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Digital Earth Africa

Monitoring Water Extent Using Earth Observation Data: Baringo Lake, Kenya

Abstract

Over the past 10 years, the Great Rift Valley lakes of Kenya have been rising because of the increasing rainfall which has led to a significant rise in the water levels. The impacts of increased water levels in the Great Rift Valley lakes cause a major problem that is affecting communities and their livelihoods. Flooding from the Baringo lake destroyed village areas including schools, farms, marketplaces, electricity lines, water supply as well as transportation systems in several areas.

This study aims to estimate the water extent of Lake Baringo in Kenya over the period from 1984 to 2021 using WOfS in Digital Earth Africa platform and to analyze the correlation between the expansion of water and the rainfall rate. The last step is to assess the effects on land use and land cover around the study area. Results indicate that rainfall has been changing over recent years with increased precipitation in 2010 resulting in water extent in Lake Baringo rising sharply. Lake Baringo has expanded by 55 percent from 1987 to 2021. In 2021 it covers around 230 square kilometers.

Keywords: Digital earth Africa, Water extent, Lake level rise, Flooding impacts, WOFs

Introduction

Situations of the Great Rift Valley Lakes

Water bodies play a crucial role in sustaining life and ecosystem stability, particularly in arid and semi-arid regions. In Kenya, the Rift Valley Lakes are sources of freshwater that support numerous ecological, economic, and animal habitats. This series of interconnected lakes, including Lake Turkana, Lake Baringo, Lake Bogoria, Lake Nakuru, and Lake Naivasha influence various economic activities, ranging from agriculture and fisheries to tourism and industrial processes. As a result, the health and well-being of these lakes have significant implications for the socioeconomic development of the surrounding communities. Over the past decade, these lakes have been experiencing a significant increase in water levels, leading to shoreline erosion, flooding of adjacent lands, and the submergence of important infrastructure. The situation has been aggravated more recently, considering the continued above average rainfall being observed in the long rainy season (Wainwright et al., 2020).

Flooding in Baringo affects villages because schools had been flooded and people had been displaced. Moreover, the rising of water levels in the freshwater Lake Baringo and alkaline Lake Bogoria has become worse because these lakes moved towards each other, threatening to become a single body of water, which would devastate the wildlife in both lakes. Most residents rely on the fishery because fish is a source of food, and people earn income from fishing so the Lake Baringo provides a career to them. People's lives will be affected largely if the lake has been decayed.

This has provoked renewed concerns about potential causes of the water level rises. Due to climate change, this has led to increased moisture availability, causing a rise in rainfall and discharge of the rivers feeding the lakes. There is also more soil in runoff, occasioned by land-use changes that have increasingly led to high sediment load in the rivers, shoreline flooding, erosion, and geological changes (Merab et al, 2021).

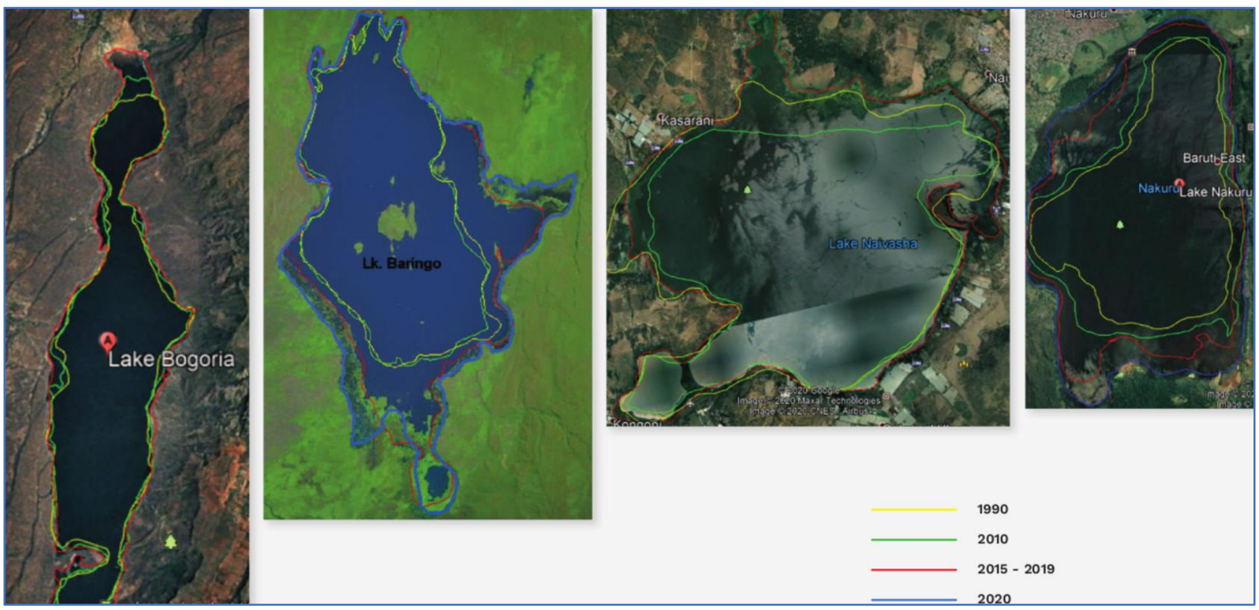

Figure 1. Changes in four rift valley lakes (Herrnegger et al., 2021).

Water extent assessment by Digital Earth Africa

The increase in the water levels, negatively impacts the local communities. Therefore, it is necessary to assess the long-term changes in water extent in order to deal with environmental problems in the future.

Digital Earth Africa provided the Water Observation from Space (WOfS) derived from Landsat satellite archive to evaluate water bodies and generate time series in Africa. The effect of flooding of the Rift Valley Lakes can be assessed using DE Africa tools and It helps users understand the location and water situations in Africa so we can estimate the effects of climate or develop water management strategies. Digital Earth Africa also has three WOfS products which are 1. An annual summary, 2. All-time summary and 3. WOfS Feature layer.

Digital Earth Africa Platform

Digital Earth Africa (DE Africa) provides a routine, reliable and operational service, using Earth Observations to deliver decision-ready products. The products and data are free and open source creating the opportunity that policymakers, scientists, the private sector and civil society to address social, environmental and economic changes on the continent and develop an ecosystem for innovation across sectors, such as agriculture and Food security, Water management, Sustainable urbanization and Coastal management.

Digital Earth Africa is developing a continental-scale platform for anyone to learn about the environments. The platform aims to provide satellite data into decision-ready products including infrastructure and tools that support data visualization and discovery which includes the following platforms.
For example,

- **Digital Earth Africa Map(DE Map)**, a website for map-based interaction with DE Africa products and services.
- **DE Africa Sandbox**, a cloud-based computational platform that operates through a Jupyter Lab environment.
- **Africa GeoPortal (Esri)**, this platform provides web GIS and geodatabase management applications that users can use imagery from Digital Earth Africa.
- **DE Africa Metadata**, a website that uses existing Open Data Cube infrastructure to inspect metadata for DE Africa services and underlying datasets. It includes a time-picker and coverage map to help users find datasets. The explorer can be used to locate and download individual data files from DE Africa.

