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Remote Sensing Based Water Surface Extraction and Change Detection in the Central Rift Valley Region of Ethiopia

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Abstract
Recent advancements in water indices techniques and the availability of multi-temporal and multi-spectral imageries, has made the task of extracting and detecting surface water changes a lot effective and simpler. By taking advantage of this advancement, this study has therefore implemented NDWI and AWEI, among other indices, to extract and analyze the surface area changes of Lakes Shala, Abjata and Langano in the Central Rift Valley Region of Ethiopia. In doing so, Landsat images of 1973 (MSS data), 1986 (TM), 2000 (ETM+), 2005 (ETM+), 2011 (TM) and 2014 (OLI_TRIS) has been used. The results show that Lake Shala and Lake Langano has shown very small changes (-3.68 sqkm & -10.2 sqkms respectively) as compared to the surface area change of Lake Abjata (-68 sqkm) between 1973 and 2014, hence making Lake Abjata the most abruptly changing lake in four decades.

Keywords: *Change Detection, Remote Sensing, surface water extraction, Water indices, Lake Abjata, Lake Shala, Lake Langano.*

1. Background and Justification

Remote sensing imageries has widely been used in environmental studies to detect changes caused either due to natural factors or anthropic factors [1, 2]. Change detection, defined by [3] as "*the process of identifying differences in the state of an object or phenomenon by observing it at different times*", essentially comprises the quantification of temporal phenomena from multi-date imagery acquired by satellite based multi-spectral sensors [4]. It is more elaborated by [5] as the process involving the application of multi-temporal datasets to quantitatively analyze the temporal change of the phenomenon. Hence, change detection can be generalized as a means of identification, recognition and quantification of temporal differences of the same features or phenomenon occupying a well-defined spatial extent.

Several multi-temporal remote sensing data based change detection approaches have been developed so far [6] making the area of change detection an ongoing research agenda [2]. Despite their varieties, however, most of the change detection approaches are commonly structured in two major steps. Feature extraction being the first step, it refers to the processing of remotely sensed imageries in order to extract pertinent information thereby preparing the input required for the decision step. The next step, decision step, involves the applications of operations on the extracted features in order to produce 'change' versus 'no-change' models that are considered as the final outputs [1]. Mapping of 'change' versus 'no-change' can be achieved using techniques including image differencing, image ratioing, or principal component analysis (PCA) and tasseled cap transformations [6] .

Water being a very crucial environmental resource, several techniques have been introduced in recent decades for its extraction as a feature from satellite data. One of which is a single-band method which utilizes a selected threshold value to extract water features. Classification techniques adopted to extract surface water are normally more accurate compared with single-band methods [7]. A recently developed approach for change detection of water bodies is water indices. Water indices refers to mathematical models that enhance the water signals for a given pixel at images obtained from visible/near-infrared scanning sensors. These models are usually calculated from two to four bands; the Green, near-infrared, mid-infrared and shortwave infrared portions of the spectrum. From among the water indices developed for the extraction of water features from Landsat imageries the Normalized Difference Water Index (NDWI) [8], Modified Normalized Difference Water Index (MNDWI) [9], Normalized Difference Moisture Index (NDMI) [10], Water Ratio Index (WRI) [11], Normalized Difference Vegetation Index (NDVI) [12] and Automated Water Extraction Index (AWEI) [13] are the most common ones.

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In Ethiopia there are plenty of places which can benefit from these multi-temporal imagery based water extraction techniques that has been developed. Among the plenty of places, the Central Rift Valley Region, part of the Great Rift Valley that runs through Ethiopia, is one potential geographic area that can make use of the water indices techniques in tracking some of its changing water bodies. This region is known for being a home to four major lakes (Lake Abjata, Lake Langano and Lake Ziway) including the neighboring Lake Shala. Lake Shala, the deepest lake (256 meter deep), is a closed highly alkaline lake which is separated from Lake Abjata by a volcanic caldera rim [14].

