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RESEARCH ARTICLE

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Monitoring Land Use/Land Cover Change Using GIS and Remote Sensing: A Case Study of Chania Catchment, Kenya

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Abstract

Sustainable Development Goal (SDG) number 15 focuses on life on land. It requires that we protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss. The challenge however is lack of sufficient historical land use and land cover information that will inform the policy makers the extent of land degradation. Land use and Land Cover (LULC) maps of a watershed gives an opportunity to visualise the areas covered by each class of LULC in order to quantify the ecological production and related ecosystem services generated in a river system. This study was thus carried out in Chania river system to demonstrate and validate the use of GIS and Remote sensing techniques as a means of providing LULC information. In order to carry out the LULC classification, Landsat 8 imageries with 30m resolution for February and March 2016 were downloaded from United States Geological Survey (USGS) site. For change detection, Landsat 7 imagery for February 2005 was used. Using the Environment for Visualizing Images (ENVI) software the imageries metadata were converted into reflectance by carrying out radiometric calibration. Maximum likelihood and Parallelepiped methods of classification were eventually used to carry out the classification. Maximum likelihood assumes that the pixel for each class in each band is normally distributed and calculates the probability that a given pixel belongs to a specific class. Parallelepiped classification uses a simple decision rule to classify multispectral data. If a pixel value lies above the low threshold and below the high threshold for all bands being classified, it is assigned to that class. Results between the two methods were compared against each other and the best result adopted. Maximum likelihood classification yielded a higher accuracy level of 97.99% and a Kappa Coefficient of 0.97. Eleven LULC classes were classified. The study revealed that GIS and remote sensing techniques provide sufficient means of detecting change in a catchment. In the Chania context the results revealed a substantive decline of forest cover by 7.78% in 11 years with a steep increase in built up areas, areas under tea, coffee and maize. The decline in forest cover and the increase in agricultural activity and settlements is an indicator that there are negative gains in SDG goal 15 and there is need for further efforts to sustainably manage forests.

Key Words: Change Detection, Land Use Land Cover, Remote Sensing, Supervised Classification, Unsupervised Classification

Introduction

Ecosystem services are the benefits that human beings derive from the natural environment. Millennium Ecosystem Assessment (MEA) of 2005 grouped the ecosystem services into various broad groups: provisioning, regulating, cultural and supporting services. The Economics of Ecosystem and Biodiversity (TEEB, 2010) and the Common International

Classification of Ecosystems Services (CICES, 2013) further refined the categories of ecosystem services and goods. All of them maintained provisioning services as the key category of ecosystem services. The examples of the ecosystem services given are biomass (food, raw materials, medicinal resources and ornamental resources), water for drinking and water for non-drinking purposes.

Shang *et al*. (2012) recognise watersheds as sources of ecosystem services listed in the paragraph above. It is however a challenge to achieve effective and sustainable balance between human and ecological needs for freshwater in these watersheds as noted by Poff, *et al*. (2003). The population growth and climate change has in addition imposed constraints on both spatial and temporal distribution of water resulting in increased competition for declining water resources (UNEP, 2012).

According to Global Water Partnership (2012), the biophysical provision of ecosystem services at continental, sub global or global scale is in general constrained by data availability. An attempt to produce a global map of ecosystem services was presented by Naidoo, Balmford, Costanza, Fisher, Green, Lehner, B, and Ricketts, (2008) who succeeded in mapping four proxies: carbon storage and sequestration, grassland production for livestock and fresh water provision. MEA (2005) and its follow-up projects such as 'The Economics of Ecosystems and Biodiversity (TEEB, 2010) raised awareness of ecosystem services in the scientific community, its stakeholders and decision-maker circles (Naidoo, *et al*. 2008). In the context of planning and decision support however, geographical mapping of services has been one of the challenges. These maps are key information source for decision makers and stakeholders (Lautenbach *et al*., 2012).

In 2014, the US Geological Survey (USGS) and Esri published the global ecological land unit map. However, these maps provide limited information on the ecosystem services provided in each individual watershed, having in mind that these watersheds have been recognised as the source of the services.

In the Kenyan context, the World Resources Institute, the Department of Resource Surveys and Remote Sensing, Ministry of Environment and Natural Resources, the Central Bureau of Statistics, Ministry of Planning and National Development, Kenya, and the International Livestock Research Institute (ILRI) produced the atlas of Ecosystems and Human well-being for Kenya, in May 2007, based on MEA (2005). The atlas focused to integrating spatial data on poverty and ecosystems in Kenya. The parameters mapped were; spatial patterns of poverty and human well-being, water, food biodiversity, tourism and wood. All these parameters were mapped at national level without elaboration of the ecosystem services that affect human well-being at the local/watershed level. In the year 2011, ILRI did a valuation and mapping exercise. However their mapping was confined to the Ewaso Ngiro watershed biased on livestock and the arid and semi-arid lands only.