In this study, Digital Earth Africa Sandbox is used for performing an analysis. The Sandbox has an installed environment on JupyterLab that is externally hosted and managed by Digital Earth Africa consisting of;

- An Amazon Web Service instance of cloud computing.
- Direct access to an Open Data Cube instance containing all of DE earth observation data.
- Pre-loaded Jupyter notebooks available to conduct earth observation analysis

Users can directly access Jupyter Notebook applications on Sandbox supported by Data Cube Applications Library (DCAL). The application library links Python code to help users utilize with their specific Data Cube applications such as cloud statistics, NDVI anomaly, Coastal Change, K-Means Clustering and Cloud-free mosaic algorithms.
Water Observations from Space (WOfS) is one of the application algorithms that the Python code is ready for performing water detection through time within the Sandbox.

Digital Earth Africa (DE Africa) is based on the Open Data Cube infrastructure, and specializes in storing remotely sensed data, particularly from Earth Observation satellites such as Landsat and Sentinel. All the data on Digital Earth Africa is hosted on Amazon Web Services(AWS) that can be accessed from the associated S3 bucket according to datasets, such as *deafrica-landsat, deafrica-sentinel-1* and *deafrica-sentinel-2.*

The Open Data Cube (ODC) is an open-source solution for accessing, managing, and analyzing large quantities of Geographic Information System (GIS) data and Earth observation (EO) data. For this functionality, Digital Earth Africa can leverage ODC to perform an analysis of large gridded data collections and an analysis of temporally-rich earth observation data. The Data Cube works well with Analysis Ready Data (ARD made available by data providers. Such data that available in Digital Earth Africa include elevation models, Landsat, Sentinel-1,2, GeoMAD, Water Observations from Space, Rainfall estimates and Global Landuse/Landcover.

The main purposes of Open Data Cube are the following points:
1. Geospatial Data Management: The ODC provides a structured and organized way to store, catalog, and manage vast amounts of satellite imagery and related geospatial data.
2. Data Access and Discovery: The ODC allows users to efficiently access and discover satellite imagery and other geospatial datasets. By employing spatial and temporal indexing, users can quickly query and retrieve data for their specific areas of interest and time frames.
3. Time Series Analysis: With the ability to organize data temporally, the ODC facilitates the analysis of time series data. This is particularly valuable for monitoring changes in the Earth's surface over time, such as vegetation dynamics, urban growth, or natural disasters.
4. Track the provenance of all the contained data to allow for quality control and updates
5. Openness and Collaboration: As an open-source project, the ODC encourages collaboration among the geospatial and remote sensing communities. It allows researchers, developers, and organizations to contribute to and benefit from shared resources, tools, and methodologies.
6. Provide a Python-based API for high-performance querying and data access

Overall, the Open Data Cube aims to democratize access to Earth observation data and empower users to harness the potential of geospatial information for a wide range of applications, from scientific research to policy-making and commercial endeavors.

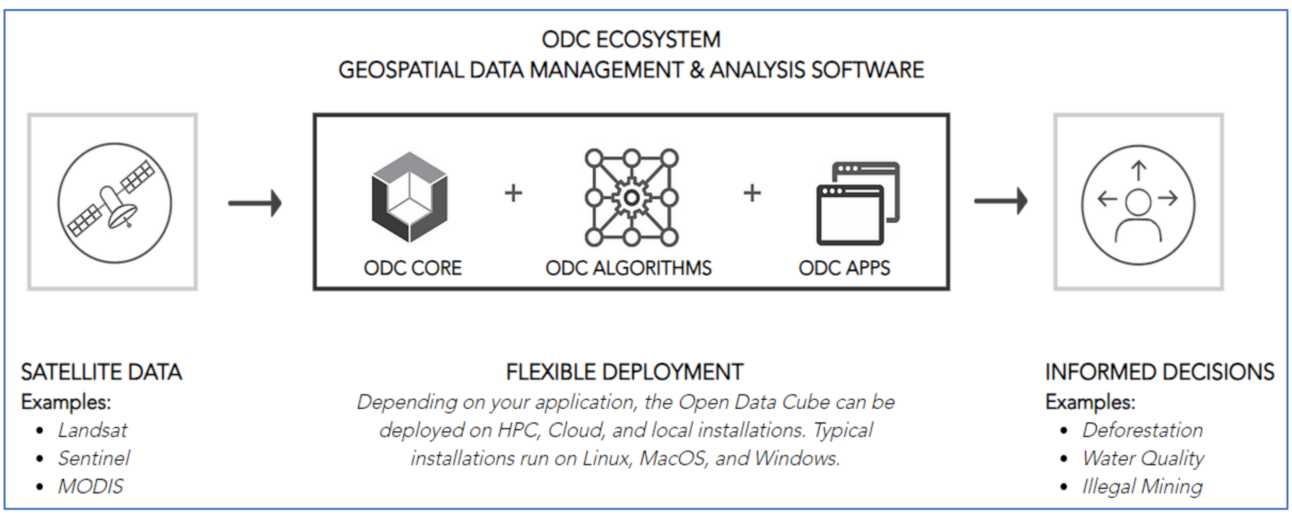

Figure 2. Open data cube infrastructure

Study area

The study area is Lake Baringo where is located in the Central Rift Valley of Kenya, the East African Rift System. Lake Baringo is a freshwater lake with a surface area of 130 square kilometers and an elevation of 970 meters. It is located in coordinate 0° 38′ 0″ N, 36° 5′ 0″ E. The lake's freshwater sustains a rich biodiversity, supporting a wide range of species also important to the communities. The basin is a source of water for domestic and agricultural use and watering livestock. Other important uses are income generation through tourism, biodiversity conservation and fishing(Omondi et al., 2014)

Despite its ecological richness, Lake Baringo faces several environmental challenges that threaten its ecosystem. Climate change rising temperatures, erratic rainfall patterns and widespread flooding affect the lake's water levels, destruction of infrastructure and increasing salinity levels.