According to [14] the neighboring Lake Langano, known in Ethiopia for being the home to recreational resorts, is fed by rivers from the highlands on eastern side of the Rift Valley and flows towards Lake Abjata through the Horakela River. Unlike the almost constant levels of Lake Langano or Shala, however, Lake Abjata has got a different story especially in relation its areal coverage changes. Different researches show that Lake Abjata has been showing a constant decline in its water level and areal extent since 1980 for reasons mostly unknown. [14] explains that water abstractions as the main cause of the decline. He further stated that Lake Abjata is sensitive to any reduction of flow in the Bulbula River, either through lake levels in Lake Ziway dropping or through direct pumping of water along the course of the Bulbula River to supply Ziway and Bulbula town water supplies, or diverted for small irrigation plots. The direct pumping of water from the Lake Abjata for commercial exploitation of soda ash by evaporation of saltwater also impacts on lake levels.

Since Lake Abjata is fed principally by spills of the upstream lakes of Ziway and Langano, and because of its terminal position in the drainage area, and its shallow depth, Lake Abjata has a more pronounced sensitivity to changes in its basin and is especially susceptible to any diversion of feeder rivers for irrigation projects along the Meki and Katar Rivers and to water abstracted directly from Lake Ziway for irrigation and domestic consumption [15].

This shows that Lake Abjata is in a very acute situation, either due to the water drained for developmental activities including the soda factory, floricultures or irrigation schemes near and around the central rift valley or due to environmental factors such as decline in rainfall, higher temperature thus higher evapo-transpiration. The aim of this research, thus, is to extract and analyze the level of surface area changes that Lakes Shala, Abjata and Langano had undergone over the past four decades (i.e. 1973 – 2014) using remotely sensed Landsat imageries.

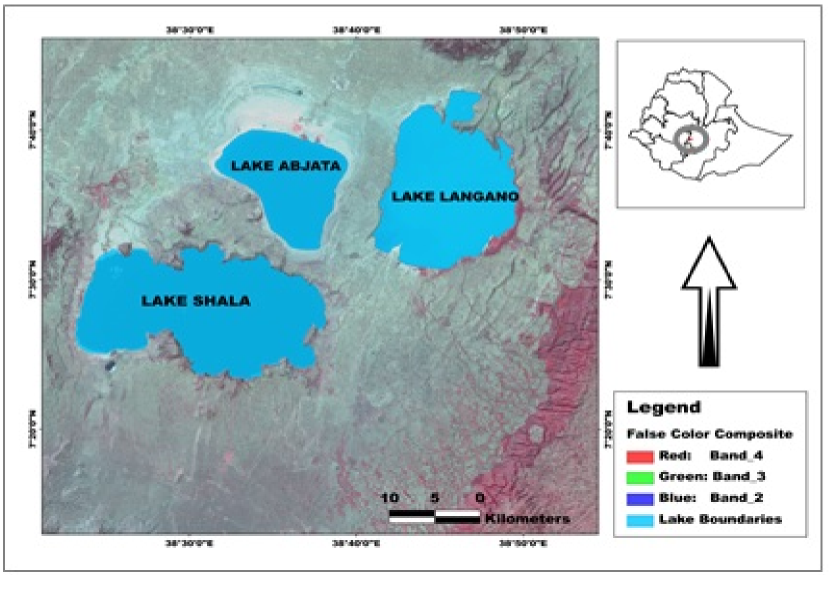

Figure 1: Location of Lakes Shala, Abjata, and Langano in the Central Rift Valley region of Ethiopia.

2. Methods and materials

In order to reach at the final aim of the study, Landsat image data types of MSS, TM 5, ETM+ 7 and OLI_TRIS of Landsat 8 were first collected from different sources. The MSS, TM and ETM+ imageries were obtained from GLCF online image download service while the OLI was obtained from US Geological Survey (USGS) Global Visualization Viewer. The acquisition date for the MSS image data was on January 31, 1973; TM image on January 21, 1986 and January 10, 2011; ETM+ image on February 05, 2000 and December 03, 2005, and OLI_TIRS on February 06, 2014. For the purpose of analyzing the image data, Quantum Desktop, Arc GIS and Erdas Imagine were used at different levels.

