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Research Article

Socio-Economic Impacts of Flooding Around Lake Victoria, Kisumu County, Kenya

Herine Pamela Auma Ondolo*, Ann Osio

Department of Geo Information and Earth Observation, Faculty of Engineering, Technical University of Kenya, Nairobi, Kenya

Abstract

History shows that people have settled around the shores of Lake Victoria and used its water for varied purposes that include, but not limited to, domestic use, trade, and agriculture. Relatedly, the lake has also been known to flood annually with devasting effect on the settlements. The purpose of this study is to identify the trend in the expansion of the lake over the years with a goal of making recommendations to alleviate the negative impact of the floods. Sentinel satellite images were obtained from internet open sources and then they were classified, leading to six classes comprising: water, built up, herbaceous, roads, bare land and woody vegetation. The period studied covered the years 2019 to 2022. From the satellite images, it is observed that water coverage was most expansive in 2021 compared to the other years. In the year 2021, it was occupying an area of 584175600 m^2, this is a significant increase from the year 2019, when it was covering, 559258200 m^2. In the year 2022, there was a reduction in the area covered by water, 583134300 m^2. Most flooded areas are along the shores of the lake. This study recommends that the previous dry lands that are now under water be used for rice farming by public private partnerships and the owners of the lands be compensated as necessary. It further recommends on adoption of geospatial technology to identify suitable spots to build structures for living and / or business, along the shores. Such policies will alleviate the destruction of properties and the loss of lives due to floods.

Keywords

Lake Victoria, Flood Impact, Flood Mitigation, Geospatial Technology, Shoreline Management, Climate Adaptation, Disaster Management, Spatial Analysis

1. Background Information on Lake Victoria and the Surrounding Communities

Water is the key element in economic, social and cultural development of any society. Throughout history people have settled next to waterways and in flood plains because of the advantages they offer. Despite these benefits, water can also cause destruction and damage. Flood devastation results in loss of lives, widespread crop destruction and associated economic disasters [1].

Although exceptionally devastating floods distort the trend, flood impact records show that the number of related fatalities is gradually decreasing thanks to, among others, better early

*Corresponding author: Ondoloherine99@gmail.com (Herine Pamela Auma Ondolo)

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warning systems; however, damages to land and property appear to be increasing due to insufficient prevention, economic growth and a lack of flood-sensitive land use planning. The Associated Programme on Flood Management (APFM) promotes an integrated flood management approach to minimize related loss of life and impacts ~~s~~ on livelihoods through protective measures while maximizing the net benefits derived from the efficient use of floodplains. APFM supports countries in implementing national strategies for integrated flood management. This approach shifts the focus from flood control to management, recognizing that floods have both adverse and beneficial impacts and that they can never be fully constrained. [2]

In June 2003, Honorable Martha Karua, the Minister of Water Resources Development and Management, Kenya, asked the World Meteorological Organization to assist Kenya in developing a flood management strategy. [3]. A pilot project for developing a strategy for flood management for the lake basin in Kenya was therefore undertaken by World Meteorological Organization, with full participation of national experts from various concerned ministries, as well as the Ministry of Water Resources Management and Development. The long-term view of the project is to strengthen national capabilities, so that eventually national experts can develop a flood management strategy for the entire country. [3].

A year of extraordinarily heavy rains, which started in April 2019 following a drought, pushed the lake's water level up to 13.4 meters in May, breaking the previous 1964 record, according to the Lake Victoria Basin Commission [4]. It put a strain on aquatic ecosystems in recent years, resulting in altered structure and functioning, biodiversity loss, reduced water quality and supply, food insecurity through reduced fish productivity, and a reduction in the quality of a variety of other ecosystem goods and services. The situation is further exacerbated by the impact of climate change on both agricultural productivity and fish production. As fragile ecosystems are threatened, scientific and technological advancements are on the rise, providing practical answers to the aforementioned concerns as well as enhancing ecosystems and communities' resilience and adaptability for a sustainable future.