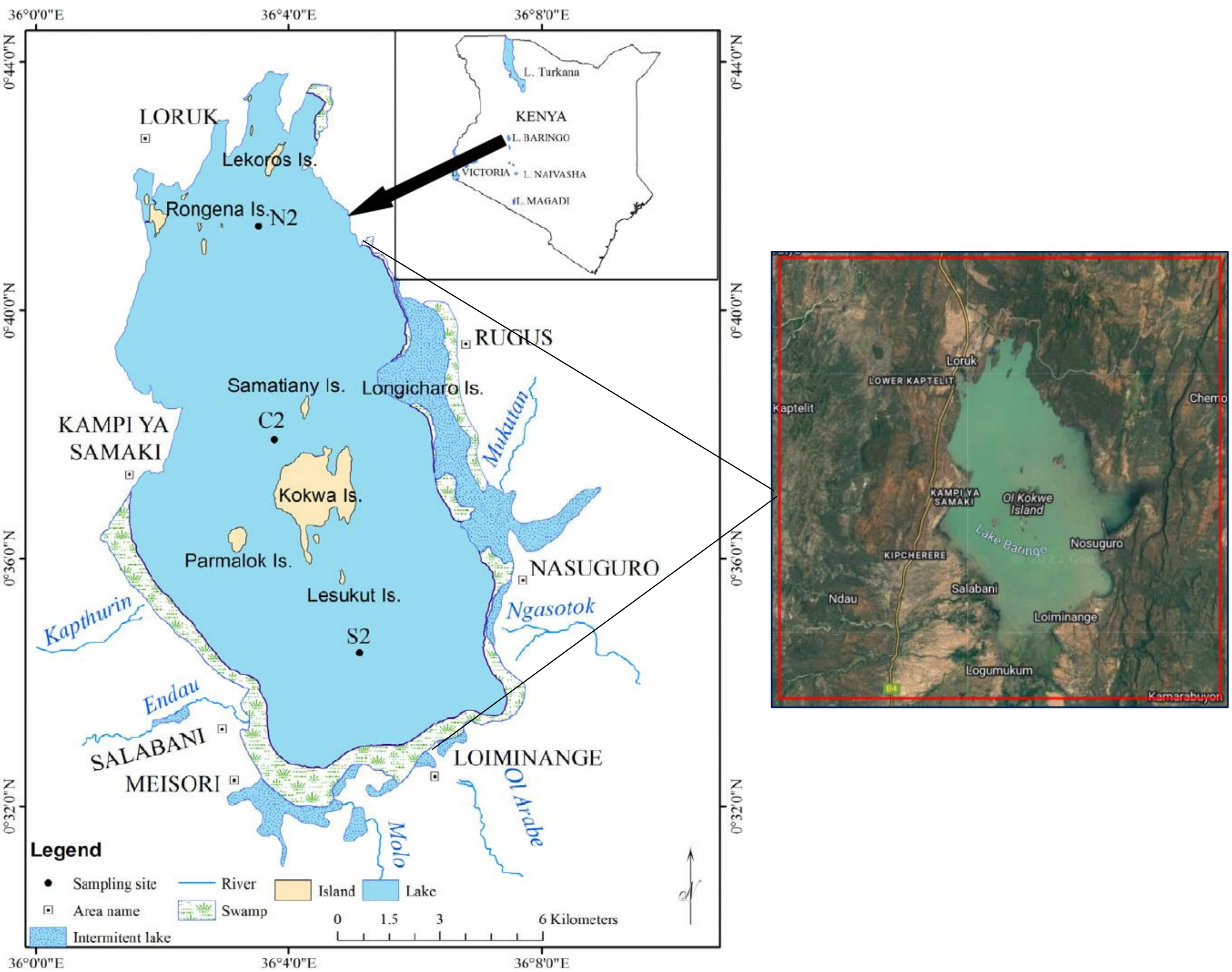

Figure 3. Study area of Lake Baringo (Omondi et al., 2014)

Datasets

Water Observations from Space (WOfS)

The analysis of water extent changes from 1984-2021 is conducted by using Water Observations from Space (WOfS) classification algorithm on Landsat satellite data indicating where water usually presents, seldom observed and where inundation of the surface. There are three WOfS products available for the African continent, as listed below;

Product Type	Description
WOfS Annual Summary	The ratio of wet to clear observations from each calendar year
WOfS All-Time Summary	The ratio of wet to clear observations over all time
WOFLs (WOfS Feature Layers)	Water and non-water classification generated per scene

Table 1. WOfS product type

WOfS Annual Summary is used for assessing water extent changes yearly, this product gives the frequency a pixel was classified as wet by requiring "Total number of clear observations" for each pixel (no cloud or shadow) in a given year. The classification algorithm will assign these as either wet or dry. Another parameter is "Total number of wet observations" for each pixel, it is the number of observations that were clear *and* wet for those years. Then the study gave an overview of the water changes by loading WOfS All-Time Summary product, it summarized WOFLs over the entire Landsat archive (1984 to 2021).

There are three measurements in WOfs summary dataset which are 1. count_wet, the number of times a given pixel was wet during a specific period. count_clear, the number of times counted in a given pixel that is classified as clear or not cloudy and that clear pixel could be classified as either wet or dry. The last one is frequency, the frequency is the ratio of count_wet to count_clear, which describes the percentage of time a pixel was wet out of all the times it could be seen during the period.

The WOfS Summaries are calculated from the following equation;

$$\text{WOfS Summary (frequency)} = \frac{\text{Number of Clear and Wet Observations}}{\text{Number of Clear Observations}}$$

Equation 1. WOfS summary equation

The two products mentioned above have a base product from WOfS feature layers and Landsat satellite data is a parent dataset of WOfS Feature layers. WOfS is stored as a binary number, where bits represent a particular feature. It has a single measurement called water, which indicates how the algorithm classifies each pixel in the image. If a pixel is 0, it means a dry pixel, and if a pixel equals 128, it will be classified as a water pixel.

The WOfS is a dataset derived from decision tree algorithm using both spectral band measurements and derived indices as input datasets. It also utilized several ancillary datasets, including slope. Tree branches are shown in green with endpoint for water and not-water displayed as blue and red respectively. Each branch indicates the variable used to split and the resulting balance of water and not-water samples created by the split (Mueller et al.,2016).

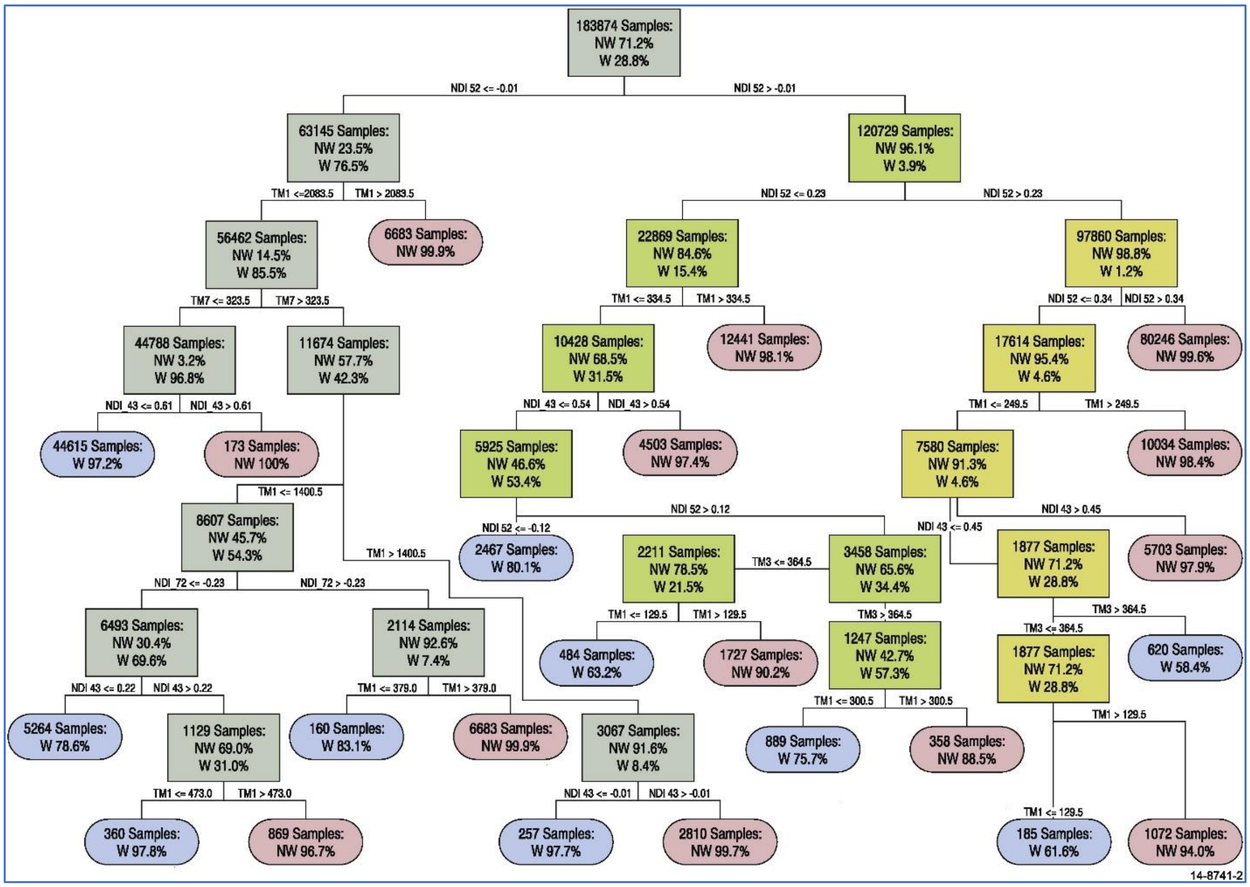

Fig. 4. Diagram of the regression tree underlying the water detection classifier (Mueller et al.,2016).

