	27	28	23	85.19%	82.14%
Forest	105	97	91	86.67%	93.81%
Total	265	265	236		
(Year 2010)					
Agriculture – Grassland	119	122	88	70.88%	69.98%
Bare land	107	101	78	72.90%	77.23%
Forest	47	52	36	76.60%	69.23%
Total	273	275	202		
(Year 2011)					
Agriculture – Grassland	202	211	176	69.32%	86.54%
Bare land	35	23	20	57.14%	86.96%
Forest	29	34	21	72.41%	61.76%
Total	266	268	217		

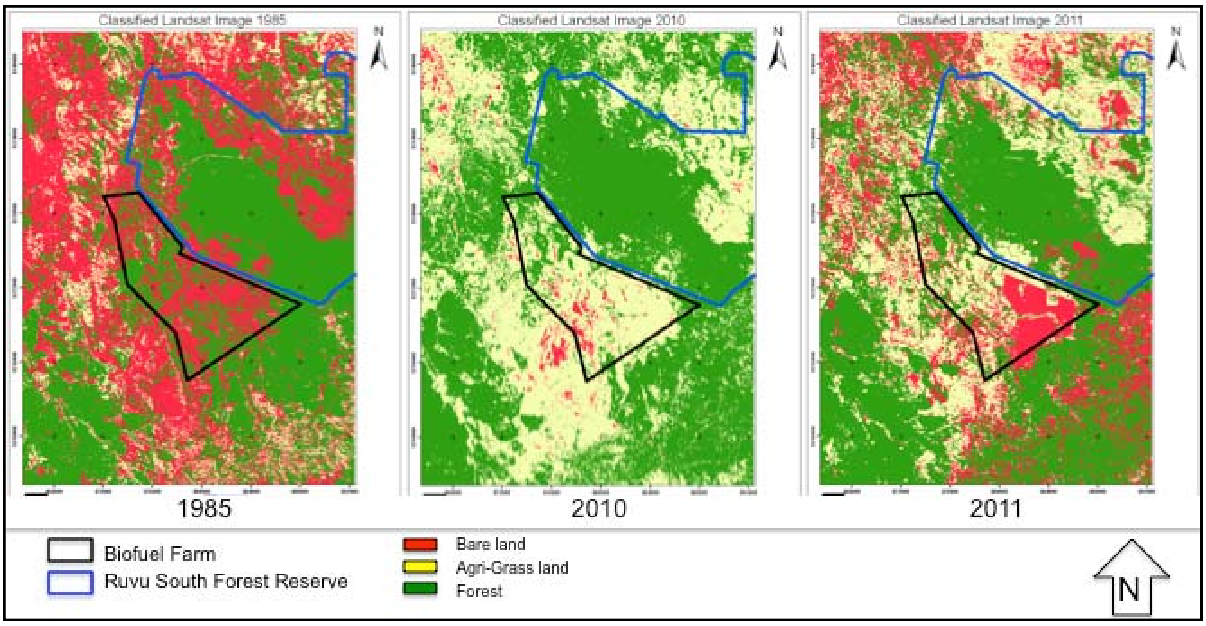

Fig. 2 Land use/cover classification of study area on Landsat image for years 1985, 2010 and 2011.

6.3 Land-Use/Cover Change

Chum and Warner (2012) states that *direct land use change* (dLUC) is caused by cultivation of biofuel crops on land earlier used for a different purpose whether its managed or unmanaged. In the study area, before land clearance for jatropha production, the land base was a mixture of agriculture and forestland with traces of grazing land [4]. The introduction of jatropha production on agriculture land was a dLUC and it caused a loss of forest through land clearing. The effect on agriculture-grass land was relatively more pronounced than that on forest (Fig. 3). A macro-economic pressure created an incentive for locals, thus, the replaced farmers ventured into forest reserves for illegal charcoal making and logging for sustenance. The situation also propelled by the necessity to cultivate land elsewhere to meet the economic pressure and demand, Chum and Warner (2012) termed it as *indirect land use change* (iLUC) due to introduction of biofuel farming in the area [4]. In the study area, the iLUC contributed in deforestation and forest degradation. The individual class change statistics for the two epochs; 1985-2010 and 1985-2011 were analysed in the land cover change matrices from 1985 to 2010, and 1985 to 2011 (Table 4). In the table, unchanged pixels are located along the major diagonal of the matrix while changed pixels are off-diagonal elements. Generally, the classes in the study area were primarily gaining and losing land but the bare land class was only losing in 1985-2010 epoch and doing both, gaining and losing, in 1985-2011. The Gains and Losses graph (Fig. 4) confirms that all three classes are dynamic within the study area.

The graphs of gains and losses by LUC classes (Fig. 3) shows the biggest gain is in the agriculture-grass category while the biggest loss is in bare land class on both epochs.