People and beach [5] businesses have been displaced as beaches and islands were submerged. [6]. More than Sh500 million has been lost since the lake water levels began to rise. The displaced people are camping in churches, while a majority are stranded with nowhere to go, [7] More than 55 per cent of Kisumu beaches have been evacuated due to flooding. These include Dunga, Kichinjio, Nduru, Oseth, Arongo, Nyamarwaka, Nyanja and Sango-Rota. [7] Tourism operations in hotels within the beaches have been thwarted. Many hotels and restaurants are deserted because they are marooned by floods [7].

Bandas where fish are weighed are filled with water. It forces fishermen to carry their catch to different places, which are not hygienic to the fish for consumption. They say land conflicts have also increased along the lake after normal boat landing sites went underwater. Many fishermen have encroached alternative private lands to dock their boats, dry omena and air their fishing nets. [7]

Objectives

Specific Objectives

1. To evaluate the spatial-temporal changes on Part of Lake Victoria (i.e., Kenyan side) from 2019 to 2022.
2. To determine the effect of flooding on Livelihoods around Lake Victoria (Kenyan side)

Research Questions

1. What are the Spatial-temporal changes on Part of Lake Victoria (2019-2022)?
2. What are the effects of flooding on livelihoods around Lake Victoria?

Lake Victoria, largest lake in Africa and chief reservoir of the Nile, lying mainly in Tanzania and Uganda, bordering Kenya. It is the second largest freshwater lake in the world after Lake Superior in North America. It is an irregular quadrilateral in shape. Its greatest length from north to south is 337 km, its greatest breadth 240 km. Its coastline exceeds 3,220 km. Its waters fill a shallow depression in the center of the great plateau that stretches between the Western and Eastern Rift Valleys. The lake’s surface is 1,134 meters above sea level, and its greatest ascertained depth is 82 meters. Many archipelagos are contained within the lake, as are numerous reefs, often just below the surface of the clear waters.

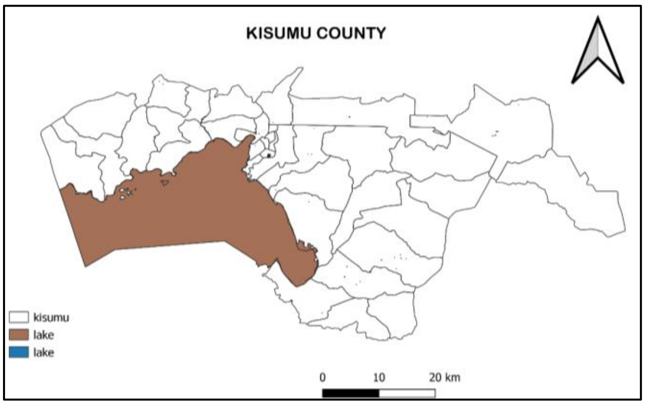


Figure 1. *Study area map.*

The lake has more than 200 species of fish, of which tilapia is the most available and most economically important. The lake basin area covers 238,900 square km. Its shores vary in aspect. The lake’s southwestern coast is backed by precises 90 meters high, which give way on the western coast to papyrus and ambatch swamps marking the delta of the Kagera river. The lakes deeply indented northern coast is flat and bare. A narrow channel leads into the Kavirondo Golf, which has an average width of 25 km and extends for 64 km eastward to Kisumu, Kenya. [9]

The climate in the lake basin varies from tropical rain forest with rainfall over the lake for much of the year to a semi dry climate with intermittent droughts over some areas, and with temperatures varying between 12-26°C. Most of the lake's water comes from rainfall 117 km^3 per annum, while almost the same amount of water is lost through evaporation 105 km^3 per annum and carried out by the Nile 33 km^3 per annum. The natural vegetation of the basin consists of patches of closed evergreen forest along the western and northern shores with open landscapes and swamp wetlands in bays, making a suitable habitat for birds, crocodiles, and hippopotamus. The lake dried out about 17,300 years ago and refilled beginning about 14,700 years ago. The Lake Victoria Basin falls under the equatorial hot and humid climate with a bi-modal rainfall pattern with long rains from March to May and short rains from October to December. Annual rainfall ranges from a maximum of 2,400 mm in Uganda to 1,350 mm in the Kenyan part of the catchment. [8]