In trying to identify the surface water area, NDWI was calculated for the MSS image data of 1973, and AWEI for TM, ETM+ and OLI_TIRS of 1986, 2000, 2005, 2011 and 2014. NDWI was selected because of the characteristics of the MSS bands and AWEI because it gave better result in representing the available surface water of all the three lakes. Raster calculator was the function used to calculate both selected indices which were further reclassified in to two different classes where by positive values were identified as water bodies and negative values as land surface.

Table 1: Specifications of Landsat MS, TM, ETM+ and OLI data used for analysis (Source: [16, 17])

Satellite	Study Years	Wavelength (µm)	Band	Spatial Resolution (meters)
Landsat 1 (MSS)	1973	Band 4: 0.50 - 0.60	Green	79
		Band 5: 0.60 – 0.70	Red	79
		Band 6: 0.70 – 0.80	Near IR	79
		Band 7: 0.80 – 1.10	Near IR	79
Landsat 5 (TM)	1986 & 2011	Band 1: 0.45 – 0.52	Blue	30
		Band 2: 0.52 – 0.60	Green	30
		Band 3: 0.63 – 0.69	Red	30
		Band 4: 0.76 – 0.90	Near IR	30
		Band 5: 1.55 – 1.75	Mid IR	30
		Band 6: 10.4 – 12.5	Thermal	120
		Band 7: 2.08 – 2.35	SWIR	30
Landsat 7 (ETM+)	2000 & 2005	Band 1: 0.450 – 0.515	Blue	30
		Band 2: 0.525 – 0.605	Green	30
		Band 3: 0.630 – 0.690	Red	30
		Band 4: 0.760 – 0.900	Near IR	30
		Band 5: 1.550 – 1.750	Mid IR	30
		Band 6: 10.40 – 12.5	Thermal	60
		Band 7: 2.080 – 2.35	SWIR	30
		Band 8: 0.52 – 0.92	Pan	15
Landsat 8 (OLI_TIRS)	2014	Band 1: 0.43 - 0.45	Coastal aerosol	30
		Band 2: 0.45 - 0.51	Blue	30
		Band 3: 0.53 - 0.59	Green	30
		Band 4: 0.64 - 0.67	Red	30
		Band 5: 0.85 - 0.88	Near IR	30
		Band 6: 1.57 - 1.65	SWIR	30
		Band 7: 2.11 - 2.29	Mid IR	30
		Band 8: 0.50 - 0.68	Panchromatic	15
		Band 9: 1.36 - 1.38	Cirrus	30
		Band 10:10.60 - 11.19	Thermal Infrared (TIRS) 1	100 * (30)
		Band 11: 11.50 - 12.51	Thermal Infrared (TIRS) 2	100 * (30)

Table 2: Satellite-derived indexes used for water features extraction in Landsat imagery (MSS: Greeen= Band 4, NIR= Band 6; 5TM & 7ETM+: Green = Band 2, NIR= Band 4, MIR = Band 5, SWIR = Band 7; OLI_TRIS: Green=Band 3, NIR: Band 5, MIR= Band 7, SWIR: Band 6) (Modified from [18])

Index	Equation	Remark
Normalized Difference Water Index	$NDWI = (Green - NIR)/(Green + NIR)$	Water has positive value
Normalized Difference Moisture Index	$NDMI = (NIR - MIR)/(NIR + MIR)$	Water has positive value
Modified Normalized Difference Water Index	$MNDWI = (Green - MIR)/(Green + MIR)$	Water has positive value
Water Ratio Index	$WRI = (Green + Red)/(NIR + MIR)$	Value of water body is greater than 1
Normalized Difference Vegetation Index	$NDVI = (NIR - Red)/(NIR + Red)$	Water has negative value
Automated Water Extraction Index	$AWEI = 4 \times (Green\text{-}MIR) - (0.25 \times NIR + 2.75 \times SWIR)$	Water has positive value