The trends of land-use/cover change, as shown on change matrices (Table 4) and change maps (Fig. 5), were as follows:

(i) Agriculture-grass land converted to bare land was 15,874 ha in 1985-2011 epoch, the decreasing trend of agriculture-grass could be attributed to the increase of rural population and introduction of jatropha farming; causing land clearance for houses, farming, roads and other infrastructures.

(ii) Forest area converted to agriculture-grass category was 123 ha (in 1985-2010) and it was 2,571

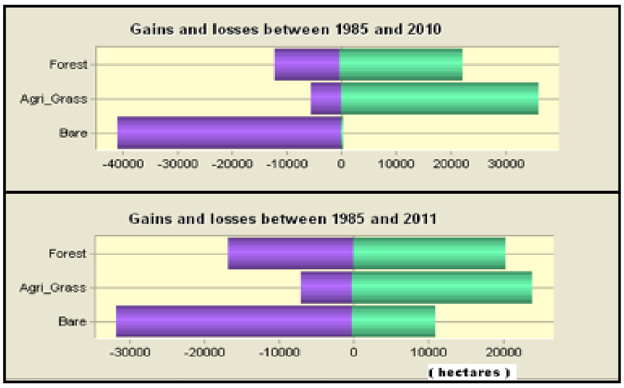

Fig. 3 Gains and losses by LUC classes of the study area for 1985-2010 and 1985-2011 epochs.

Table 4 Matrices of land use/cover changes from 1985 to 2011 of the study area.

(a) 1985-2010					
	1985			2010 Total (Ha) (%)	
	Agri-Grass	Forest	Bare land		
2010					
Agri-Grass	**1599**	123	222	1944	1.88
Forest	23949	**4742**	12009	40700	39.28
Bare land	16943	5417	**38614**	60974	58.84
1985 Total (Ha)	42491	10281	50845	103617	
(%)	41.01	9.92	49.07		100.00
(b) 1985-2011					
	1985			2011	Total
	Agri-Grass	Forest	Bare land	(Ha)	(%)
2011					
Agri-Grass	**10838**	2571	8613	22023	21.25
Forest	15778	**3206**	8183	27167	26.22
Bare land	15874	4504	**34050**	54428	52.53
1985 Total (Ha)	42491	10281	50845	103617	
(%)	41.01	9.92	49.07		100.00

ha (in 1985-2011) the deforestation was mainly due to urban expansion and macro-economic growth in the form of more demand for agriculture land.

(iii) In 1985-2010 epoch, the bare land area which was converted to agriculture-grass was 222 ha while in 1985-2011 epoch the conversion was 8,613 ha, which is mainly because the demand of agriculture land increased due to introduction of the jatropha farming in the study area.