Soils in the Kano plain is derived from Holocene alluvial deposits. Luvisol, Vertisol (locally known as Black Cotton soils), Planosol, Cambisol and Solonetz types (are common, frequently in saline or sodic phases with deep profiles and moderate to low fertility. Highland soils are derived from a wide variety of parent materials including phonolites, quartzites, nephelinites, granitoid gneisses and intrusives such as dolorites, monzonites and granidiorites, which are representative of a large part of the Kenyan portion of the lake basin. Predominant soil types include Ferrasols, Nitisols, Cambisols and Acricsols and are structurally stable. The infiltration rate is defined as the volume flux of water flowing into the profile per unit of soil surface area. For the special condition in which the rainfall rate exceeds the ability of the soil to absorb water, infiltration proceeds at a maximal rate, which Horton called the soil's infiltration capacity, for which later Hillel suggested for the term infiltrability. Therefore, infiltrability can be measured using soil-controlled infiltration tests, such as cylinder infiltrometer and sprinkling infiltrometer. In general, soil infiltrability is relatively high in the early stages of infiltration, particularly when the soil is initially quite dry, but it tends to decrease and eventually to approach asymptotically a constant rate known as steady state infiltrability or final infiltration capacity.

Scrub forests are the intermediate in structure between forest and bushland. Vegetation types intermediate between rain forest and evergreen bushland probably occurred more extensively in the Lake Victoria basin than in other parts of Africa, but only few relicts remain [10].

Fishing is a major economic activity for the lake communities, providing employment and nutrition and contributing greatly to the national economies [11] lake supports freshwater fishery in the world, producing 1 million tons of fish per year and employing 200,000 people in supporting the livelihoods of 4 million people (Kishe, 2003).

Wildlife

The lake supports a wide range of wildlife. The region of the lake is home to many mammal species, like the hippopotamus, the marsh mongoose, and the giant otter shrew. It also contains reptiles such as the Nile crocodile and the African helmeted turtle, and many crustaceans, including 4 different species of freshwater crab. The lake contains over 200 species of fish and the haplochromine cichlid is the main endemic group. However, many species have become extinct in the last 50 years and scientists estimate that Lake Victoria's indigenous fish species have decreased by 80%. [12].

Wildlife includes Roan Antelope, Oribi, giraffe, hartebeest, impala, hippos, Vervet monkeys, monitor lizards and more. Bird species found around the lake include the Blue-breasted Bee-easter, Blue Swallow, Swamp Flycatcher, Greater Swamp-warbler, White-winged Warbler, Papyrus Yellow Warbler, Carruthers' Cisticola, Papyrus Gonolek, Red-chested Sunbird, Red-headed Quelea, Slender-billed Weaver, Yellow-backed Weaver, Northern Brown-throated Weaver, Black-throated Seedeater and the Papyrus Canary. [13]

2. Study Methods, Materials, Results and Discussion

This study used sentinel 2 image for different years with a 2- year epoch. A 2019 sentinel 2 image is the first as this was a year the lake flooded in in May.

Sentinel 2

Sentinel-2 was launched on 23 June 2015 on a Vega rocket from Europe's spaceport near Kourou in French Guiana. Sentinel-2 is an Earth Observation mission from the Copernicus Programme that systematically acquires optical imagery at high spatial resolution (10 m to 60 m) over land and coastal waters.

Revisiting every 10 days under the same viewing angles. At high latitudes, Sentinel-2 swath overlap, and some regions will be observed twice or more every 10 days, but with different viewing angles.

Data Type

Images used for classification were those that had the least cloud cover. Cloud free images were highlighted and used for classification in google earth engine.

Software

The software used in this study are:

1. Google Earth Engine
2. Arc GIS
3. Google Earth Pro
4. Data Source

Table 1. Data types and sources.