3. Result and Discussion

Surface water area for each of the three lakes was calculated by using Normalized Difference Water Index (NDWI) for 1973 (MSS) and Automated Water Extraction Index (AWEI) for years 1986 (5 TM), 2000 (7 ETM+), 2005 (7 ETM+), 2011 (7 ETM+) and 2014 (OLI_TIRS). Figure 2 shows that both Lakes Shala and Langano (Left bottom and Right top) has shown very little change both in their shape & spatial coverage for all years. Unlike both lakes, however, Lake Abjata (middle top) has shown a very significant and discernible change in its surface area cover for each study year.

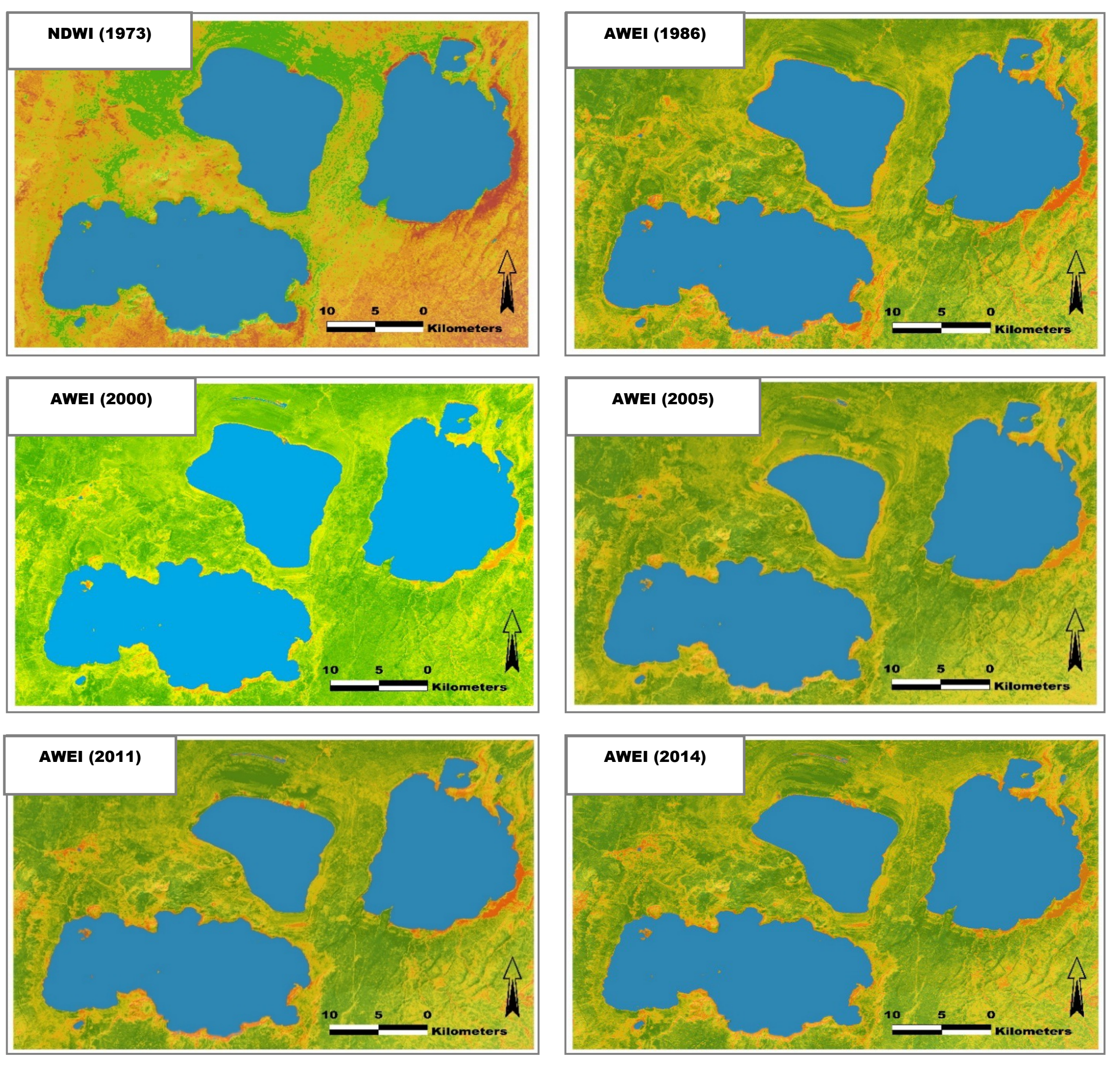

Figure 2: Water Index maps developed using NDWI for 1973 and AWEI for years 1986, 2000, 2005, 2011 and 2014.

The surface area change detection (Figure 3) confirms that Lake Shala and Lake Langano has shown lower change in their surface area over the study years. Lake Shala has seen its maximum surface area reduction of 5.53 sqkm between 1973 and 1986. Surface water area increment was evident in 2011 with a magnitude of 0.27 sqkm. The overall surface area change for Lake Shala between 1973 and 2014 totals to -10.21 sqkms (negative sign indicating a decreasing trend).

Similarly, the surface area change for Lake Langano shows a decreasing trend for years 1986 (-2.3sqkm), 2005 (-1.22sqkm) and 2014 (-1.51sqkm). Surface area increment for this lake only occurred in 2000 (+0.07sqkm), 2011 (+1.28sqkm) with an overall change of -3.68 sqkm between 1973 and 2014.

