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Research Paper

Detecting Change in Wetland around Addis Ababa Akaki sub Basin, Ethiopia

Galfato Gabiso Gada [1]
Gudina Legese[2]

[1]Africa Center of Excellence for Climate Smart Agriculture and Biodiversity Conservation (Climate SABC), Haramaya University and Hawassa University, College of Agriculture Department of plant and Horticultural Science, Community Service Directorate
[2] Center for Environmental Science, Addis Ababa University, Ethiopia.

Abstract
Change detection is an important process for monitoring and managing wetland and urban development because it provides quantitative analysis of spatial distribution of the water resources. Wetlands are the main custodians water resourcesact as 'banks' from where water may be drawn, and groundwater replenished. It plays a noticeable role in the growth of human civilizations and development. Investigating of wetland changes is crucial for decision-making. In this study supervised classification was performed and analyzes the temporal and spatial wetland change patterns over 33 years (1986–2019) intending to evaluate its impact on around Addis Ababa Cityin Akaki watershed, Ethiopia. Estimation of detection were conducted by employing ArcGIS using change detection inputs of the year 1986 and 2019 from Global earth explorer. To characterize the dynamics of changes a multi- temporal set of images has been processed. Landsat 5 and Landsat 8 ETM+ applying in watershed. The results showed that wetlands had decreased by 27.72% (366.24 ha) from base year coverage, while built-up area increased by 261.4% (+27279. ha). Cultivated land had decreased from far more others 73.7% (366546ha) within 33 years.The good points observed is positive change in forest coverage 200.7% (9657.7ha). The study had an overall classification accuracy of 80.2 % and 92% and kappa coefficient (K) of .67 and 0.81for 1986 and 2019 respectively.The result conclude that detection of wetland using GIS and remote sensingare suitable for monitoring such decreasing with expansion of City to periphery.
Key words- *wetland, change detection, land cover digital image, GIS*

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I. Introduction

Change detection is an important process for monitoring and managing wetland because it provides quantitative analysis of spatial distribution in the area of interest. Accurate information on wetlandis critical for understanding the sources of change and for developing effective policies to slow and reverse degradation. Anthropogenic activities such as urban development and agricultural management have caused a significant loss of wetland and riparian areas (Feto 2018, Syphard and Garcia 2001).Wetland is crucial for fast developing city that growth of population at alarm rate with economic and industrial expansion. Degradation of forested land in the watershed reduces the volume of water and high sediments in the reservoir wetlands. In areas like Gafarsa Reservoir edges is a good habitat and suitable feeding ground for a sizable population of Cyanochen cyanopterus. Away from the water, grassland species such as Macronyx flavicollis can be seen (in small numbers), and Serinus nigriceps often occurs. The woodland around the reservoir supports a further range of afro-tropical highlands biome species. A good variety of Palearctic and Afro-tropical ducks and geese occur at Gefersa, the most common Afrotropical species being Cyanochen cyanopterus which is registered in Bird international (Bird Life International, 2021). The wastage of city is discharged to water directly affects the quality and quantity of fresh water for their drinking and other use including urban agriculture (Alan 2021 and Yohannes 2017)