Data	Source
Sentinel images	Google earth engine
Kisumu County Shape file	Diva Gis

Flow Chart

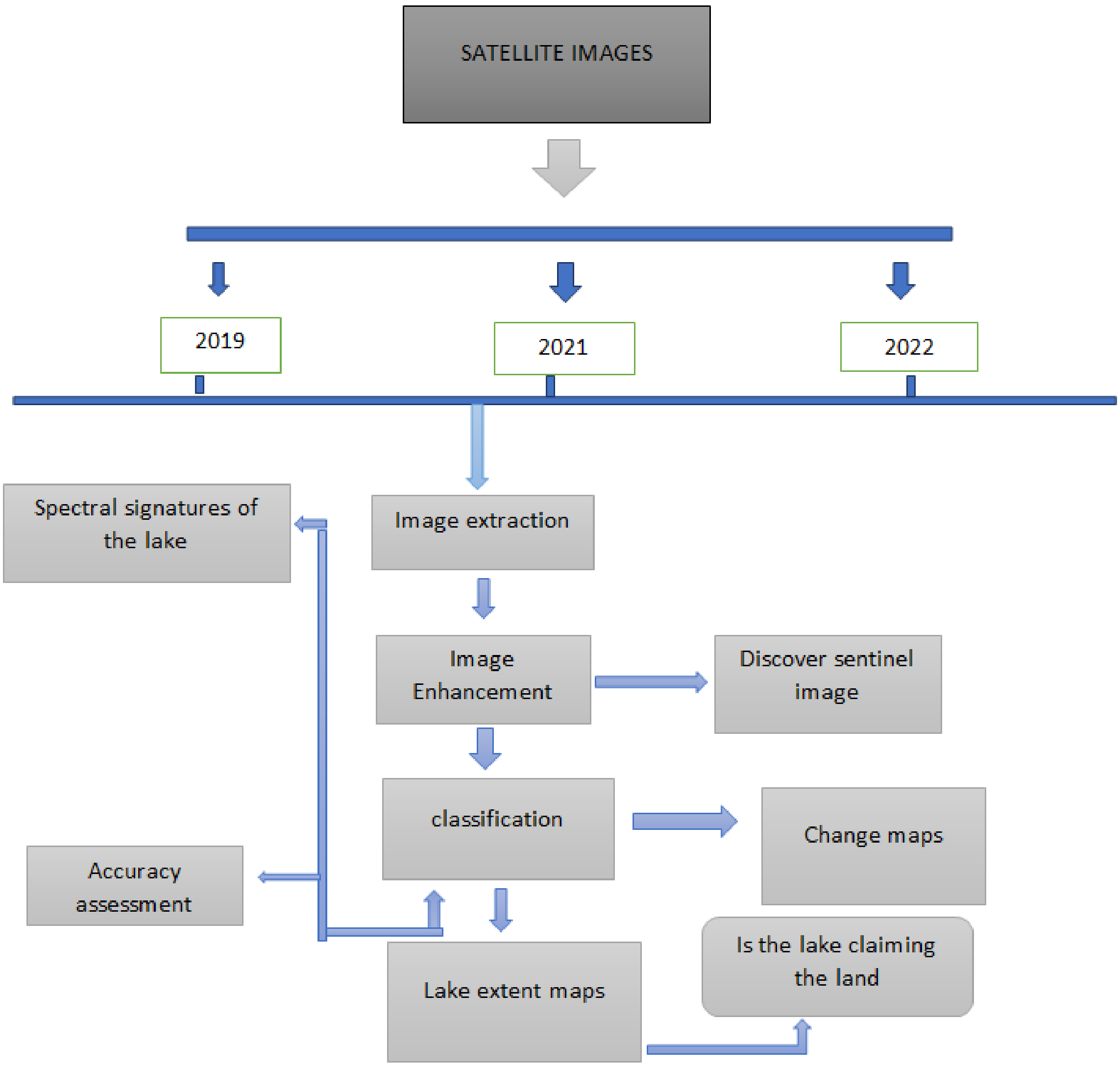


Figure 2. Project plan.