Chania River has not been exempted from the challenges of inefficient and unsustainable use of ecosystem services. The Lower Chania Sub-Catchment Management Plan of 2010 has listed water scarcity, pollution, deforestation, siltation, over abstraction, water unfriendly vegetation, inadequate water infrastructure, water related conflicts among other problems in the watershed. Several studies have been done in the catchment in an effort to counter these challenges. Most of the studies (Karuri, Wamicha, Maina, & Bartilo, 2003; Mwangi, Thiong'o & Gathenya, 2012) have focused on pollution. In order therefore to clearly understand the distribution, capacity, constraints and value of ecosystem services, it is necessary to carry out a study to quantify and value ecosystem services and present them spatially in temporal and spatial form. This study therefore focused on the distribution, quantities and values of ecosystem services and goods on a landscape in temporal and spatial scale in the Chania river basin.

Study Area

The study watershed lies between longitudes $36^0 32'59''$ E to $37^0 3'1''$ E and latitude $0^0 37'09''$ S to $0^0 62'10''$ S. The watershed is generally hilly with the elevation ranging between 2100m above sea level, (ASL) in the upstream to 1500m ASL downstream areas. The watershed straddles across Mang'u, Chania, Kariara, Gatanga, Thamuru, South Kinangop and Thika Municipality Divisions. It is drained by River Chania which enters the watershed at Ragia location in Nyandarua County and flows downstream to the confluence of Thika and Chania rivers near Blue Post Hotel covering a distance of 50km and an area of 531km^2.

The main economic activities in the watershed are cash crop and subsistence farming, quarrying, fish farming, livestock keeping, cottage industries, horticulture, agro-forestry and business enterprises. The watershed experiences two rain seasons, long rains from March to May (Masika Season) and short rains from October to December (Vuli Season), receiving an average of 1200-1500mm per annum of rainfall. The hydrology of the watershed is influenced greatly by climate variability, topography and land use among other factors which have impacted on the resource quality and quantity.

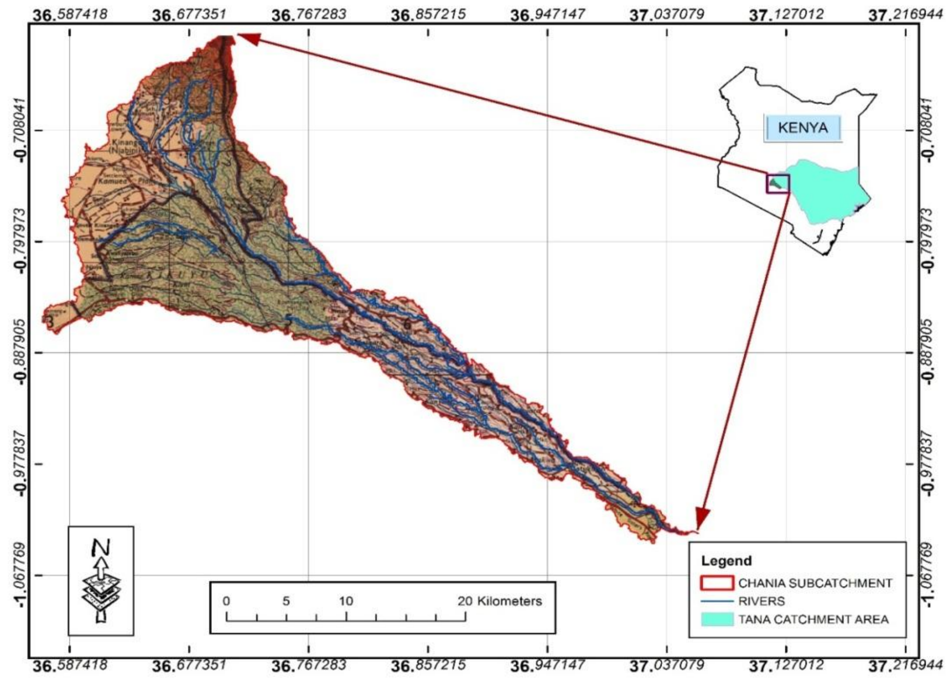


Figure 1. Location Map of the Chania River System

The Chania River system is served by Karimenu, Nyakibai, Mataara and Kimakia, as the main tributaries all forming a dendritic drainage pattern.

Materials and Methods

Acquisition of Imageries

Landsat 8 (Operation Land Imager) imagery for 12th March 2016 with 30m resolution was downloaded from USGS website.