According to Addis Ababa Resilience Project report, fresh water sources in and around Addis Ababa city, including rivers, lakes and ground water are utilized for irrigation, sand mining, industrial consumption, electric power generation, making food, recreation purpose, habit for birds, and aquatic animals, drinking and sanitation purposes. In southern parts of Addis Ababa city, the same rivers and streams serve for horticulture, watering cattle, and for other domestic activities (City resilience project, 2020). Coupled with rapid natural population growth, Addis Ababa is one of the fast growing cites in Africa, posing critical challenges, including high rate of unemployment, housing shortage and environmental deterioration mainly stress of water scarcity. Activities such as agriculture, road building, and urbanization often cause indirect damage to wetland systems. The hydrological alterations associated with these activities affect water supply and drainage patterns of surface and subsurface moisture, reducing the size and distribution of ecosystems dependent on these water sources (Ehrenfeld 2000, Winter et al. 2001, Kentula et al. 2004; Ethiopian Wildlife and Natural History Society (EWNHS), 2018). Moreover, population outside central cities has grown faster than downtown areas in many developed regions, demonstrating a certain tendency of the outward expansion of urban areas (Angel et al., 2005). The population of Addis Ababa increased from 1,534,000 in 1986 to nearly 4,592,000in 2019 (https://www.macrotrends.net/cities/20921/addis-ababa/population). In fact, Addis Ababa is quickly growing at their fringes, transforming the surrounding Oromia region into dense industrial and commercial ones, or less dense suburban developments [Huang et al., 2009]. Nowadays, the total water supply is 580,000 m^3 per day, while the city demand is 1.1 million m^3 per day of which only 35% from reservoir and the remaining gets from ground water sources (City resilience project, 2020). Bisrat et al (2017) also shows that unmeet water demand will be trendy even with low population growth and the dry climate of RCP 4.5 and RCP 8.5 climate change scenario.

To detect wetland, it was necessary to identify an ancillary data source to aid in the delineation of wetland boundaries. The best freely available source of Earth explorer (https://earthexplorer.usgs.gov/) developed in United State Geographic Society (USGS) which used criteria generated from a knowledge system that contained spectral information from Landsat images (Mulder et al., 1991).So, the development of ad hoc GIS and RS techniques is very helpful to detecting changes in wetland and to understand the factors that are able to drive the dynamic processes of rural-urban transformation (Eyasu et al.,2019).Therefore, this study will be detecting the wetland change in a period of thirty tree years with every increasing demand for water under changing climate in and around Addis Ababa.