Classification

This study employed supervised classification. Supervised classification is preferred to unsupervised classification since it yields better results due to the usage of training data. GIS analysts can also zoom in on any place, decode the problem minutely, and use accurate data to train the classification algorithm.

Training sites

The image classification tool was used to create training sites for all six classes. Random forest model was used to train the training points which yielded an accuracy of 99.89%.

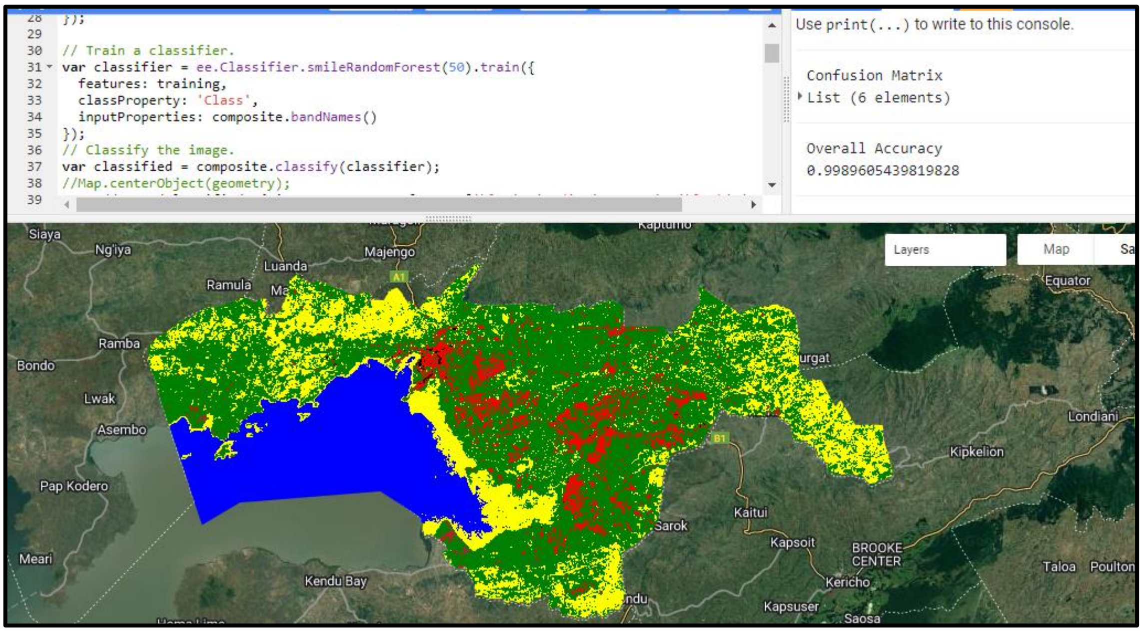


Figure 3. Land use map in google earth engine.

The NDWI (Normalized Difference Water Index) is an index from the SWIR (Short-Wave Infrared) and NIR (Near-Infrared) bands. The SWIR reflectance reflects changes in vegetation water content. The Near-Infrared) band is affected by leaf dry matter content and leaf internal structure. A combination of the Near Infrared and Short-wave infrared removes leaf dry matter content and leaf internal structure induced variations, thereby` improving the accuracy in retrieving vegetation water. Amount of water in the internal leaf structure largely controls the spectral reflectance of the SWIR interval of the electromagnetic spectrum (Ceccato et al, 2001, Gao, 1996). Leaf water content is therefore indirectly proportional to SWIR reflectance [14]. NDWI studies have proved important for early warning of droughts and drought monitoring in various studies as computed using SWIR and NIR. [15]

