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Research Article

Time series exploration of change detection analysis in Arba Minch Zuria woreda, Ethiopia

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ABSTRACT

The interaction of human activities and the natural environment can cause a change in land use/ land cover. Mapping and Monitoring the change in land use/land cover changes is vital for sustainable development, planning, and management. The study was conducted to monitor the change in LULC of Arbaminch Zuria Woreda between 1986 and 2017 by using remote sensing (RS) and GIS techniques. Images from Landsat4/5 thematic mapper(TM) and Landsat 8 operational land imager (OLI) of multispectral bands were used to extract land-use maps. Supervised classification methodology was applied using a maximum likelihood algorithm to formulate a LULC map of the watershed. The image of the study area was categorized into five different classes; namely agriculture, built-up, waterbody, forest, and river. The accuracy of the classified image was assessed through ground GPS referenced data. The result showed that forest and built-up areas have increased by +41.59 % (7428.5 ha) and +5.78 % (1033.1ha) while agriculture and waterbody have decreased by -47.1 % (8414.14 ha) and -3.01 % (479.6 ha) respectively. The finding of the study points out policy suggestions for sustainable LULC management in Arbamich Zuria Woreda.

INTRODUCTION

During the last three centuries, human activities have been transformed the natural environment through land use land cover change. Land use/land cover is one of the most important pointers of interaction between human activities and the natural environment (de Sousa-Neto et al., 2018, Sun et al., 2016). Though both natural and anthropogenic factors have a role in the change in land use/land cover, anthropogenic influence has an unprecedented impact on Earth's ecological system (Lambin et al., 2001). The main driving force for land use land cover change (LULCC) are demography, the demand of farmland, land policy, economy, culture, urbanization and climate which occurs at a different scale of dimensions in the world (Li et al., 2016, Liping et al., 2018, de Sousa-Neto et al., 2018).

Land use/land cover (LULC) has a profound impact on the ecosystem, loss of biodiversity, hydrological cycle (de Sousa-Neto et al., 2018) and biological cycle due to the change in carbon balance and nutrient flow in the landscapes (Krkoška lorencová et al., 2016; Liping et al., 2018, Halmy et al., 2015). These losses have a considerable impact on local and global climate change (Lambin et al., 2001; Sun et al., 2016). Land use/ land cover has a major involvement from the total anthropogenic carbon emission to the atmosphere. Over the past 150 years, 33 % of carbon was emitted from land use/ land cover. In the 1980s and 1990s, it was holding about 30 %; in 2000 up to 2009 also 12.5 % of carbon emissions were contributed from the total anthropogenic carbon emission (Houghton et al., 2012).

One of the prominent indicators of air pollution is the exceedance presence of small suspended solid particles and liquid droplets in the atmosphere, so-called particle matter (PM). The existence of those particles matters has a significant influence on the quality of air and also exposed to those particles have short and long term adverse human health effect (Kloog et al., 2013, WHO, 2016). The interaction of human activities with nature can cause a dynamic change in land use/ land cover practices such as the conversion of forest, grassland, and agriculture to residential areas is higher especially in urban areas. This has generated particles matter and cause for the reduction of air quality (Superczynski & Christopher, 2011).

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LULC change detection analysis is feasibly to establish a model to predict the trend of land use through the retrospective period. It provides some basis for effective land use planning, management, and ecological restoration for the area and guidance for regional socio-economic development (Halmy et al., 2015). The availability of multispectral remote sensing imagery data over long time series can provide accurate and timely spatial data for detecting the changes on the earth's surface at different scales (Halmy et al., 2015; Liping et al., 2018; Sun et al., 2016). The main objective of this study was to assess the change detection of Arba Minch Zuria Woreda watershed from 1986 to 2017. (Zewdu et al., 2016) showed that, there has been a variation in land use/ land cover dynamics in Arba Mich Zuria Woreda Gamo Gofa zone because of irrigation. According to the study, long term irrigation practices have an impact on soil salinization and this has also effect fo LULC change. As a result, an increase in soil salinity, a decrease in land productivity, and developed as fallow, cultivated, and barren land has occurred. Another study was also conducted in Arba Mich town, so-called the driving force for urbanization and land-use pattern. According to the result physical expansion of infrastructure, tourism investment and population growth are the main cause for urbanization and those factors have played for 41 % of annual rate of growth of built-up land in the town (Jenberu & Admasu, 2019).

MATERIAL AND METHOD

Study Area

The present study area is found in the Southern Nation Nationalities People Regional State (SNNPRS) of Ethiopia in Arba Minch Zuria woreda. Geographical it's located between latitudes 5049'36" N and 608'49" N, and longitudes 370 28'42" E and 37037'7" E as shown in Fig 1.