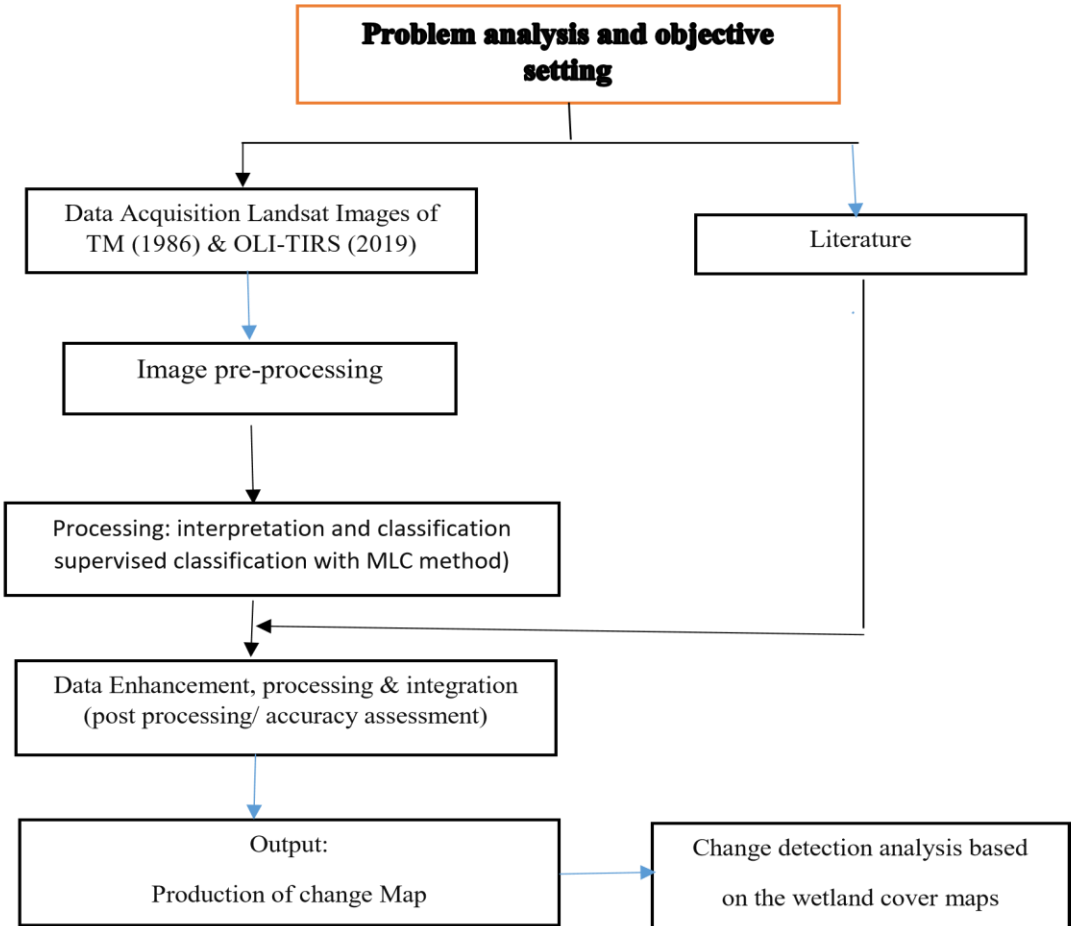

Figure 1 Work flow of the wetland cover change detection analysis

II. METHODS

2.1 Study Area

The study was carried out in Akaki sub basin (including big and small Akaki watershed) around Addis Ababa and surrounding zones of Oromia. (Figure 2). The project area boundary generally follows the boundary of the watershade to words surrounding Oromia region. The Big and Little Akaki water shade is two only wetland areas found and the main water source of the city of Addis Ababa. The Big Akaki have shaped the majority of landscape.