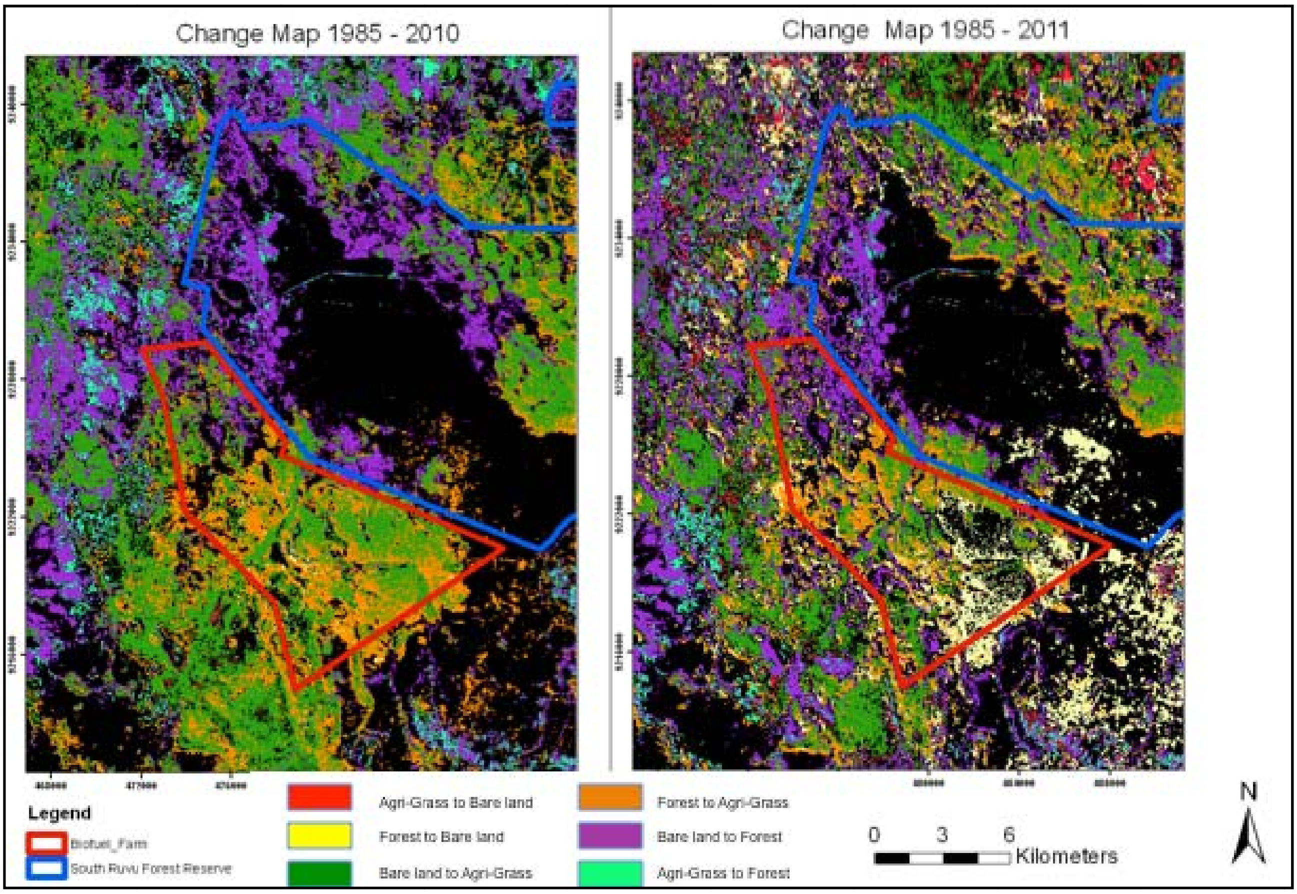

Fig. 4 Change Maps of land use/cover of the study area for years 1985-2010 and 1985-2011.

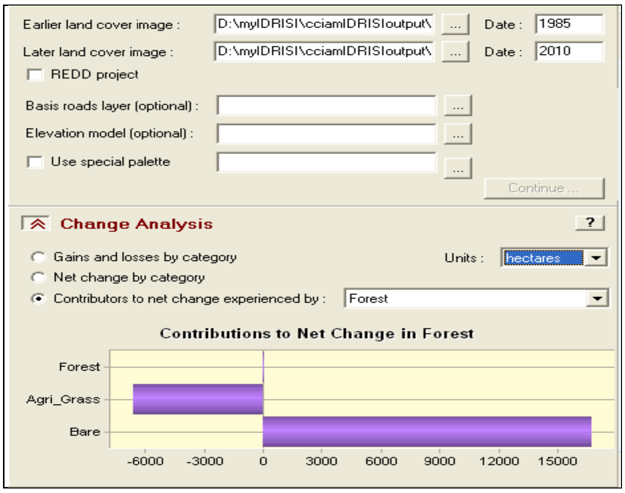

Fig. 5 Agriculture-grass and bare land classes contribution to study area net change in forest category in 1985-2010 years.

6.4 Transition and Trend Maps

Usage of Map the Transition tool produced change maps (Fig. 6), which showed the areas that changed from all classes to the agriculture-grass category for 1985-2011 epoch.

The change pattern was enhanced and more detailed by using Spatial Trend of Change tool in LCM module, a third-order trend of all classes to bare land class and to agriculture-grass class are shown in Fig. 7.

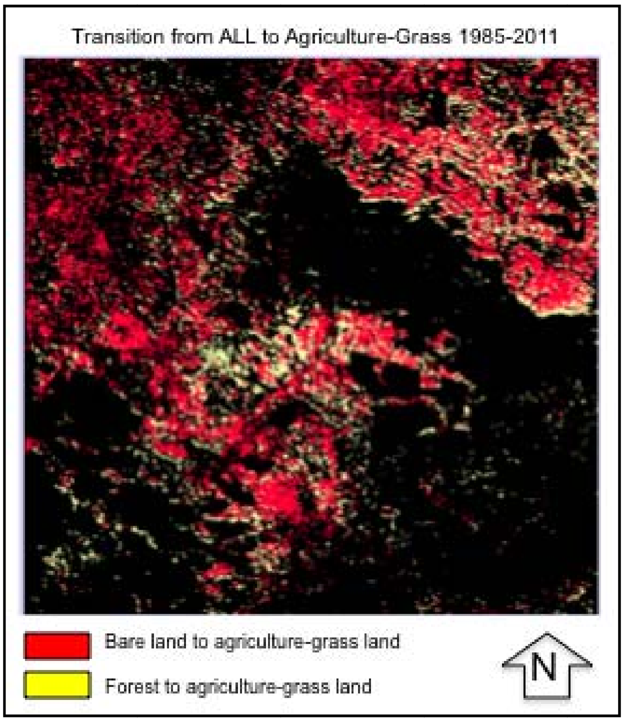

Fig. 6 Transition map to agriculture-grass category in 1985-2011 epoch.