Landsat images were used because they are freely available and are of a fairly good resolution. Cloud removal was achieved by replacing portions of the imagery affected by cloud cover with portions of another image of 24th February 2017 from the same path and row using the Seamless Mosaic tool within ENVI. According to Helmer and Ruefenacht, (2005), histogram matching based on image overlap areas permits seamless mosaicking of scenes that have undergone cloud removal with regression tree prediction. Other studies have also found image mosaicking as an appropriate way of removing cloud cover from images (Suming *et al*., 2013).

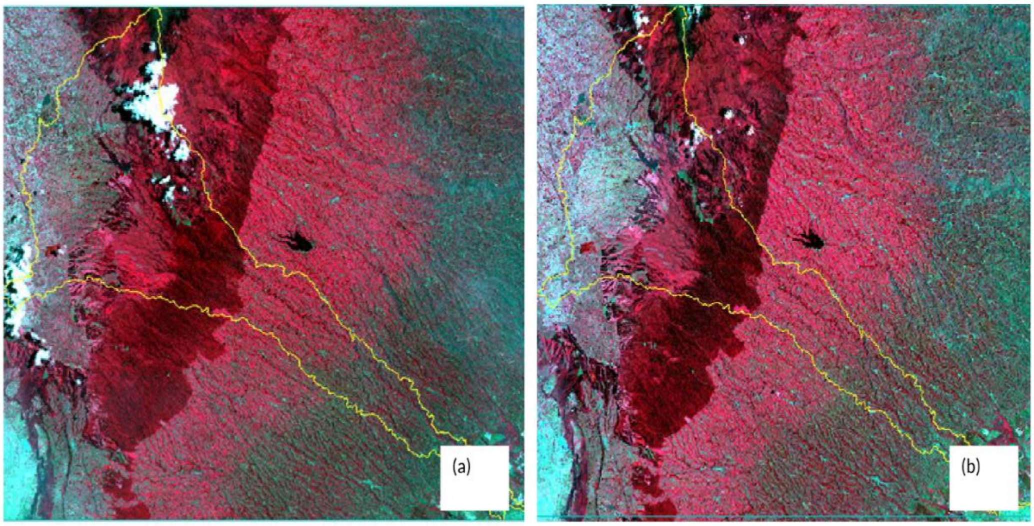


Figure 2. Landsat Images of Chania Catchment (a) Before and (b) After Cloud and Shadow Removal

LULC Classification

The cloud free image was pre-processed with ENVI software before LULC classes were generated. Prior to performing supervised classification, the study carried out an unsupervised classification of the LULC, which is the easiest and quickest way of LULC classification. In this system the software generates land use classes by assigning unique signatures to a pre-processed imagery giving special regard to the number of classes that the user inputs into the software. With the unsupervised classification however, it was difficult to interpret the classes. There was also a possibility of the same classes being split into different classes. A total of eleven (11) LULC classes were generated. Exelis Visual Information System (ENVI) Software environment was used in this LULC classification process. Figure 3 is the LULC map that resulted from unsupervised classification.