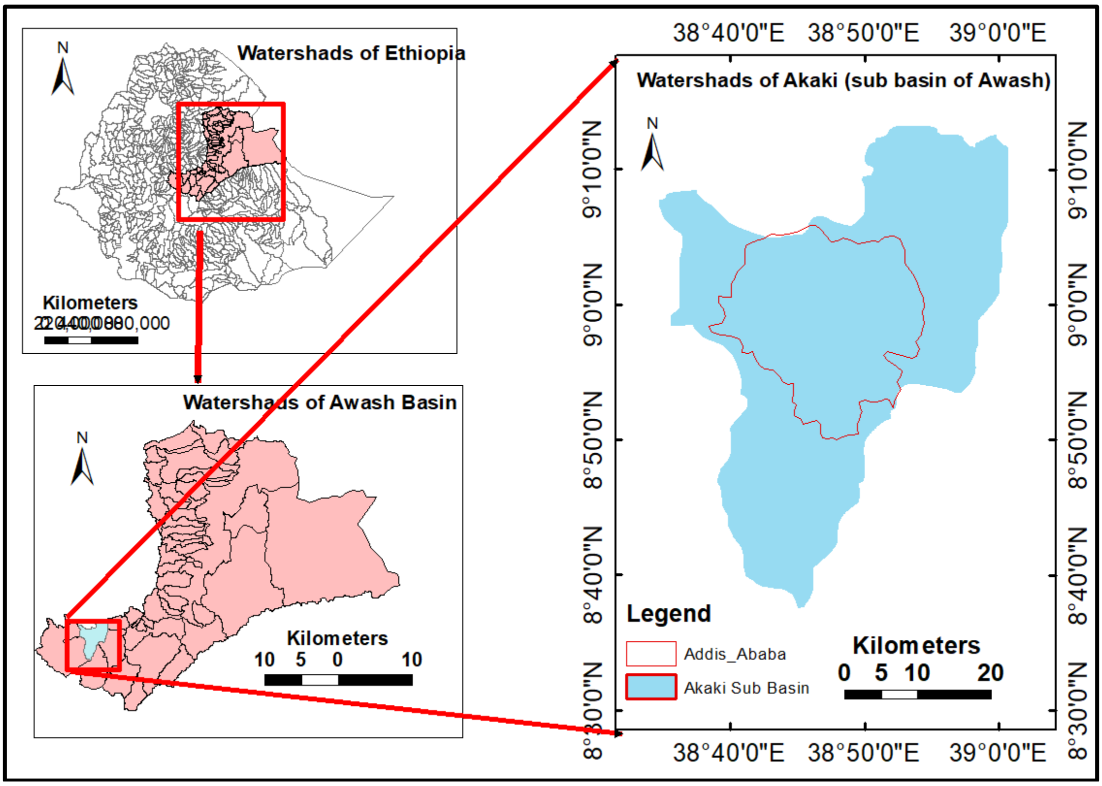

Figure 2. Study area map

2.2 Image Processing

I use the flow of work for detection of wetland are shown in figure 1. After problem analysis and object setting, acquisition of data and searching review literature to process Images of study areas are carried out. Landsat image was used Thematic mapper 1986 (Landsat 4-5 TM), and Landsat Enhanced Thematic Mapper Plus (ETM+) images from 2019 (Landsat 8 OLI-TRIS) 01 January, 1986 and 04 January, 2019 were the spectral data sources used in the classification procedure. The Landsat sensors records 7 bands of spectral data in the visible, infrared, and thermal portions of the electromagnetic spectrum. The spatial resolution of this sensor is 30 m *30m resulting in a 900 m2 (0.09 ha) minimum mapping unit. To help identify wetlands, the images were merged into a single classification using known wetland, Built up, Forest and agricultural land areas as training sites. In addition, the watershed area delignated data was used from World Bank data catalog which is accessed freely (https://datacatalog.worldbank.org/dataset/watersheds-ethiopia). A total of 1,787,647 pixels were used to classify the 300 pixels contained in the study area. All the acquired images were referenced to the Ethiopian Coordinate System using UTM projections and WGS 84 datum. Considerations made while obtaining these images were on dry seasons of the years were utilized. This is because during dry seasons, there is minimal cloud cover hence higher precision, and also various anthropogenic activities are predominant particularly on the wetland during such periods (Theau, 2011) This involved the process of geometric image correction for clarity over the identified periods (1986 & 2019). For digital image processing, false color composites were created using bands 5, 4, and 3 for each of the images. Supervised classification of the satellite imagery was used to produce for those land uses and wetland cover classes. In all image processing steps, nearest neighbor resampling was used to preserve radiometric integrity.Differences between Landsat TM and ETM+ sensors were standardized through established radiometric correction procedures prior to change detection analysis (Ramsey and Laine 1997, Masek et al. 2001).

2.3 Change Detection

The change detection techniques have been used in remote sensing to identify the changes in geographical location, recognizing, classifying and quantifying the type of changes and finally assessing the accuracy through change detection statistics. Change information obtained here is simple binary differencing i.e. change vs. no change. A total of 4 well separable land-use/land-cover classes were identified on both considered data sets. Support Vector Machine multispectral classifier results in classifying Water Body, Built up, Forest and Agricultural Fields more effectively. For resulted classified sets, change of information obtained by simple binary differencing using change detection technique. Then change detection statistics are generated for the difference map.

Image Differencing

Image differencing is a method of subtracting the DN (Digital Number) value of one data with the other one of the same pixel for the same band which results in new image. Mathematically, image differencing can be represented as follows

$$ID(X,Y)=I1(X1,Y1)-I2(X2,Y2)$$

Where ID-image difference, I1 and I2 represents images taken from two different time periods and (x,y) are coordinates and represents difference image(H. Sciences,2012). I1 image was obtained from Land sat 5 fromJanuary, 1986 and image I2 is obtained from Landsat 8 from January, 2019. Both data are taken from same month in order to have a better change detection results under same climatic condition. A set of threshold values based on standard deviation from mean value are used to determine difference in pixels. Pixels with change in radiance are distributed in the tails of the distribution curve whereas pixels with no change are distributed around the mean(D. Lu et.al. 2009, Michael et al, 2007). As changes can happen on both directions, the analyst has to decide the order of the image to be subtracted (H. Sciences, 2012). In change detection statistics table, initial state of classes is represented in columns and final state of classes are represented in rows. Statistics shows how initial state pixels were classified in the final state image percentage wise(Baker et al, 2007). The Class Changes row represents the total percentage of initial state pixels that changed classes. The Image Difference row is the difference in the total number of equivalently classed pixels in the two images, computed by subtracting the Initial State Class Totals from the Final State Class Totals. An Image Difference that is positive indicates that the class size increased, if it is negative indicates that the class size decreased.