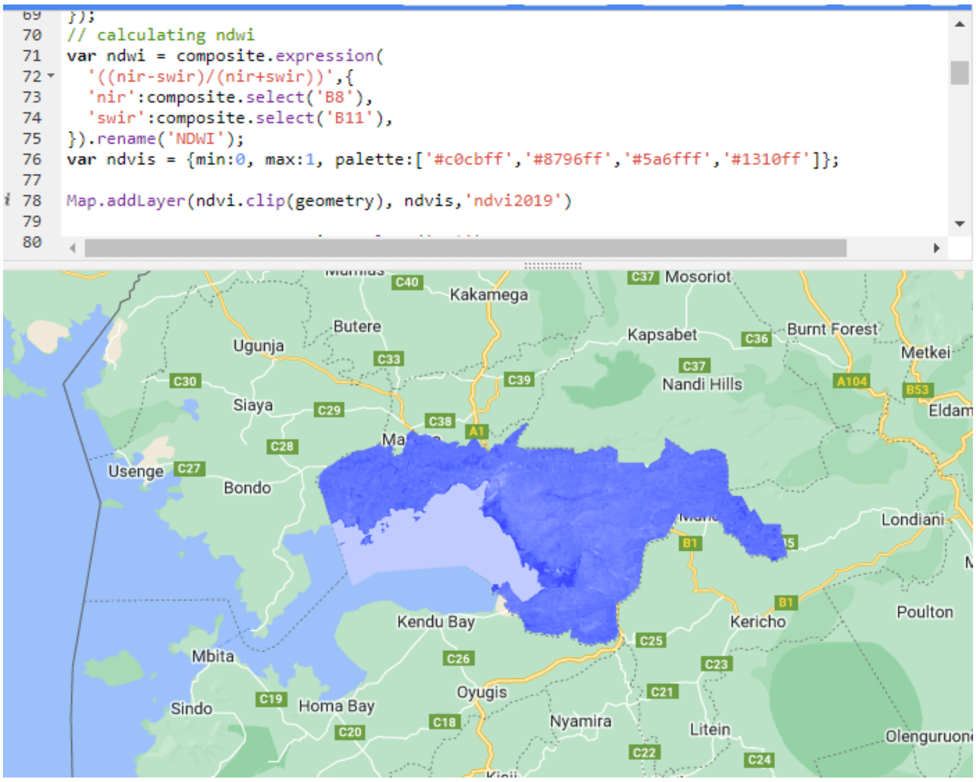


Figure 4. Ndwi map in google earth engine.

Dissolve

The dissolve geoprocessing tool was used to form simplified classes by merging classes with similar grid code.

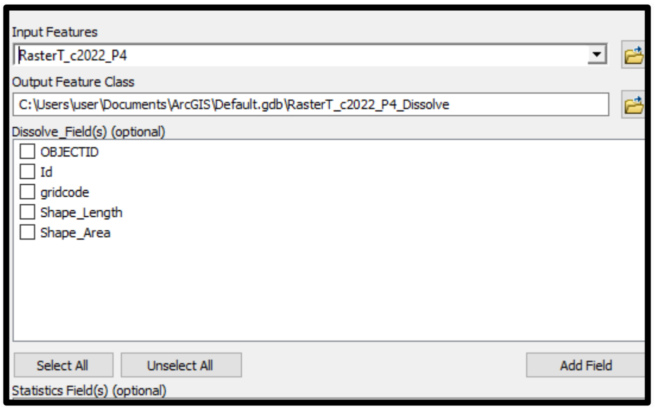
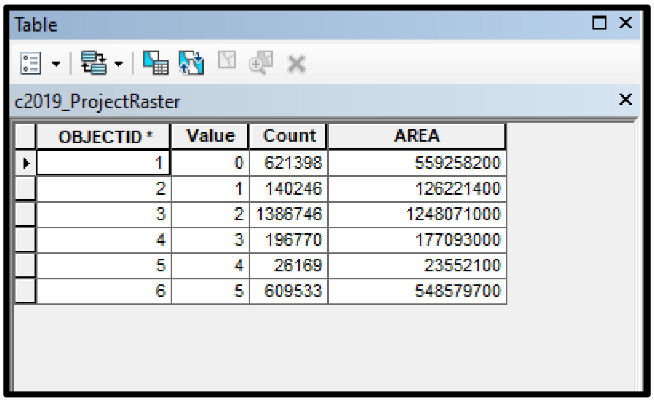


Figure 5. Dissolving raster data.

Area calculation

On the attribute table of dissolve results above, a field Area was added. Using the Calculate Geometry function, the area of the land classes is computed in square meters.