Rainfall - Climate Hazards Group InfraRed Precipitation with Station data (CRIPS)

The Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) is a quasi-global rainfall data set. It combines data from real-time observing meteorological stations with infra-red data to estimate precipitation. The precipitation data is retrieved from NASA and NOAA to build high-resolution 0.05 degrees (approximately 5.55 km) gridded precipitation climatologies. The dataset is available from 1981 to the near present. However, the CRIPS dataset is only available from 1994-2021 for this study area.

For the study, this dataset is used for understanding the interactions between climate systems and water body extension. Changes in climate patterns can have a profound impact on the extent and behavior of water bodies.

ESRI Global Land use and Land cover

The ESRI global land use land cover (LULC) is free and open access available in Digital Earth Africa derived from the European Space Agency (ESA) Sentinel-2 imagery. The resolution is 10 meters. The temporal range is from 2017-2021 but this study area is only available in 2020. The product was developed by the Impact Observatory (IO) with the Environmental Systems Research Institute (ESRI) and in partnership with Microsoft AI for Earth. The product name in Sandbox is io_lulc.

The classification classes are derived by utilizing UNET deep learning model to Sentinel-2 imageries across a year, accessed via Microsoft's Planetary Computer and Microsoft Azure Batch is used for scaling. There are 10 classes of land use/land cover classification consisting of rangeland, clouds, snow/ice, bare ground, built-up area, crops, flooded vegetation, trees, water and no data.

Sentinel 2

Sentinel-2 dataset contains Level-2A data of the African continent in Digital Earth Africa platform. The image covers all Earth's land surfaces, large islands, inland and coastal waters every 3-5 days. The temporal range is available from 01/01/2017 to the present.
Sentinel-2 imagery has a resolution higher than WOfS so it is used for validation because WOfS has trouble in areas with mixed pixels where a pixel covers both water and land. These areas tend to be on edges of lakes and in wetlands where there is a mix of water and vegetation. For this reason, The Sentinel-2 imagery can identify these edges at a higher resolution than the current Landsat WOfS product.

Methodology

To work with Digital Earth Africa datasets, loading data from the Digital Earth Africa (DE Africa) instance of the Open Data Cube is required and need to understand data query because datasets are stored in form of multi-dimensional data or xarray data structure.
Xarray is designed to work with labeled multi-dimensional arrays, particularly useful for working with gridded datasets, such as climate data, satellite imagery, or numerical model outputs. It is built on top of the NumPy library, extending its functionality and adding support for labeled dimensions and coordinates. Once we need to request the Digital Earth Africa dataset, we need to load the datacube package and connect to the datacube database which is hosted by Amazon Web Services. This will allow us to query the datacube database and load some data. Water Observations from Space has been used to assess the changes in the water extent sizes through time since 1984 - 2021 with respect to WOfS measurements. There are two

requirements of Wofs in order to derive the frequency of water detection at a location. Firstly, each pixel of parent dataset Wofs feature layer, will be considered either wet or dry and then count_wet measurement counts how many times that a pixel was wet. Secondly, clear observation can be classified as wet or dry.

Therefore, to be counted as a water pixel, it needs to be classified as both clear and wet then the frequency of water occurrence will be assigned either 1(presence) or 0(absence) in each pixel. Since the Wofs feature layer has a temporal range every 16 days, the Wofs annual summary will be the result of the Wofs feature layer summation.

```
#Load wofs
ds = dc.load(product="wofs_ls_summary_annual",**query)
```

▸ Dimensions: (time: 38, y: 1277, x: 966) 38 years

▾ Coordinates:

time	(time)	datetime64[ns]	1984-07-01T23:59:59.999999 ... 2...
y	(y)	float64	9.976e+04 9.974e+04 ... 6.148e+04
x	(x)	float64	3.465e+06 3.465e+06 ... 3.493e+06
spatial_ref	()	int32	6933

▾ Data variables:

count_wet	(time, y, x)	int16	0 0 0 0 0 0 0 0 ... 0 0 0 0 0 0 0 0
count_clear	(time, y, x)	int16	1 8 8 8 8 8 8 ... 24 24 23 23 22 22
frequency	(time, y, x)	float32	0.0 0.0 0.0 0.0 ... 0.0 0.0 0.0 0.0

Figure 5. dimensions of WOfS Annual Summary data

The next step is water extent calculation. The number of pixels can be used for the area of the waterbody, the size of pixel from resolution can be extracted, then convert the area of a single pixel from square meters(30*30 sq.m) to a square kilometer so we know how much area is covered by one pixel. After that the number of water pixels or frequency pixels can be summed up and multiplied it by area per pixel so we will get the total area covered by water each year.

The comparison between the changes of the first(1984) and last year(2021) can be calculated by comparing an existing water value in each pixel. The dataset array is transformed list to 1(water pixel) or 0(non-water pixel) using the "astype(int)" function. If a pixel of 2021 subtracts a pixel of 1984 and gets a value 1, it will be classified as a class of water increase. Conversely, If a pixel of 2021 subtracts a pixel of 1984 and get a value -1, it will be classified as a class of water decrease. And if a pixel of 2021 (only if it has a value 1) substracts a pixel of 1984 and the result returns a value 0, this will be permanent water.

```
[49]: #The dataset array is transform list to 1 and 0 using the `astype(int)` function
      analyse_total_value = compare.isel(time=1).astype(int)
      print(analyse_total_value)
      change = analyse_total_value - compare.isel(time=0).astype(int)
      water_appeared = change.where(change == 1)
      permanent_water = change.where((change == 0) & (analyse_total_value == 1))
      permanent_land = change.where((change == 0) & (analyse_total_value == 0))
      water_disappeared = change.where(change == -1)
```