$$\text{Percentage} = \frac{(final\ state - intial\ state)}{intial\ state}$$

2.4 Accuracy Assessment

Quality evaluation is one of the steps in making change detection for accuracy assessment (Giri, 2012: Meng et al, 2017). Thus, to check the accuracy and performance of classification for 1986 and 2019 imageries, Goggle Earth e were used instead of ground points and stratified random sample strategy was adopted to assess the accuracy of the classified map. Therefore, assuming 1986 is similar future for image and 2019 images GCPs generated from Google Earth were used and random pixels were generated for each classified image. Then, comparison of classified images and reference data was carried out statistically using error matrix. Accordingly, the overall accuracy of this study for initial and final year was 80.2%, and 92% with kapa value of 47% and 76%, respectively. The Kappa quantity, which measures the difference between the actual agreement of classified map and chance agreement of random classifier compared to reference data, was also calculated as (Congalton, 1991):

$$Khat = \frac{N\sum_{i=0}^{r} - \sum_{i=0}^{r} *(X_{i+} * X_{+i})}{N^2 - \sum_{i=0}^{r}(X_{i+} * X_{+i})}$$

Where r is the number of rows, xi is the number of observations in row i and column i, xi+ and x+i are the marginal totals of row and column, and N is the total number of observed pixels.