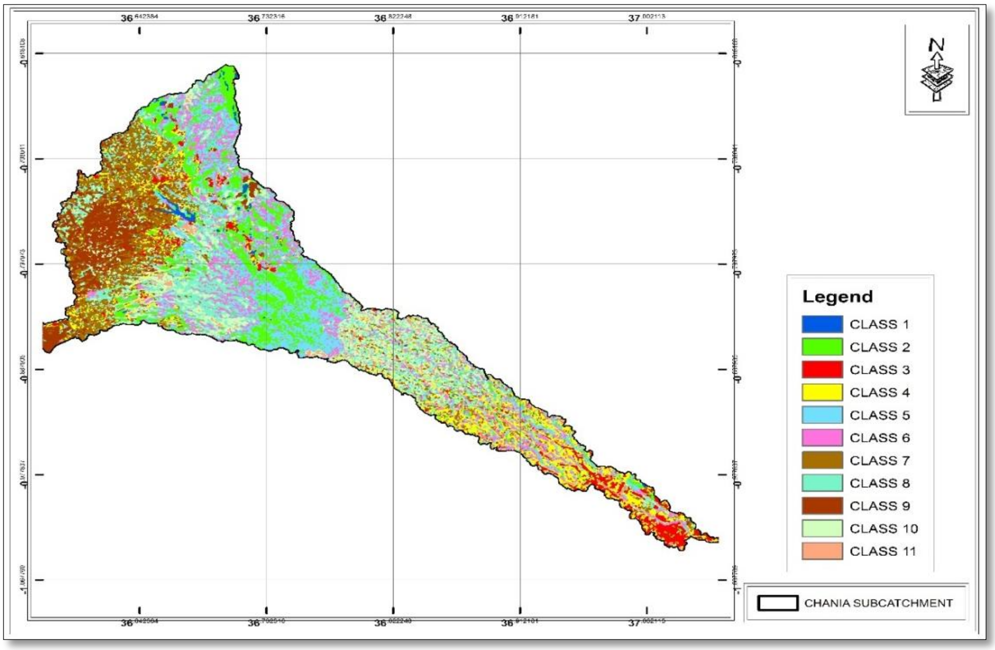


Figure 3. LULC Generated from Unsupervised Classification

Due to the shortcomings of the unsupervised classification system, this study then utilized supervised classification and both the methods for supervised classification (Parallelepiped and Maximum likelihood) were used. Results between the two methods were then compared against each other and the best result was adopted. Parallelepiped classification uses a simple decision rule to classify multispectral data. The dimensions of the parallelepiped classification are defined based upon a standard deviation threshold from the mean of each selected class. If a pixel value lies above the low threshold and below the high threshold for all bands being classified, it is assigned to that class. If the pixel value falls in multiple classes, ENVI assigns the pixel to the first class matched. Areas that do not fall within any of the parallelepiped classes are designated as unclassified. Maximum likelihood classification assumes that the statistics for each class in each band are normally distributed and calculates the probability that a given pixel belongs to a specific class. Unless you select a probability threshold, then all pixels will remain classified. Each pixel is assigned to the class that has the highest probability

In using supervised classification of LULC, actual land cover and land uses were identified in the field from the areas mapped in Figure 5 below. These guided the generation of training sites. The training sites were areas with known LULC that the classification software would use in assigning LULC class to all pixels in the catchment. In order to carry out supervised classification, Regions of Interest (RI) were first generated using the training data for the classification of both methods. The RIs created were later on used to perform both Parallelepiped and Maximum likelihood. This was done to ensure that the same input parameters were observed so as to highlight the differences with the two outputs generated.

Since the same RI was used for the two methods, the output files obtained the same symbology, thus this was easy in comparing the results generated for the two land use maps. Figure 4 indicates the visual differences obtained from the two types of supervised classification.

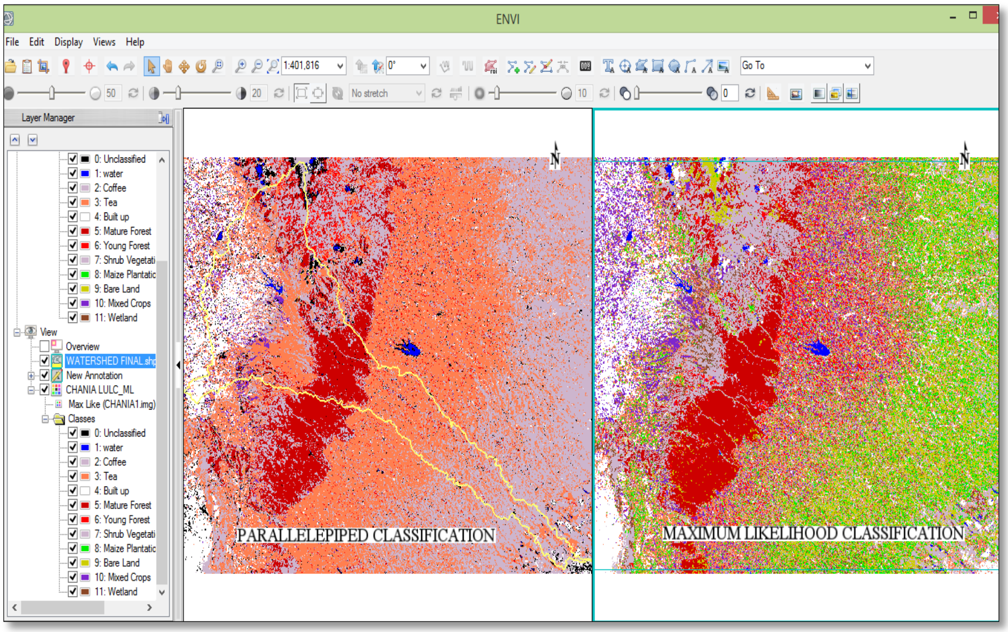


Figure 4. Comparison between Parallelepiped and Maximum Likelihood Classification

From Figure 4 above, Maize plantation symbolized as green is only distinct and visible through Maximum Likelihood method. Parallelepiped system of classification usually tends to generate lots of unclassified data depicted as black portions.

Ground Truthing

Ground truthing was necessary in order to confirm that the classification methods yielded results that match the actual situation on the ground. Ground truth RIs were created in ENVI software from ground truth data that had been collected during training data collection exercise (Figure 5).