Figure 6. Calculation method of area changes

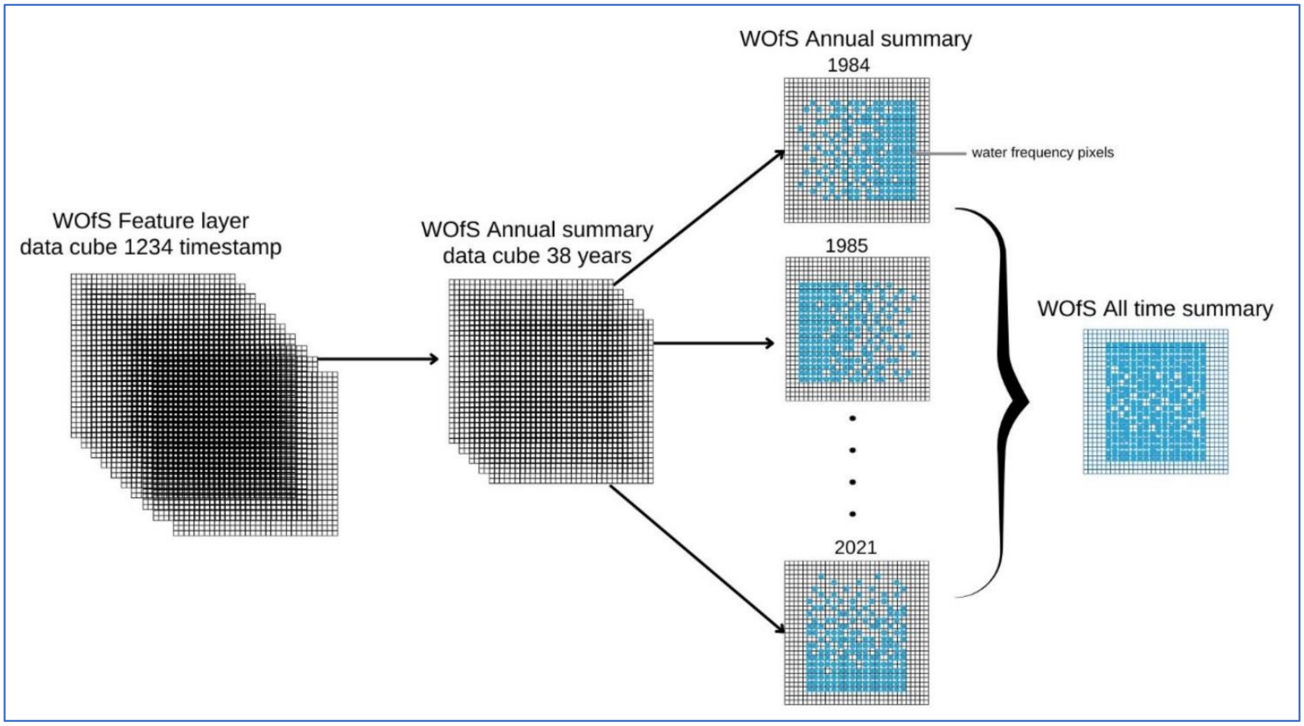

Figure 7 . WOfS summary workflow

The Climate Hazards group Infrared Precipitation with Stations (CHIRPS) is used for assessing the correlation between total rainfall and the changes of water body sizes. This section allows visualizing where change occured. CRIPS monthly rainfall product can be connected directly by calling the name “rainfall_chirps_monthly” and grouped them by year.

For ESRI Global land use and land cover, the data has 10 meters resolution, it gives 10 classes of land use and land cover around the Baringo Lake. Each class is calculated the total area in the form of data array.

The last analysis is the result validation, since WOfS has an issue of mixed pixel, it is better to compare the result to Sentinel-2 dataset because of higher spatial resolution. The Sentinel-2 can be loaded by identifying the name “s2_l2a” and defining water index MNDWI in the product. MNDWI is the normalized difference of Green Band and SWIR Band so these two bands are needed to be selected when we set the measurements.

According to some factors such as cloud obscuring the region, missed cloud cover in layers, the data will have a lot of noise. For this reason, the data needs to be resampled to ensure that the data has been working with a consistent time series. In this study, the data is resampled the sample frequency to annual time-steps so it is easy to compare with WOfS annual summary results.

Results

Annual water extent changes

The WOfS analysis generated annual water extents from 1984-2021. The water body size in the beginning of study period (1984) is around 148.36 km². The last year of the dataset archive (2021) is 230.19 km². The area increased around 82.02 km² within 38 years. The water extent in Lake Baringo has been rising in during the study period and it has been particularly high in 2021 since this year has the highest frequency of water appearance, and the minimum water area is around 119.94 km² in 2002.

For all the analysis scripts can be found in this Github repository: https://github.com/parindapannoon/WOfS-water-extent-DE-Africa.git

The limitation of the study is that some years have no data available which are 1988, 1989, 1990, 1991, 1992, 1993, 1996, 1997 and 1998. For this reason, it is necessary to filter only the available years.

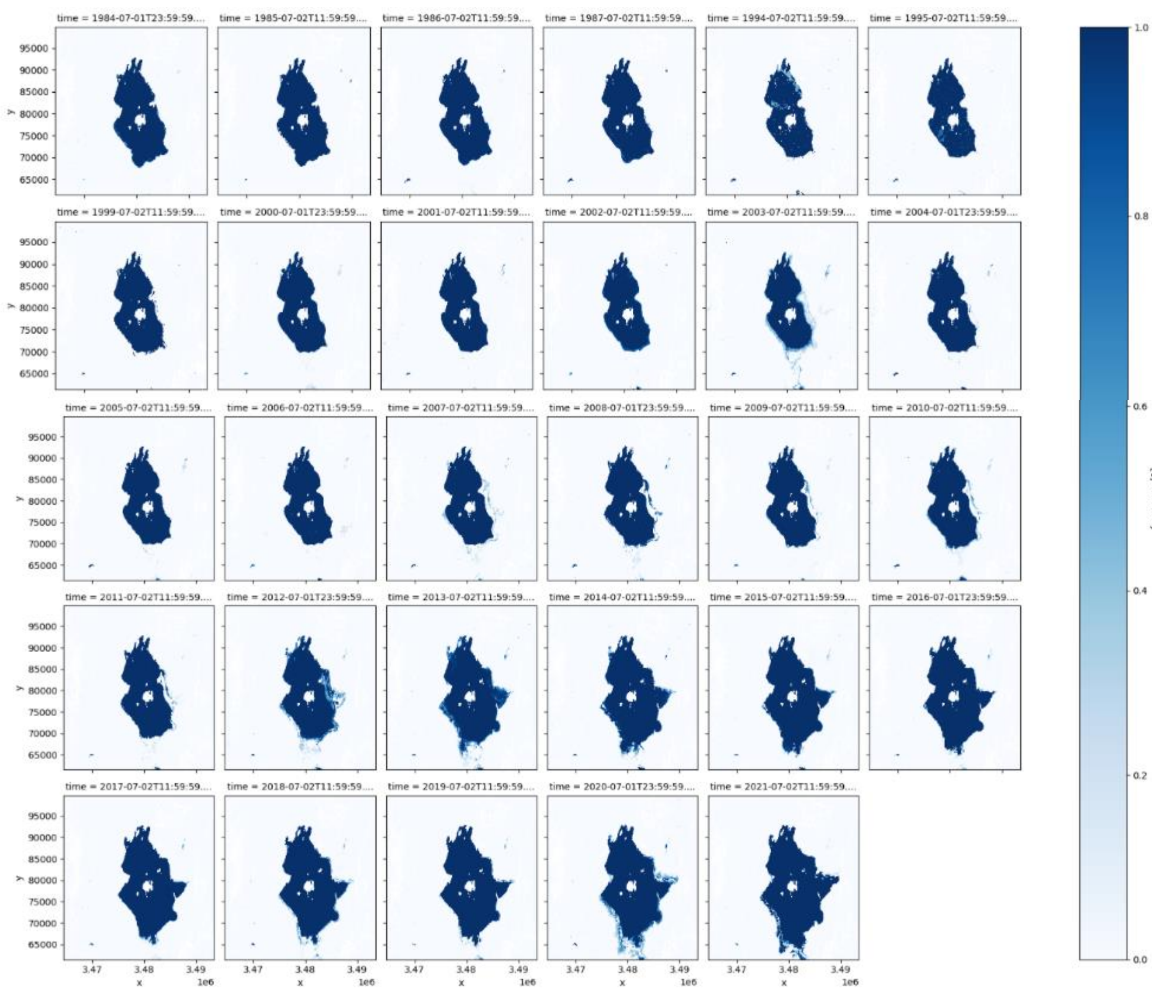

Figure 8. Water frequency from 1984 to 2021 of Lake Baringo (1=water, 0=non water)