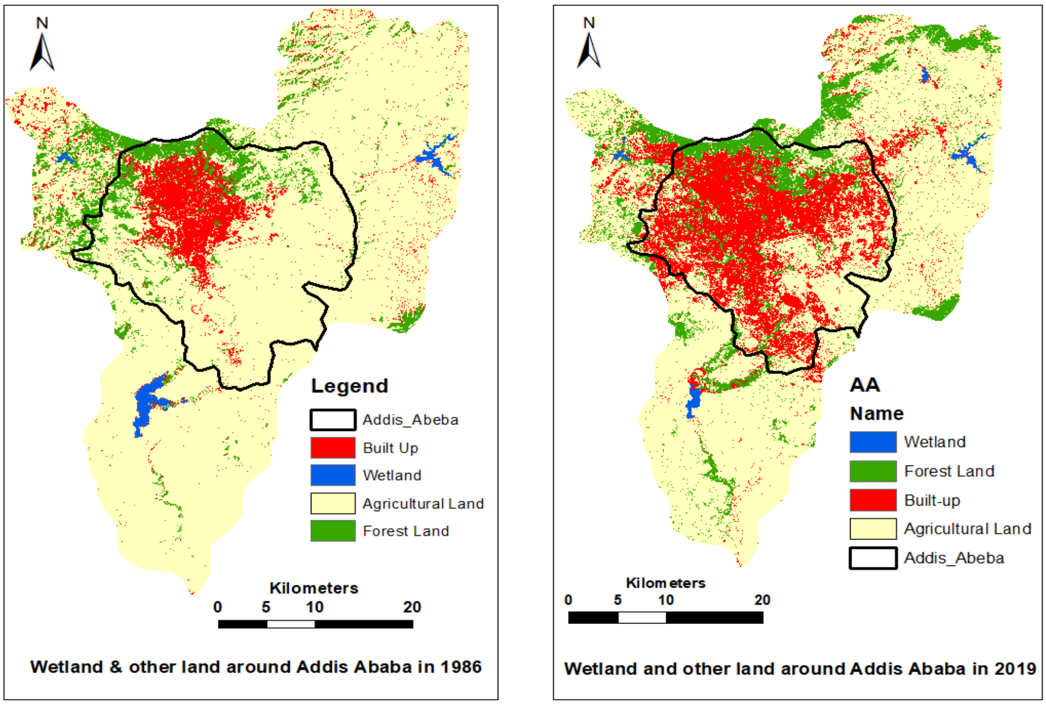

Figure 3 Land use of 1986 and 2019 around Addis Ababa, Akaki watershed

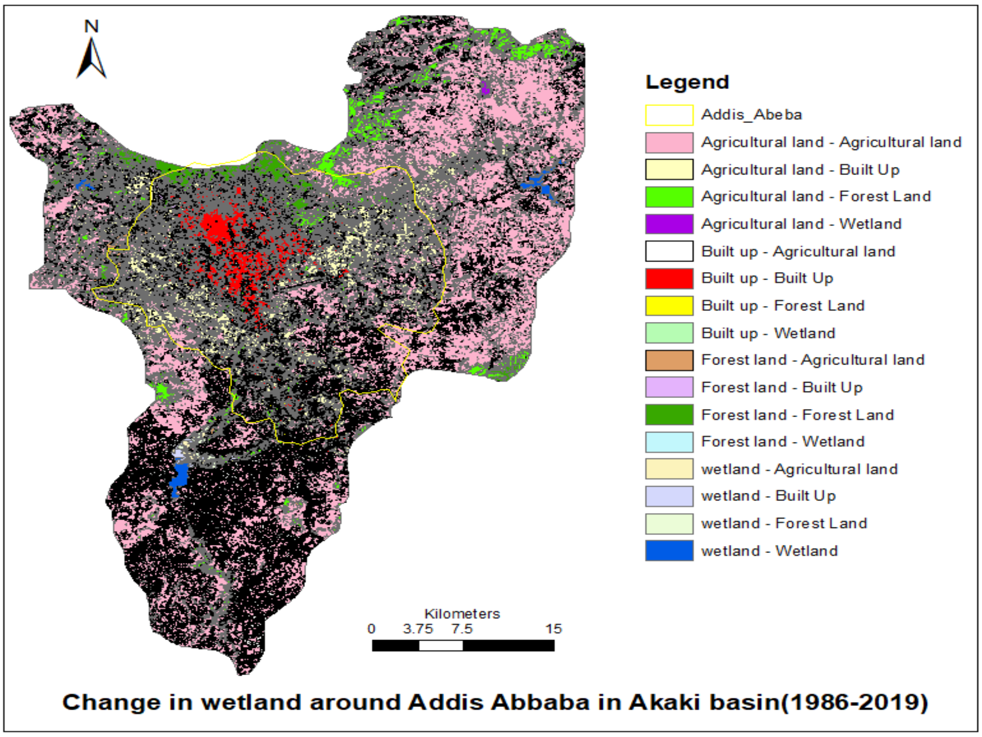

Figure 4. Detection Difference Map of (1986Vs2019)

III. Results

3.1 Classification

The potentially changed pixels in the 1986 image were classified using to identify wetland and non-wetland land cover classes but for more detail information about the change I would have used additional other major land uses types. The classes were then compared to the same classes identified in the 2019 classification to determine the land cover changes in regards the two image dates (Table 1 and figure 4).. To search the main cause of wetland loss or gain we apply other main land use types in to study.

Table 1 LULCC around Addis Ababa in Akaki watershed (1986- 2019)

LULC Class	1986		2019		Net change from 1986-2019	
	Ha.	%	Ha	%	Ha.	%
Agriculture	139414.3	87%	102759.7	64%	36654.6	23%
Built up	10441.47	6%	37739.15	23%	-27297.7	-17%
Forest	9657.735	6%	19381.49	12%	-9723.76	-6%
Wetland	1321	1%	954.76	0.4%	366.24	0%
	160834.5	100%	160835.1			