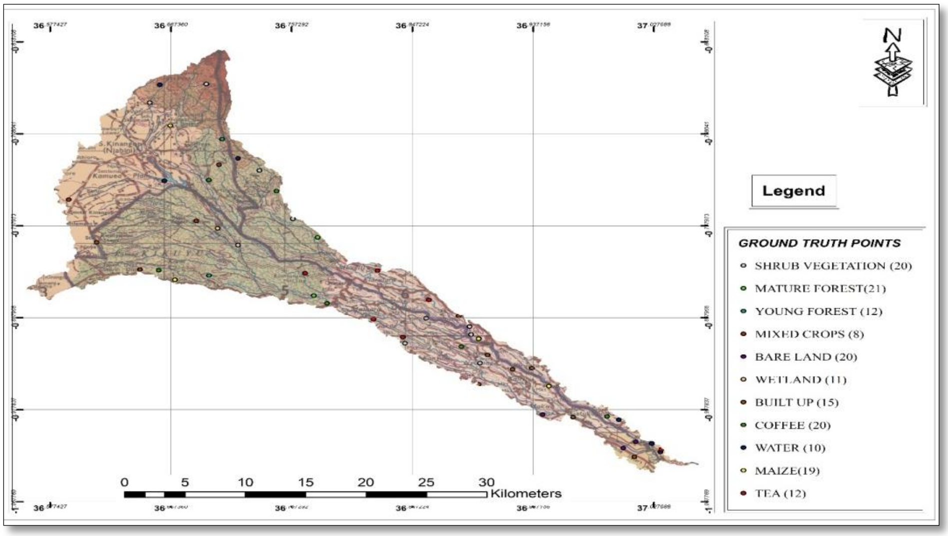


Figure 5. Ground Truth and Training Points for Each Class

Participatory GIS where interviews and focus group discussions were carried out with the community as well in order to confirm the LULC classes as well as shedding light on the validity of the change detection findings of this study.

Figure 6. Focus Groups Discussion for PGIS in Mbugiti, Chania (a) men group (b) women group

To understand the differences between Parallelepiped and Maximum Likelihood better, the study generated confusion matrix (also referred to as contingency matrix). Table 1 below illustrates overall accuracy and the Kappa coefficient. It also indicates percentage accuracy for each and every class generated, both for producer and user accuracies.

Table 1. Contingency Matrix Obtained through Maximum Likelihood Classification

Overall Accuracy = (2980/3041) 97.9941%
Kappa Coefficient = 0.9698

Class	**Producer Accuracy (%)**	**User Accuracy (%)**	**Producer Accuracy (Pixels)**	**User Accuracy (Pixels)**
Water	99.88	99.77	855/856	855/857
Coffee	94.61	100.00	228/241	228/228
Tea	80.00	77.78	8/10	7/9
Built up	100.00	100.00	165/165	165/165
Mature Forest	98.88	100.00	1497/1514	1497/1497
Young Forest	95.65	97.78	132/138	132/135
Shrub Vegetation	81.48	82.22	22/27	37/45
Maize Plantation	81.81	81.81	9/11	9/11
Bare Land	71.42	75.00	5/7	15/20
Mixed Crops	88.14	94.55	52/59	52/55
Wetland	92.31	84.21	12/13	16/19

Table 2. Contingency Matrix Obtained through Parallelepiped Classification

Overall Accuracy = (2791/3041) 91.7790%
Kappa Coefficient = 0.8773

Class	**Producer Accuracy (%)**	**User Accuracy (%)**	**Producer Accuracy (Pixels)**	**User Accuracy (Pixels)**
Water	99.07	99.88	848/856	848/849
Coffee	100.00	96.02	241/241	241/251
Tea	100.00	5.18	10/10	10/193
Built up	99.39	100.00	164/165	164/164
Mature Forest	97.29	100.00	1473/1514	1473/1473
Young Forest	3.62	55.56	5/138	5/9
Shrub Vegetation	40.74	36.67	11/27	11/30
Maize Plantation	0.00	0.00	0/11	0/0
Bare Land	0.00	0.00	0/7	0/0
Mixed Crops	66.10	100.00	39/59	39/39
Wetland	0.00	0.00	0/13	0/0

Maximum Likelihood classification method produced more accurate results following an overall accuracy of 98.0% versus 91.8% produced from the output classes for Parallelepiped classification. Another indication on accuracy while performing image classification is the Kappa coefficients that range between 0.0 – 1.0, with values closer to 1.0 indicating high level accuracy of image classification. Therefore, from the contingency matrix generated by the study, the Kappa coefficients obtained from parallelepiped classification was 0.88, with Maximum likelihood classification method having a Kappa coefficient of 0.97, also confirming that Maximum likelihood had the highest accuracy. Following the above comparison and the results of ground truthing, the study used the output generated from Maximum likelihood classification. The output LULC file generated was clipped against the study area as illustrated from Figure 7.