Year	Total water areas (km²)
1984	148.36
1985	141.93
1986	142.50
1987	135.29
1994	120.11
1995	121.16
1999	131.73
2000	128.77
2001	123.44
2002	119.94
2003	136.54
2004	129.44
2005	128.22
2006	127.25
2007	137.97
2008	142.62
2009	138.87
2010	146.47
2011	147.36
2012	176.26
2013	199.98
2014	200.31
2015	195.12
2016	193.03
2017	188.50
2018	195.95
2019	193.27
2020	228.52
2021	230.19

Table 2. Water extent areas from 1984 to 2021

The area changes associated to “count wet” measurement result, that is, the rate of count wet area and total water extent increases in the same direction. The water level has sharply increased, causing the number of water frequencies and the amount of water to increase. Since 2010 rainfall and flooding has strongly increased in the lake catchments (Herrnegger, 2023) leading to the years after 2010, the lake size has been increasing continuously. The largest wet area is 246.39 km² in 2020.

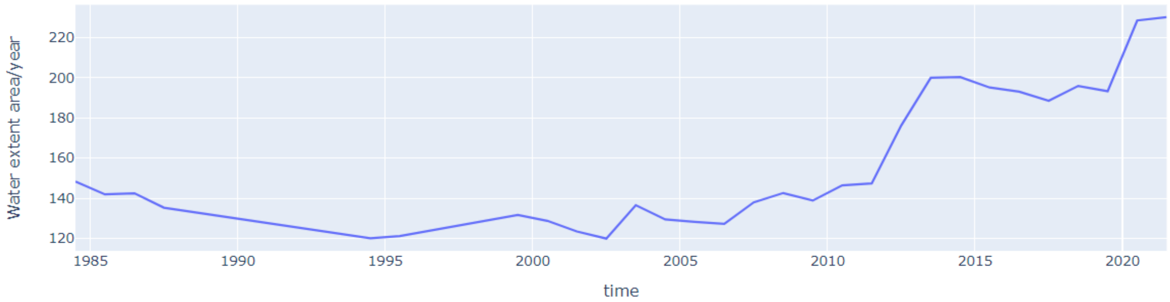

Figure 9. The trend of the increasing of annual water areas

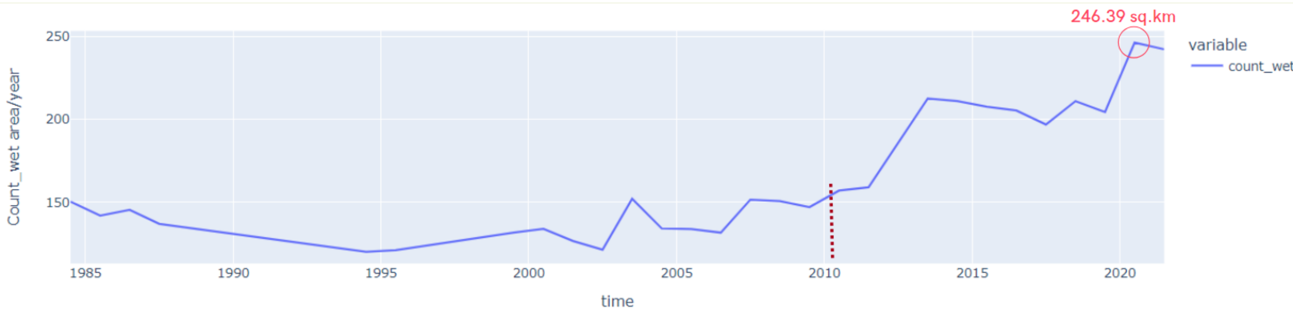

Figure 10. The trend of the increasing of annual water areas

Considering the count clear area, there is 1010.34 km² in 2003 which means most of the images in this year have less clouds or shadow.
On the other hand, in 1985, this year has the least number of clear areas which is 997.07 km². Most of the images are covered with clouds and cloudy terrain so the count wet and water frequency in this year are less detected since wet pixels are the result of count of clear pixels.

Figure 11. Total count clear areas

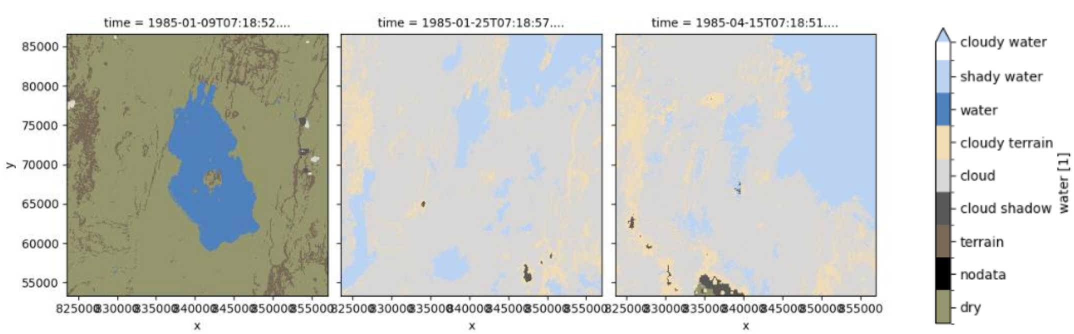

Figure 12. Land use characteristics in 1985 by using WOFL measurement for the classification

Over the years, there have been rising of water levels in Lake Baringo. When comparing the change between 1984 and 2021, there is a huge transformation from non-water area in 1984 to a water area in 2021 which is around 82.02 km² or 55.34%. The amount of water loss is very low 0.19 km² and the permanent area or unchanged water area of the two periods is 148.18 km².

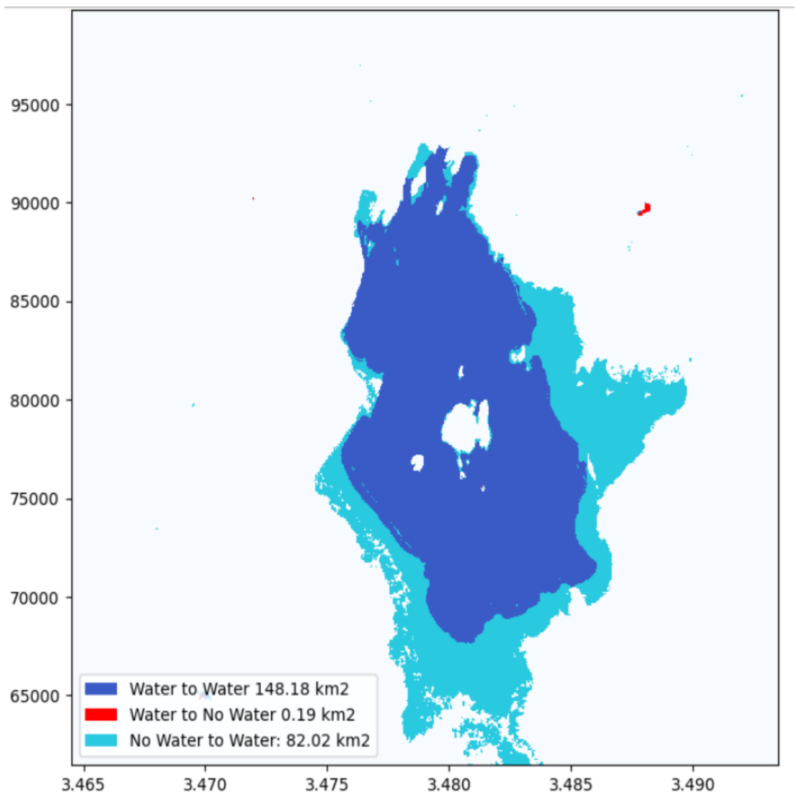

Figure 13. Change in water extent between 1984 and 2021

The correlation between rainfall and water extent

One of the potential factors that could affect the water area expansion includes the increase in rainfall, changes in regional climate patterns, and possibly human activities affecting local hydrology. According to a Kenyan government report, there are about 80,000 households and 400,000 people have been affected by the floods since 2010. (Herrnegger, 2021). The water areas has been increasing dramatically since this year. After 2010, annual rainfall increased by around 18% compared to the average rainfall from 1984 to 2009.