On graph of the Contributors to Net Change experienced by forest, it shows that the forest is losing land to agriculture-grass category, and it gains land from bare land class; probably in the secondary forest form. From comparison of the trend map of change to bare land and to agriculture-grass land, also from transition map it can be concluded that the main driving forces of LUC change in the study area is agriculture.

The general change to bare land is primarily concentrated to the north-west and southern part of the study area, while the trend towards agriculture-grass category is concentrated to the north-east and western side of the study area. These trends shows that the biofuel farm caused the bare land class to be introduced at the farm location (during clearance) and also towards the north-west where those displaced acquired land parcels, while the agriculture-grass class encroached the Ruvu South Forest Reserve.

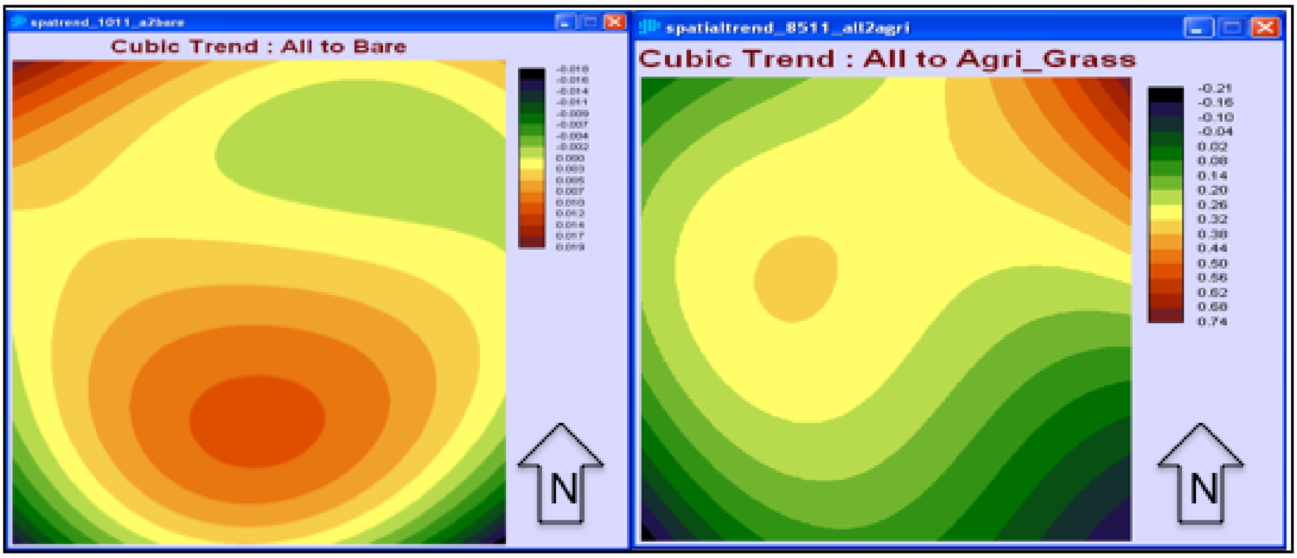

Fig. 7 Trend map of change to bare land and agriculture-grass classes on study area.

7. Conclusion

The aim of the study was to investigate the LUC resulting from biofuel production (in the form of jatropha) carried out by Sunbiofuel Company in villages within Kisarawe District, Coast Region. For goal achievement, Landsat multidate satellite imagery and secondary data in GIS environment were used to establish patterns of LUC using ERDAS Imagine 9.1 and IDRISI Selva software. The results from classified imageries and analysis revealed that in year 1985 the agriculture-grass land was 42,491 ha which is 41% of the whole area, while the forest land was 10,281 ha which is 10% of the whole land. For year 2010 agriculture-grass land was 1,944 ha, that is, 2% of the whole area, while the forest land was 40,700 ha which is 39% of the whole lot. Lastly, for year 2011 agriculture-grass land was 22,023 ha (21%) and forest land was 27,167 ha (26%) of the whole coverage. Analysis on contributors to forest net change showed that agriculture-grass class contributed negatively while bare land contributed positively to the forest change in the study area. From the study it was noted that on-going biofuel development in the study area has been implemented on the expense of fertile agriculture land, deforestation and forest degradation in the vicinity of the biofuel project area. The outputs from the study can be used in management and policy making in the biofuel projects; also as inputs to the models and methodologies for quantifying LUC effects due to introduction/expansion of biofuels production within a district.

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