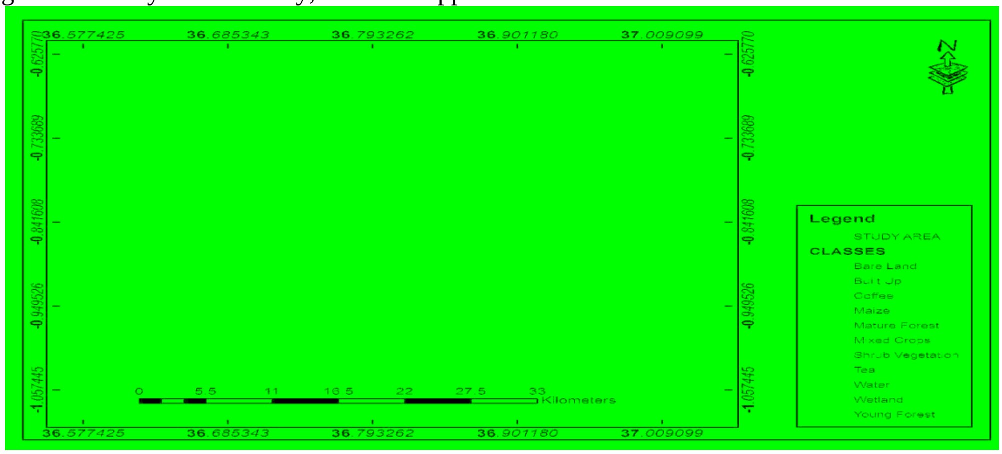


Figure 7. Land Use Land Cover Map Adopted for 2016

Finally, the generated LULC map was vectorised to pave way for the determination of the area of each land use and land cover class as illustrated in Figure 7.

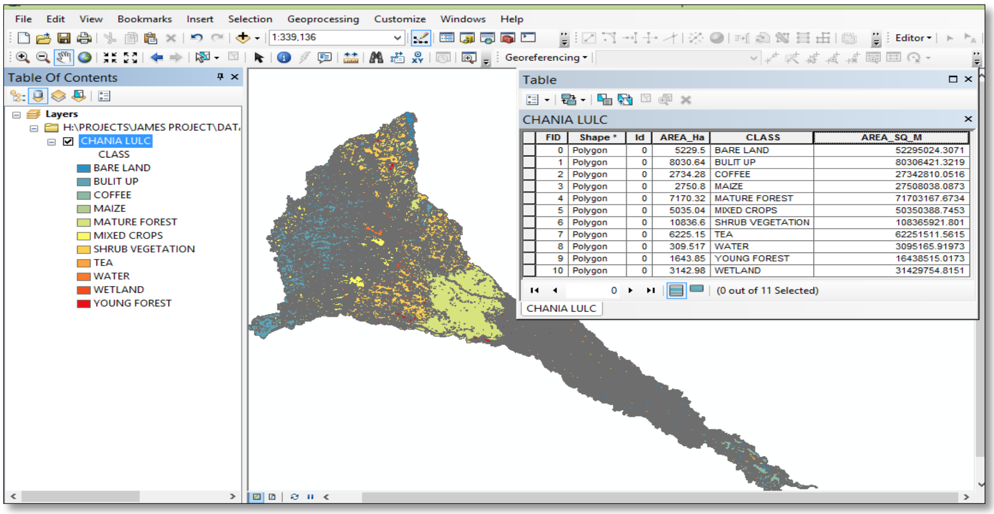


Figure 8. Vectorised Classes for 2016

To detect the change in land use and land cover in 11 years, a LULC map for the year 2005 was generated following the same process described above. Following the accuracy of the results that yielded from land use land cover classification for the period February 2016, a similar approach was utilized in processing the Landsat 7 imagery for February 2005, and Maximum likelihood supervised classification was used. The study utilized the same training data as the one used for Landsat imagery dated February 2016, supervised classification paying attention to the consistency of the colour of the imagery in order to avoid using the sites that land use and land cover have already changed as training sites.