The result shows that 2020 has the highest average annual rainfall which is 113.38 mm. resulting the increase in lake areas. From 2010 to 2020, the mean annual rainfall increased by up to 30%, which is the rainfall in 2010 is 85.47 mm. By the end of 2020, the mean rainfall had risen by several meters from 2019 which is 28.31 mm). Lake Baringo had grown from 193.27 to 228.52 km² accounting for about an 18% increase within just 1 year.

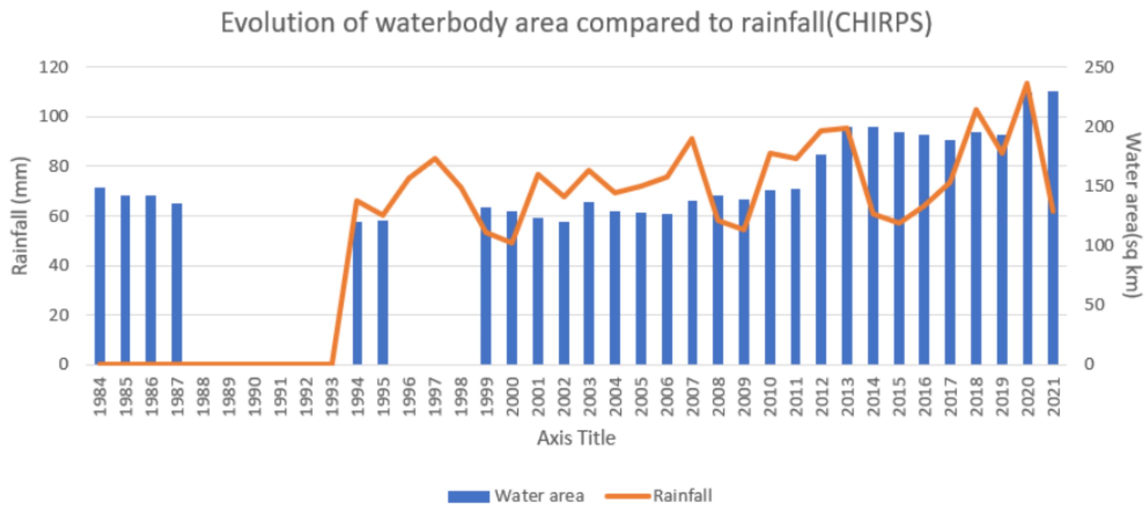

Figure 14. The correlation between water extents and average rainfall

Land use and land cover assessment

The main sources of livelihood in Baringo are agriculture and fishery. Crops and fish are not only provide food to local people but also offer employment opportunities. Flooding and rising water levels in Lake Baringo has affected the livelihood. Moreover, water chemistry changes in the lake has destroyed vegetation and fish products.

ESRI Global land use and land cover data in 2020 indicates that most of the areas around Lake Baringo is rangeland which are the land that is occupied by herbaceous or shrubby vegetation, it is 561.45 km². Around 204.48 km² are covered by trees, 95.61 km² are crops and 22.07 km² are flooded vegetation. Water areas from ESRI land cover result are less than WOfS result about 10 km². Vegetation near the lake may get damaged from water expansion because when floods carry sediments and deposit them in low-lying areas. This can alter the land surface, leading to changes in soil structure and fertility.