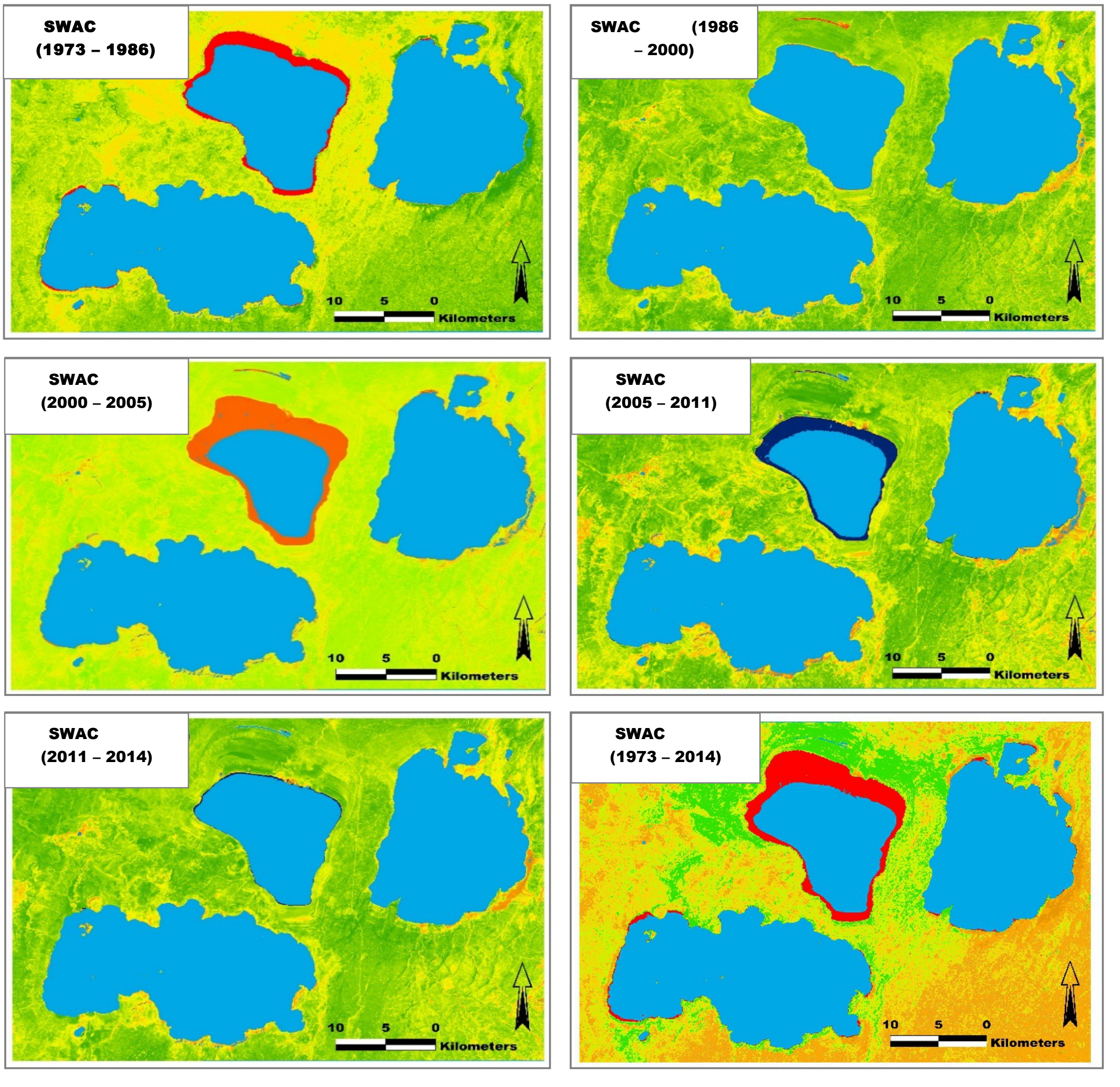

Figure 3: Surface Water Area Change (SWAC) maps showing the area changes between study years and over four decades.

Table 3: Surface area changes for Lakes Abjata, Shala and Langano both in percent and square k*ilometers (sqkm)*

Year	Lake Abjata			Lake Shala			Lake Langano		
	Estimated Surface Area (sqkm)	SA change from previous year (sqkm)	% of SA change from previous year	Estimated Surface Area (sqkm)	SA change from previous year (sqkm)	% of SA change from previous year	Estimated Surface Area (sqkm)	SA change from previous year (sqkm)	% of SA change from previous year
1973	200.13			315.36			233.68		
1986	165.22	-34.92	*-17.45*	309.84	-5.53	*-1.75*	231.39	-2.30	*-0.98*
2000	164.83	-0.39	*-0.24*	307.97	-1.87	*-0.60*	231.46	0.07	*+0.03*
2005	94.69	-70.13	*-42.55*	306.20	-1.77	*-0.57*	230.23	-1.22	*-0.53*
2011	128.01	33.32	*+35.18*	306.47	0.27	*+0.09*	231.51	1.28	*+0.56*
2014	131.94	3.93	*+3.07*	305.16	-1.32	*-0.43*	230.01	-1.51	*-0.65*

Unlike Lake Shala and Langano, Lake Abjata has experienced very dramatic changes over the years (see Table 3). The lake lost 34.92 sqkm of its surface area between 1973 & 1986, 0.39 sqkm between 1986 & 2000, 70.13 sqkm between 2000 and 2005. Almost half (42.55%) of the surface area occupied in 2000 was lost by 2005, hence the biggest loss in four decades. And then, the lake recovered back by occupying a significant area coverage of 33.32 sqkm (35% of surface area covered in 2005) and 3.93 sqkm by 2011 and 2014 respectively. The below shown graphs illustrate the leaps that Lake Abjata has made in its surface area in four decades.