Figure 1: Study area location

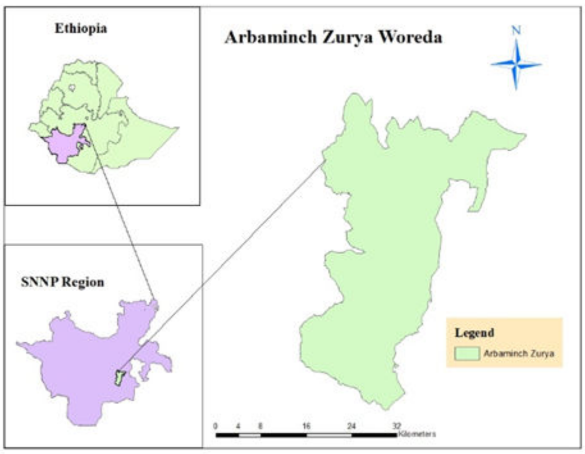


Image pre-processing

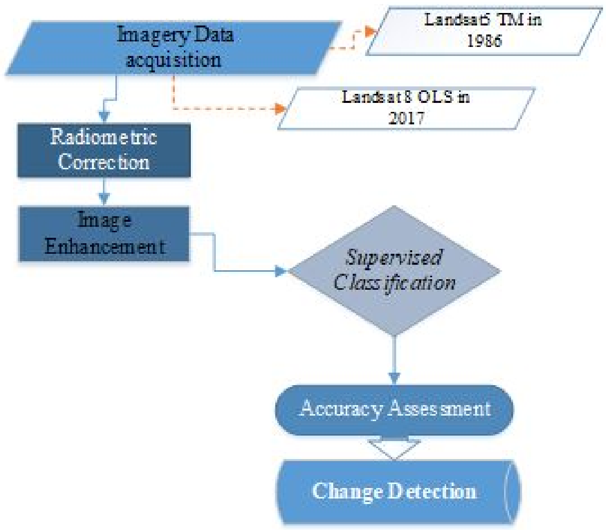
The imagery data for analysis was acquired from Earth explorer of Landsat 5 TM and images (p169/r56) and Landsat 8 OLI on 28/01/1986 and 17/01/2017 respectively. Different multispectral bands Landsat imagery row data were merged to form and depict true color landscape imagery. All the spatial imagery data were extracted based on the size of the study area and both radiometric and geometric pre-processing image enhancement calibration were conducted before further image investigation was executed (Y. Y. Li et al., 2012).

Image classification

The maximum likelihood supervised classification algorithm was used to categorize the land use type on the landscape. This algorithm quantitatively evaluates both the variance and covariance of category spectral response patterns when classifying an unknown pixel (Ahmad & Quegan, 2012; Markos et al., 2018; Superczynski & Christopher, 2011). Five land use/ land cover types such as agricultural land, settlement, forest, waterbody, and roads were identified. Then, the accuracy value of each temporal imagery data was calculated by using ground truth collected data, and finally, change detection was calculated to explore the transformation of each land-use type as shown in Figure 2.

Land use/ land cover change detection was executed by using the quantitative analysis of the relationship between different variables, called the cross-tabulation method. Change detection analysis is used to quantify the difference between images that have the same scene in different periods (Hegazy & Kaloop, 2015; Mishra et al., 2019; Rawat & Kumar, 2015). The exploration was performed by using remote sensing software which could give on pixel basis of comparison changes 'from,-to' information (Wenq, 2001). In this case, the total quantitative areal information of each land use/ land cover change, as well as losses/gains of each category of land between 1986 and 2017, was gathered.

Figure 2: Flow chart of change detection procedure in LULC.



RESULT AND DISCUSSION

Land use/land cover change

Based on the analysis result, the LULC has occupied five types of class: Agriculture, Built-up, Forest, Water bodies, and River of 1986 and 2017 as specified below in Figure 3. The classified maps in 1986 indicate that the built-up area was 253.9ha (0.26 %), agriculture was 69.9%, the forest was 28.6%, the river and waterbody was 0.16% and 1.13% respectively. In 2017, the forest and agricultural land use type were occupying a higher percentage of coverage,i.e. 36.2% and 61.2% respectively. The same land-use features were also occupied a higher percentage rate in 1986.

Table 1: Areal coverage of each land-use type in 1986 and 2017.

LULC (Ha)										
Year	Built-up	Δ (%)	Agriculture	Δ (%)	Forest	Δ (%)	River	Δ (%)	Waterbody	Δ (%)
1986	253.9	0.26	67855.9	69.9	27749.4	28.6	146.8	0.16	1093.5	1.13
2017	1287	1.33	59441.5	61.2	35177.9	36.2	597.2	0.62	595.9	0.61
Δ (Ha)	+1033.1		-8414.4		+7428.5		+450.4		-497.6	
Δ (%)	+5.78		-47.1		+41.59		+2.52		-3.01	

For the last three decades, between 1986 to 2017, some land-use type has increased and others have decreased by their total area coverage. Built-up, forest land, and river type of land features were maximized by 1033.1 hectares (5.78 %), 7428.5 ha (41.59%), and 450.4 ha (2.52 %) respectively. The positive sign here implies that there is gaining of land use type and the negative sign point out the loss of land use type between the specified years. There were about 253.9 areas of hectare were covered by a built-up area in 1986, and this was significantly enlarged into 1287 hectares (1.33 %) in 2017. (Jenberu & Admasu, 2019) showed that, there has been an expansion of urbanization in Arba Mich city for the previous years. The causes of overspreading of urbanization in the city are population growth, settlement expansion, dislocation of rural to urban, tourism, and investment activities have the lion's share for urbanization. The agricultural land has decreased from 67855.9 ha in 1986 to 59441.5 ha in 2017 which accounts for -47.1 %. The water body has also drastically decreased from 1093.5 hectares to 595.9 ha in 1986 and 2017 respectively and this account for -3.01%.