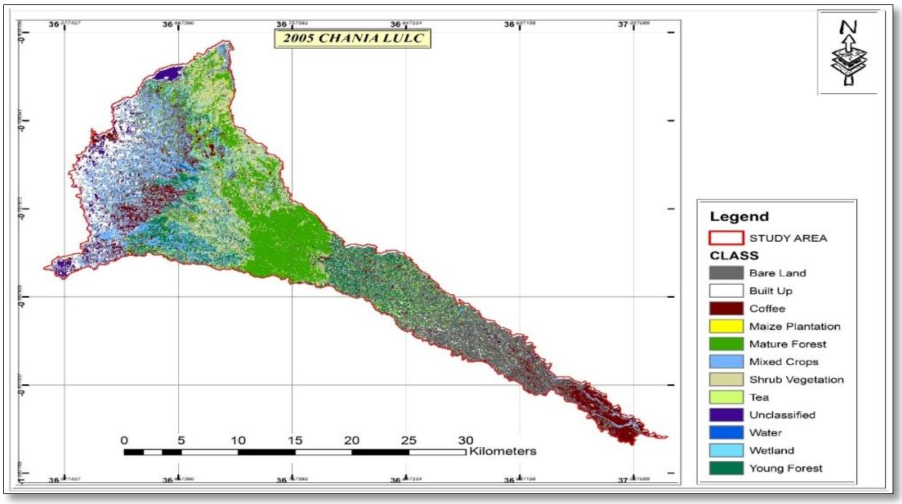
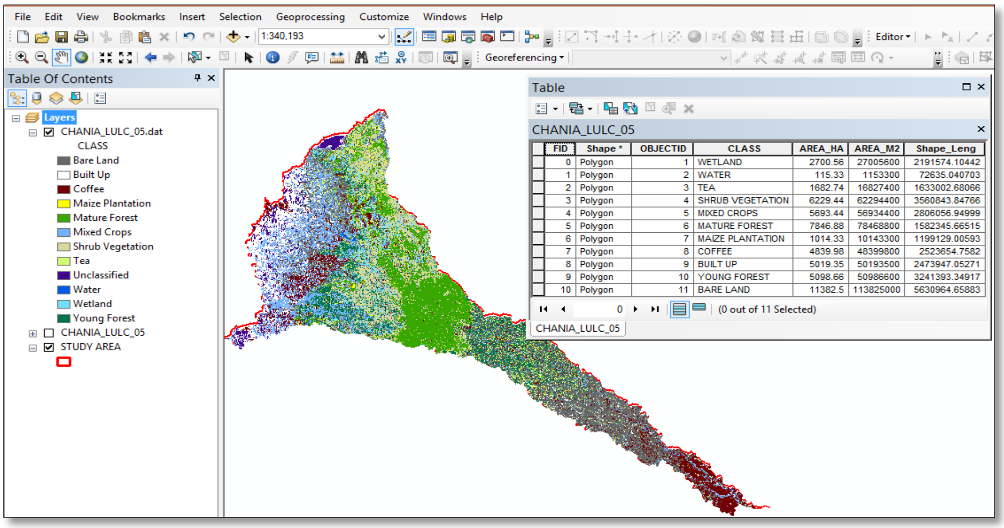


Figure 9. 2005 Land Use Land Cover map



FID	Shape *	OBJECTID	CLASS	AREA_HA	AREA_M2	Shape_Leng
0	Polygon	1	WETLAND	2700.56	27005600	2191574.10442
1	Polygon	2	WATER	115.33	1153300	72635.040703
2	Polygon	3	TEA	1682.74	16827400	1633002.68066
3	Polygon	4	SHRUB VEGETATION	6229.44	62294400	3560843.84766
4	Polygon	5	MIXED CROPS	5693.44	56934400	2806056.94999
5	Polygon	6	MATURE FOREST	7846.88	78468800	1582345.66515
6	Polygon	7	MAIZE PLANTATION	1014.33	10143300	1199129.00593
7	Polygon	8	COFFEE	4839.98	48399800	2523654.7582
8	Polygon	9	BUILT UP	5019.35	50193500	2473947.05271
9	Polygon	10	YOUNG FOREST	5098.66	50986600	3241393.34917
10	Polygon	11	BARE LAND	11382.5	113825000	5630964.65883

Figure 10. 2005 Land Use Land Cover Areas Generated

Results and Discussion

The study established that in 2016, shrub vegetation had the highest area of coverage covering 20.41 % of the total area. This high percentage is attributed to the fact that in classifying shrub vegetation, the signatures captured for this class would be the same for orchards, shrubs in the forests, along rivers, in coffee and tea plantation as well as irrigated farms. The classification software lumps this land uses as shrub vegetation. Built up areas and mature forest were the next LULC classes that covered the highest areas covering 15.12% and 13.5% of the total area respectively. Water had the least area of coverage covering 0.58% of the total area. Table 3 is an illustration of the areas in hectares generated for the classes within ArcGIS for the year 2016.