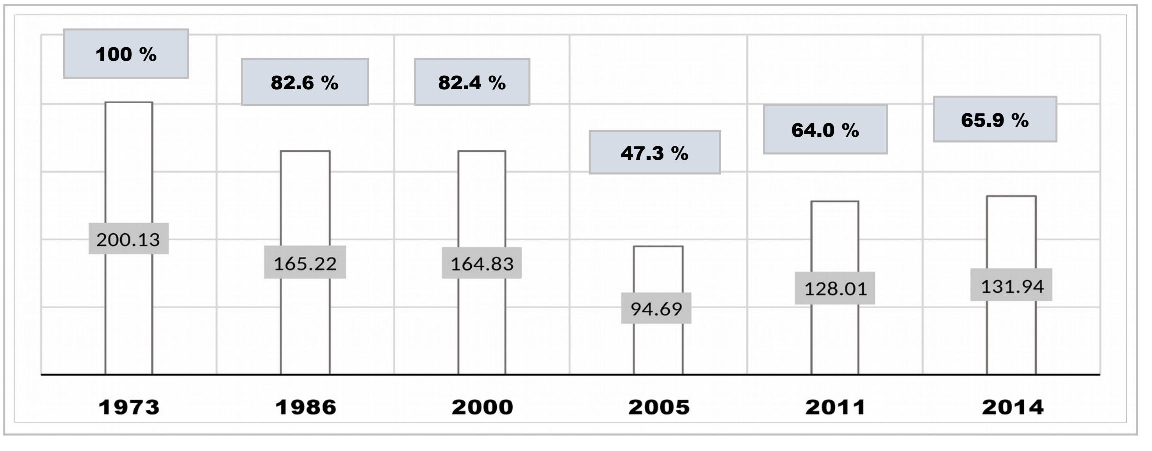

Figure 4: Lake Abjata's surface water area changes in percent and square kilometers

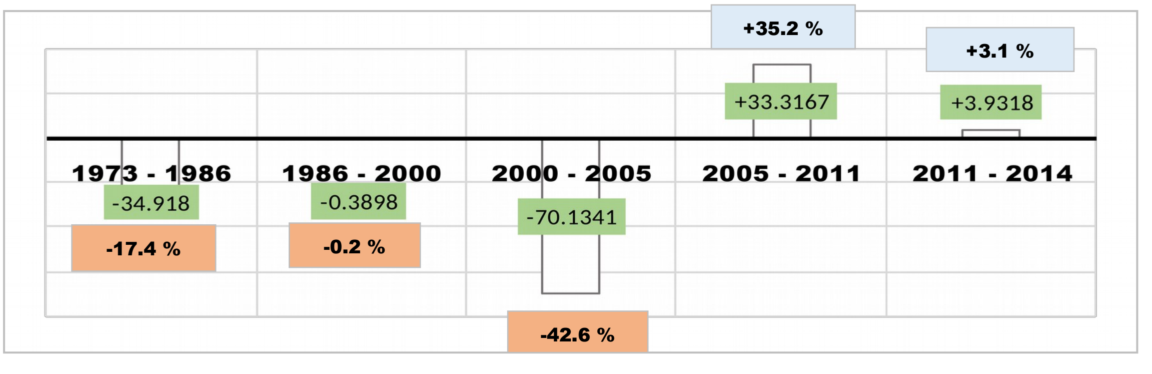

Figure 5: Lake Abjata's surface water area (SWA) changes between 1973 and 2014 both in percent and Squared Kilometers (sqkm). (N.B: negative values represent a decreasing trend and positive values an increasing trend)

4. Conclusion

The results of the analysis reveal that both lake Langano and lake Shala has shown very little changes (-3.68 sqkm & -10.2 sqkms respectively) in their surface area coverage over the past decades. Unlike the two lakes, however, Lake Abjata has shown a very significant decline (-68.19 sqkm) between 1973 and 2014. This lake has shown very erratic changes in its area coverage by losing almost 105 sqkm between 1973 and 2005 and then climbing back up by 37.25 sqkms in 2014. This, thus, makes Lake Abjata a central rift valley lake with a very dramatic decline and rise history in about forty years period.