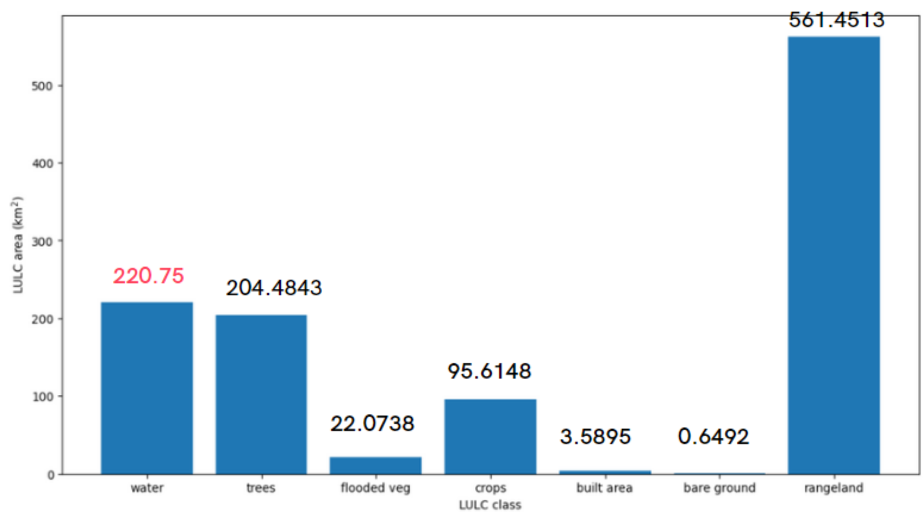

Figure 15. Total area of land cover classes around Lake Baringo

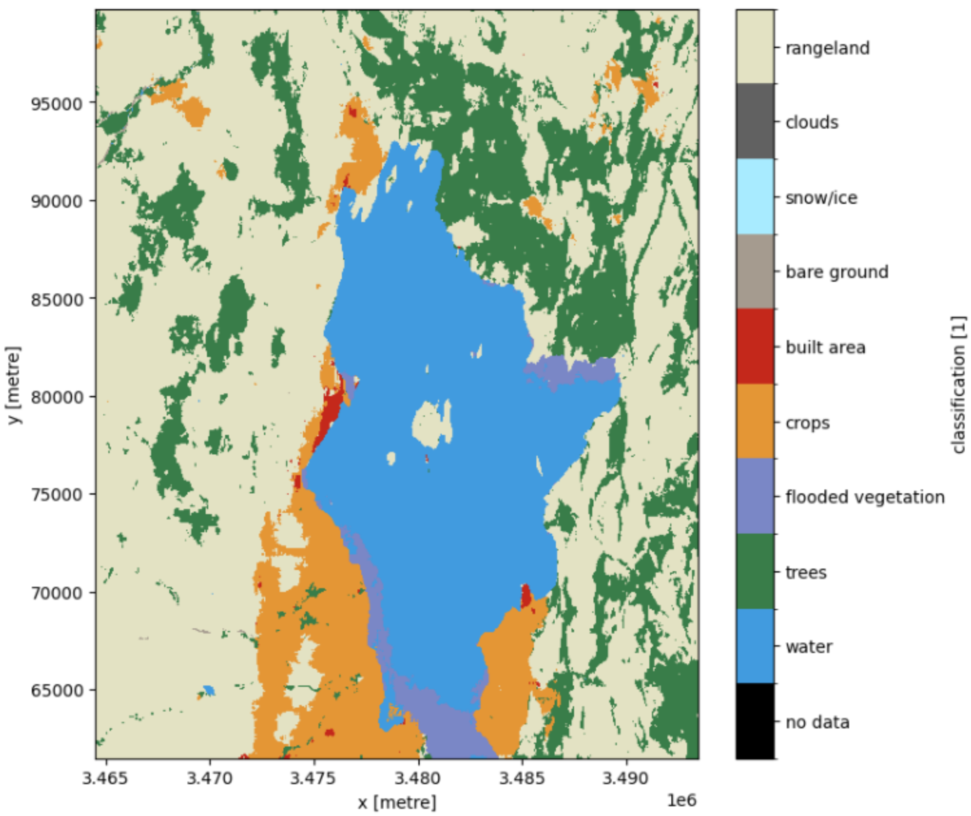

Figure 16. ESRI Global land use and land cover 2020 in the study area

Validation by Sentinel-2 imagery

The result from MNDWI of Sentinel-2 data(20 m) gives higher resolution than WOfS (30 m) from Landsat. Using high resolution satellite can give a better outcome because this 30 meters of WOfS may not preserve the water body sizes as good as a higher resolution 20 meters. Moreover, a higher resolution can visualize a better details of small water bodies at the edges where tends to have mixed pixels of land and water. Moreover, the image can significantly impact water extent results.

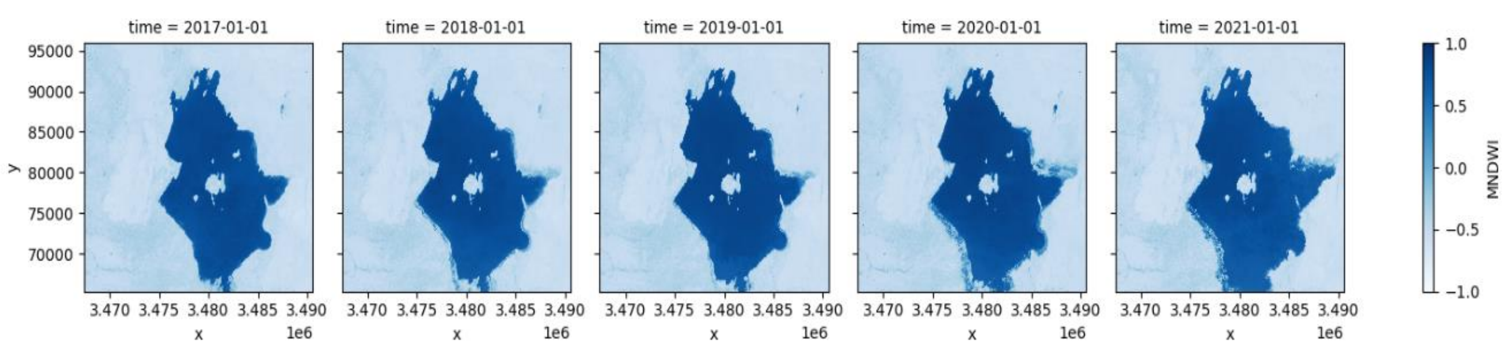

Figure 17. MNDWI index from Sentinel-2 image in Lake Baringo

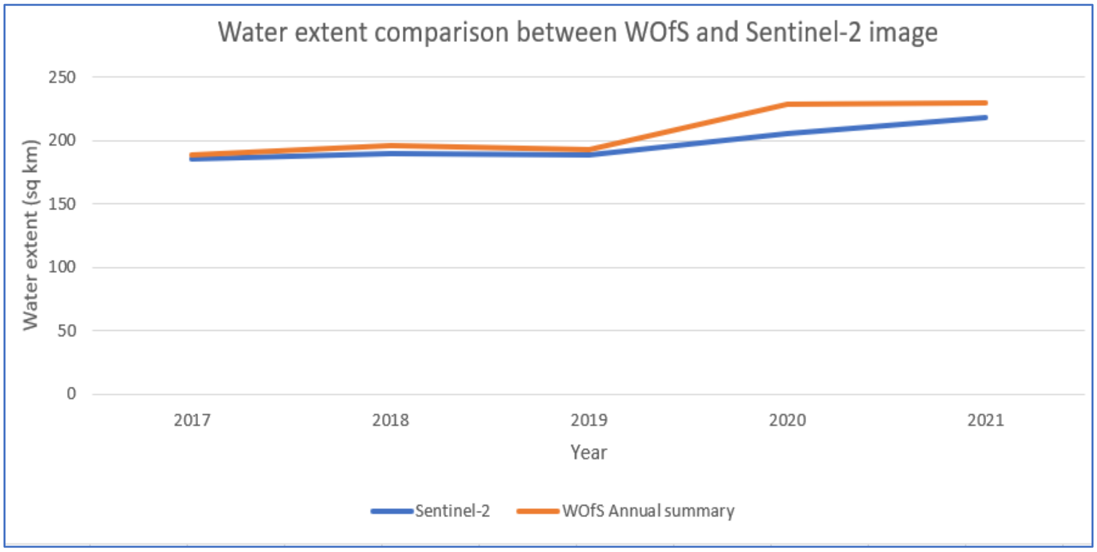

Figure 18. The difference of water extent changes between Sentinel-2 and WOfS data

The analysis of historical records from both satellite datasets indicates a consistent increase in water extent. The average of different areas is 9.70 km². From 2017 to 2021, WOfS product gives higher area results than Sentinel-2 in every year. Especially in 2020, there is 22.79 km² difference between these two products which is the highest difference among these five years. In 2017-2019, the area values are very close, with only 3 km² difference in 2017 and 6, 4 km² in 2018 and 2019 respectively.

Conclusion and Discussion

Water observation from space(WOfS) is able to analyze annual changes in the water extent of Lake Baringo since the products provide annual, all-time summaries, and also feature layers that allow users to investigate the water classification generated per scene.

One of the challenges in Lake Baringo is a notable increase in water levels. This rise in water extent has affected the communities living around the lake. Flooding nearby areas has displaced residential areas and crops. Strong rainfall is one of the main causes that trigger the rising water levels. The year 2020 is the highest average annual rainfall, reaching 113.38 mm, leading to a considerable expansion of lake areas in the following year.

The mean annual rainfall rose up to 30% from 2010 to 2020. Lake Baringo has a rising trend over the study period. At the beginning of the study period, the water body size was approximately 148.36 km² in 1984. Over the 38-year, the water area increased by approximately 82.02 km², reaching a size of 230.19 km² in the last year of the dataset in 2021.

Understanding the effects of flooding on land cover could be useful for preparation and countermeasures since most of the land cover around Lake Baringo is agricultural areas, the flooding has caused damage to livestock and crop products, as well as infrastructure and homes. This also could potentially lead to alterations in the populations of aquatic species that depend on specific water level conditions. Moreover, aquatic animals will be affected by the chemical changes in the lake since Lake Bogoria, the alkaline lake can overflow and merge with the freshwater Lake Baringo.

Therefore, local authorities should closely monitor the situation to better understand the factors affecting to the water extent changes in Lake Baringo. They could develop appropriate strategies to manage and mitigate the impacts. Such efforts may involve water management practices, disaster preparedness plans, and initiatives to promote community resilience.

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