3.2Analysis of data and accuracy assessment

A total of 4 well separable land use (LU) classes were identified on considered two data sets. To validate the classification results, spatial accuracy assessment was carried out for resultant classified images. In order to measure the agreement between the reference and classified information Kappa coefficients were calculated. In 1986, the overall classification accuracy of 80.20% and Kappa coefficient 0.67. The result of wetland detection reveal that wet land coverage decreased within 33 years period. In 2019, Landsat-8 ETH+ data was classified with overall classification accuracy of 92% and Kappa coefficient 0.76accuracy values. Once again, each of the land use user accuracy and producer accuracy had been evaluated, the wetland area are lower than others. This may be the reflection of wetland (wetsoiland Chafe grazing land) presented as wet land in 1986 image and absence or few area of chafe land in 2019.

Wetland has seen a decrease in its cover by about 0.04% during the study period which is not significant. Major contributor for decrease in wetland cover may the expansion of agriculture to some wet grazing land (cheffe), deforestation, and urbanizationand decrease the amount of precipitation with increase of temperature which cause for evaporation of water in changing climate. In addition to that siltation also affects the dams around city by reducing water holding areas.

Table 2. Land use change from 1986 to 2019 around Addis Ababa Akaki sab basin

Change (1986 Vs2019)	Hectare	%
Agricultural land - Agricultural land	98849.86	61%
Agricultural land - Built Up	26965.44602	17%
Agricultural land - Forest Land	13506.41415	8%
Agricultural land - Wetland	92.565687	0%*
Built up - Agricultural land	23.7483	0%*
Built up - Built Up	10382.52676	6%
Built up - Forest Land	30.515306	0%%
Built up - Wetland	4.863288	0%%
Forest land - Agricultural land	3433.121579	2%
Forest land - Built Up	386.880663	0%%
Forest land - Forest Land	5837.308	4%
Forest land - Wetland	0.424835	0%%
wetland - Agricultural land	452.990941	0%*
wetland - Built Up	4.299929	0%*
wetland - Forest Land	7.254325	0%*
wetland - Wetland	856.905175	1%
Grand Total	**160835.1211**	**100%**

green color	No change,
Yellow	Changed except wetland
whit (no color)	add for wetland
Red	Deducted fromwetland

8* _ is not really zero, small number calculated as zero.

For detection of wet land accuracy, it divides in to two parts includes wet land and excluding agriculture, forestry and built up as non-wetland. The high user (80%) and producer (100%) accuracies for the unchanged wetland class. The unchanged non-wetland class had markedly lower user (62%) and producer (71%) accuracies. Using the change threshold mask, we determined a total of 1699 pixels (0.5% of the study area) had change magnitude values greater than the 0.130 change threshold and were considered potentially changed in each land uses (Table 2). Only 7981 pixels (99.5% of the study area) of these potential change pixels were classified in 1986 than in 2019 and thus represented estimated ecological change. The landscape area classified as wetland was somewhat inflated since each pixel could be comprised of as little as 47% wetland vegetation. The results of this change detection analysis (Table 2) showed that wetlands have generally decreased with the water shade at 23 % from base year covered by wetland (not all land uses compared). Wetland change locations occurred in the interior of existing wetland clusters and around the peripheral areas of unchanged wetland as stated in difference map (Figure 4). The signature detected in wetland basically in reservoir are different because of may have sediment deposition and other chemicals discharge into the wetlands.

Table 3. Change between wetland and non-wetland around Addis Ababa in Akaki sub basin (1986 V 2019)

From	To	Area (Ha)	Change Detection class
No wetland	No wetland	159415.8208	No Change
No wetland	Wetland	97.85381	Positive change for wetland
Wetland	No wetland	464.545195	Negative change in wetland
Wetland	Wetland	856.905175	No Change