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References

[1]. Gregoire M., Stephane D., Emmanuel T., Lionel B., (2010). Change detection in remote sensing observations. ISTE Ltd and John Wiley & Sons Inc, pp. 95-142, Digital Signal and Image Processing Series.

[2]. Masroor Hussain, Dongmei Chen, Angela Cheng, Hui Wei, David Stanley. (2013). Change detection from remotely sensed images: From pixel-based to object-based approaches. ISPRS Journal of Photogrammetry and Remote Sensing 80, 91–106.

[3]. Singh, A. (1989). Digital change detection techniques using remotely-sensed data. Int. J. Remote Sens., 10:989-1003.

[4]. Pol R. Coppin and Marvin E. Bauer. (1996). Change Detection in Forest Ecosystems with Remote Sensing Digital Imagery. Remote Sensing Reviews 13:207-234.

[5]. Lu D, Mausel P, Brondizio E, Moran E. (2004). Change detection techniques. Int J Remote Sens 25:2365–2404.

[6]. T. F. Ng, D. H. Jiang, X. Jiag, D. J. Paull and X. H. Wang. (2013). Change detection for sustainability monitoring using satellite remote sensing data. The University of New South Wales at Canberra, Northcott Dr. Campbell, ACT 2600, Australia.

[7]. Du, Z.; Linghu, B.; Ling, F.; Li, W.; Tian, W.; Wang, H.; Gui, Y.; Sun, B.; Zhang, X. (2012). Estimating surface water area changes using time-series Landsat data in the qingjiang river basin, China. J. Appl. RemoteSens.

[8]. McFeeters, S.K. (1996). The use of the normalized difference water index (NDWI) in the delineation of open water features. Int. J. Remote Sens., 17, 1425–1432.

[9]. Xu, H. (2006). Modification of normalized difference water index (NDWI) to enhance open water features in remotely sensed imagery. Int. J. Remote Sens., 27, 3025–3033.

[10]. Wilson, E.H.; Sader, S.A. (2002). Detection of forest harvest type using multiple dates of Landsat TM imagery. Remote Sens. Environment. 80, 385–396.

[11]. Shen, L.; Li, C. (2010). Water Body Extraction from Landsat ETM+ Imagery Using Adaboost Algorithm. In Proceedings of 18th International Conference on Geoinformatics, 18–20 June, Beijing, China; pp. 1–4.

[12]. Rouse, J.W.; Haas, R.H.; Schell, J.A.; Deering, D.W. (1973) Monitoring Vegetation Systems in the Great Plains with ERTS (Earth Resources Technology Satellite). In Proceedings of Third Earth Resources Technology Satellite Symposium, Greenbelt, ON, Canada, 10–14 December; Volume SP-351, pp. 309–317.

[13]. Feyisa, G.L.; Meilby, H.; Fensholt, R.; Proud, S.R. (2014). Automated water extraction index: A new technique for surface water mapping using Landsat imagery. Remote Sens. Environ., 140, 23–35.

[14]. Ester Raventós Vilalta. (2010). Water Resources Management in the Central Rift Valley of Ethiopia. MSc Thesis. Universitate Politecncia De Catalunya, Barcelona, Spain.

[15]. Halcrow Group Limited and Generation Integrated Rural Development Consultants (GIRDC) and Ministry of Water Resources (MoWR). (2009). Rift Valley Lakes Basin Integrated Resources Development Master Plan Study Project.

[16]. Global Land Cover Facility (GLCF). (2004). Landsat Technical Guide. University of Maryland Institute for Advanced Computer Studies, Department of Geography.

[17]. US Geological Survey. Using the USGS Spectral Viewer. Available on *http://landsat.usgs.gov/instructions.php* [accesses date: August 4, 2015].

[18]. Komeil R., Anuar A., Ali S., Sharifeh H. (2014). Water Feature Extraction and Change Detection Using Multitemporal Landsat Imagery. Remote Sensing, 6, 4173-4189; doi:10.3390/rs6054173.