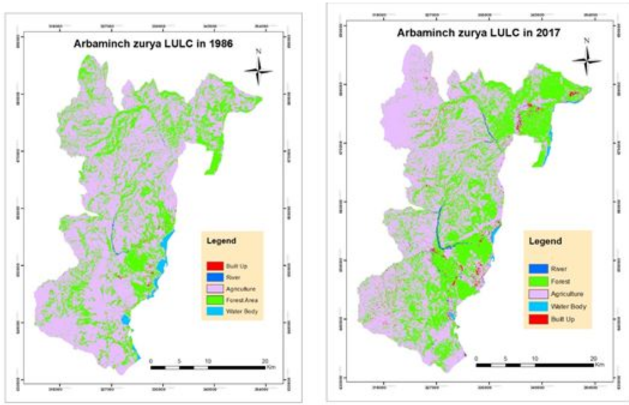


Figure 3: LULC status of Arbamich Zuria Woreda in 1986 and 2017.

Classification Accuracy assessment

One of the most frequently used Kappa statistics techniques was selected to assess the accuracy assessment of 2017 imagery. This method of accuracy assessment is to quantitatively determine how pixels were categorized into the corrected feature classes in the area during an investigation (Liping Cai, Wenzhong Shi, 2018). The number which is written in the bold point out, correctly classified data as compared to the ground truth referenced collected points. Overall accuracy classified image of 2017 was found to be 84.87 % with the Kappa statistics of 0.8l. Individual user accuracy and producer accuracy of each class are presented in Table 2 below.

Table 2: Overall accuracy assessment error of matrix for image 2017.

	Reference Data						
Classified Data	River	Forest	Agriculture	Water Body	Built-Up	Total	User Accuracy (%)
River	11	0	0	0	0	11	100
Forest	2	28	1	0	0	31	93.33
Agriculture	0	1	35	0	0	36	97.22
Water Body	0	0	0	12	0	12	100
Built Up	4	0	8	2	15	29	88.24
Total	17	29	44	14	15	119	
Producer Accuracy (%)	91.67	93.33	97.22	85.71	55.56		
	Over all classification accuracy = 84.87%						

Kappa statistics = 0.81

Change detection analysis

LULC change matrix result shown in the table below shows that the major land cover change in Arba Minch Zuria woreda in the periods of 1986-2017. The values in bold letters imply no change in land use/land cover categories for the given periods.

Table 3: LULC change matrix between 1986 and 2017.

Change from	**to 2017 (Ha)**				
1986 (Ha)	River	Forest	Agriculture	Water Body	Built-Up
River	98.01	10.35	32.76	0	5.67
Forest	103.59	16934.9	10144.98	187.47	378.45
Agriculture	383.31	17912.1	48673.17	86.76	800.64
Water Body	10.53	198.18	470.97	321.66	92.16
Built Up	1.8	122.4	119.61	0.09	10.08

According to the result, about 10144.98 hectares of forest land were converted into agricultural land. Change from agricultural land to the forest was accounted for 17912.1 ha. This occupies the largest areal coverage of conversion rather than other land-use alteration. The conversion of each classified land to built-up is highly increased and from those land-use types, 800.64 ha of agricultural land was completely converted into built-up with a higher amount compared to others. Besides, the conversion of the water body to other types of lands was also significantly increased and about 470.97 ha of water body was infested by agricultural land. Such change has a prolonged impact on aquatic species specifically and also influence on the ecosystem goods and services generally (Burkhard et al., 2012).

CONCLUSION

This study assessed the change in land use/ land cover change in Arba Minch Zuria woreda, South of Ethiopia using Landsat TM/OLI images from 1986 to 2017. The result of this analysis revealed that the major land land-use type in the watershed was agriculture in 1986. In this year, agricultural land was recorded 67855.9 ha (69.9%). The coverage of agricultural land was reduced and changed into other types of classified land at a different rate. In 2017, the forest land was improved by a 36.2 % change in rate. Besides, the built-up area was also increased by 1287 hectare and 1.33% rate of change. This is because of settlement expansion, population growth, tourism, and investment activities. Between 1986 to 2017, both built-up and forest land-use types have been significantly increased and gained an extra amount of areal coverage. Whereas, agricultural and war body land-use types have been decreased and lost their amount of coverage in the watershed.

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