In the year 2005, mature forest had the largest area of coverage (19%). The next LULC which covered large areas were shrubs, mixed crops and young forest which covered 15.05%, 13.76% and 12.33% respectively.

By comparing the two columns with areas of coverage in 2005 and 2016 in Table 3 below, the study was able to quantify land use change both by hectares and percentages as illustrated in the last column of the table.

Table 3. Land Use Change for 2005 and 2016

CHANIA LULC 2005		**CHANIA LULC 2016**		**LAND USE CHANGE**
CLASS	**AREA_HA**	**CLASS**	**AREA_HA**	**INCREASE (+) / DECREASE (-)**
Bare Land	11382.5	Bare Land	5229.5	-11.59%
Built Up	5019.35	Built Up	8030.64	+5.67%
Coffee	4839.98	Coffee	2734.28	-3.96%
Maize Plantation	1014.33	Maize	2750.8	+3.27%
Mature Forest	7846.88	Mature Forest	7170.32	-1.27%
Mixed Crops	5693.44	Mixed Crops	5035.04	-1.24%
Shrub Vegetation	6229.44	Shrub Vegetation	10836.6	+8.67%
Tea	1682.74	Tea	6225.15	+8.55%
Water	115.33	Water	309.517	+0.37%
Wetland	2700.56	Wetland	3142.98	+0.83%
Young Forest	5098.66	Young Forest	1643.85	-6.51%

From Table 3, the built up areas increased by 5.7% as a result of increased human settlement. Increased human settlement is explanation as to why there was drastic decrease in the area under bare land which experienced a drop of 11.6% in terms of the areas covered. From the focused group discussions, coffee farming has become unattractive due to poor market prices. This has led to many people adopting tea farming as a source of income. This is the reason as to why we have a sharp increase in the area under tea (8.7% increase). The study however established that there was a decrease in the areas under mature and young forests and a marginal increase in the area under wetlands. This is an indicator of environmental degradation. This therefore means that, there is destruction of the natural infrastructure that support catchment ecosystems in terms of water storage, rain catchment and flood protection. This degradation has led to reduced rainfall trend as shown in the figure below.

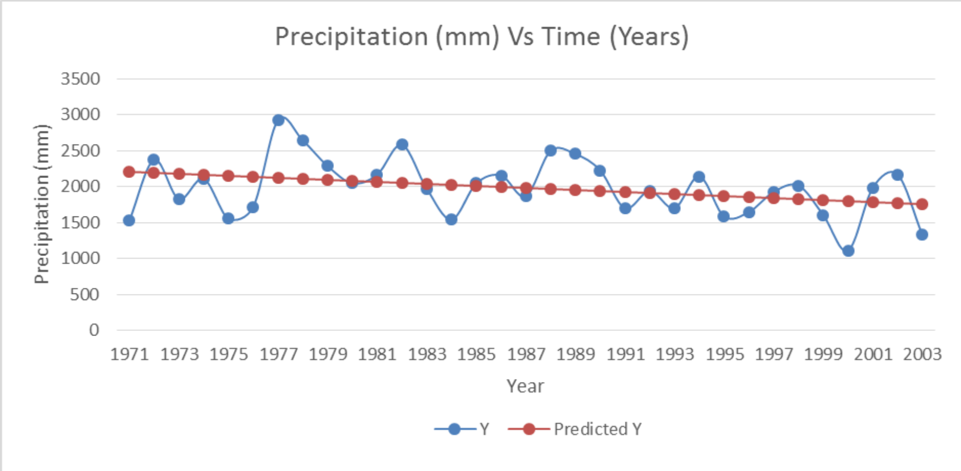


Figure 11. Reducing Rainfall Trend

Conclusion

With open source remote sensing data such as Landsat, it is possible to detect the disturbance in the ecosystem (e.g. forest disturbance). From the study, it was clear that Maximum likelihood system of supervised classification provides the best means for LULC mapping and subsequently detecting change in a catchment. In the Chania catchment, it is clear that there has been a downward trend in terms of area covered by important natural infrastructure; forests, wetlands and water, while there has been increased settlements as depicted by the increase in built up areas and shrinkage of bare land. This trend has already had an effect on the amount of rainfall received and also exposes the catchment to the risk of flooding due to reduced natural infrastructure that support ground water storage. The policy makers should therefore pay attention to conservation activities in particular targeting forests and wetlands. Afforestation efforts and wetland protection should be given priority in the Chania catchment. The LULC change detection should also be done periodically in order to monitor the gains or losses made in these interventions. These efforts will restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, halt and reverse land degradation, biodiversity loss in the catchment and subsequently contribute to the attainment of the SDG goal 15.

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