IV. Discussion

Change detection is an important process for monitoring and managing nattural resources and urban development. The decrease in wetland accuracy was partially the result of changes tha have carried in past 33 years during the accuracy assessment. The individual 2019 and 1986 image classification accuracies (92% and 80.2%, respectively) indicated that distinguished wetland sites from other land cover types effectively.The two change classes and the non-change wetland class were heavily sampled in the stratification of the accuracy assessment. This sampling method thoroughly tested the accuracy of the areas associated with wetland areas. Overall accuracies would be substantially higher, a proportionate number of the more prevalent unchanged non wetland pixels had been sampled, instead of intensively sampling the changed locations (Getinet, 2017, Mengesha 2017), The results demonstrate that the assessments of the proposed adaptation strategies are effective, but not ensure water sustainability (Houssam et al 2020).Capturing the nature of changing ecosystems such as wetlands is a difficult proposition. These ecosystems occupy a wide variety of habitats and display an equally expansive range of vegetation and hydrology.

In order to measure the agreement between the reference in measuring Kappa coefficients of 0.67 and 0.76 indicate that image processing an acceptable. But user accuracy and producer accuracy of wetland had been evaluated, the wetland are lower than others. This may be reflection of wetland (wet soil and Chafe grazing land) presented as wet land in 1986 image and absence or small area of chafe land in 2019 in imaging process. In both the 1986 and 2019 classifications, the majority of error resulted from non-wetland locations being incorrectly classified as wetlands or others. This over-classification of wetlands, as opposed to under-classification, is advantageous for inventories designed to locate all possible wetlands. These errors, however, also likely contributed to errors in the change detection analysis. In general wetland is decreasing may need future intervation on restoration of water shade wetland. This result also agree with Kinfe Kidanewald(2018) shows increase on built up and vegetation cover than agricultural land use in selected three sub city of Addis Ababa.Also, some studies show that, under the influence of climate change, future unmet water demand is expected to reach 64 million cubic meters (MCM) by 2100. The identified major threats are drainage for agriculture; overgrazing; invasion of alien species; degradation of catchment lands; over harvesting of their resources, settlement and urban expansion; population growth, water diversion, destructive tree plantation around the wetlands and pollution also agree with study by Kinfe (2018) at three sub city of Addis Ababa and Diriba Megersa and Hailu (2020) in country level. While, policy related issue; institutional arrangement issues; issue of capacity shortage; On-site management problem; Off-site management problem and Ecological issue are driving factors those contribute to the threats to the wetlands (Diriba Megersa Soboka, Leta Hailu Gemechu, 2020). Similarly Zinabu and Michael (2020 0adds high living standard scenarios have a great negative impact on the water supply system

V. Conclusion

The dynamic nature of wetland ecosystems requires an equally dynamic change detection procedure as any land cover change in given period of time. In this study indicate an increase in the area of built up and forest by17% and 12% of its original coverage respectively whereas wetland decrease by 1%. The reason behand decrease includes the forest degradation on hill of mountain out of the reservoir areas. Agricultural Fields has seen decrease from its original value highly than any other land use. This could be due to expansion of city to neighboring farm land and industrial boom out of Addis Ababa. This is indeed as a good development if the growth become without affect ecology including wetland. Most of from Forest cover as seen by the statistics increase may help to reduce the problem of ecosystem functioning.The ecosystems can exhibit a variety of vegetative or hydrologic changes (Whigham 1999, Mitsch and Gosselink 2000, Wondimu et al., 2018) that might not be detected when using one or two spectral bands. This approach achieved our goal of maintaining accuracies without the need for separate reference data for the second classification and was, therefore, an efficient method for locating historical wetland communities. Similarly, change in Addis Ababa and surrounding Oromia region are overseen by a combination of geographical, environmental and socio-economic factors. In addition to this Imagery analysis, the many research shows that multiple effects of land use change in the study area have happened between1986 and 2019. Is polluted by various discharges from tanneries, breweries, wineries, battery factories, and abattoirs (Yohannes, 2017). The conclusion of this study was it is possible to integrated problem solving approach through realizing the collaboration of relevant stakeholders from policy level down to grassroots community is indispensable opportunity around Addis Ababa akaki watershed wetlands for better water service for growing population and economy of Ethiopia.

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