Table

c2019_ProjectRaster

OBJECTID *	Value	Count	AREA
1	0	621398	559258200
2	1	140246	126221400
3	2	1386746	1248071000
4	3	196770	177093000
5	4	26169	23552100
6	5	609533	548579700

Figure 6. Land classes area coverage.

Accuracy Assessment

After completing supervised classification, validation was done, which entails ground-truthing. Ground truthing was done to give the classified classes accuracy based on what was on the ground when the imagery was taken. The aim of accuracy assessment is to quantitatively assess how effectively the pixels had been sampled into the correct land use and land cover classes. The key emphasis for accuracy assessment pixel selection was on areas that could be clearly identified on both Google earth Pro and Bing Maps.

Ground Truthing.

The data was converted t kml format. T confirm the points, the kml data was imported to Google Earth Pro.

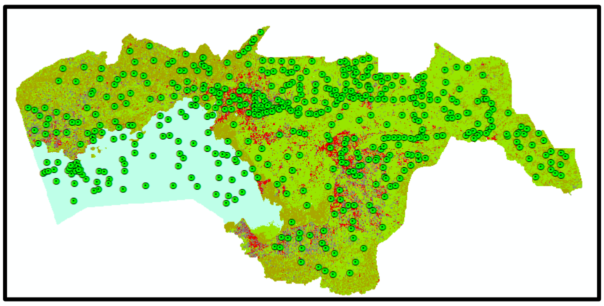


Figure 7. Validation points.

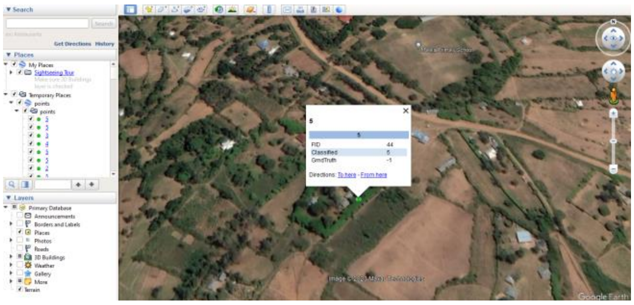


Figure 8. Data validation in google earth pro.

Validation in google earth pro.

Appending ‘Union’ geoprocessing tool in ArcGIS

This step involved union of two vector maps resulting to change matrices from one class to another and change maps thereof.

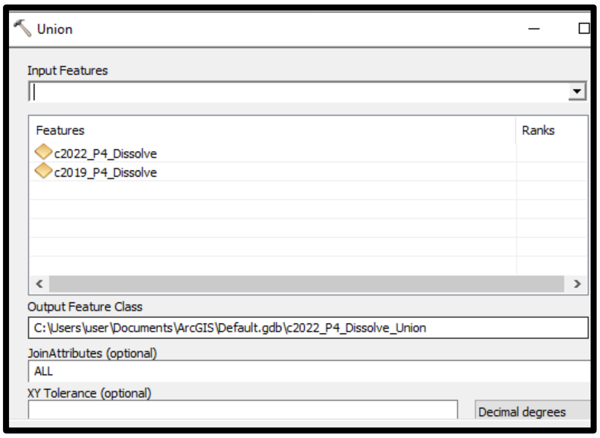


Figure 9. Landcover map union.

Appending ‘union’ geo-processor.

Normalized Difference Vegetation Index (NDVI) Maps

The result, calculated for every pixel in every daily orbital pass, is a value between -1.0 and 1.0, where 1.0 represents maximum photosynthetic activity, and thus maximum density and vigor of green vegetation. Green areas of the map are vegetation areas and have their pixel values more than 1.0. High level of vegetation reflectance was obtained in 2019, and the reflectance reduced in the year 2021. Low reflectance was in 2022 this is due to floods that have covered the vegetation.

Kisumu region experienced rainfall of higher intensity in 2019. This probably caused a vegetation abundance. Vegetation of high reflectance is along the lake shores than area far from the shores. hyacinth can also be easily detected in the lake.

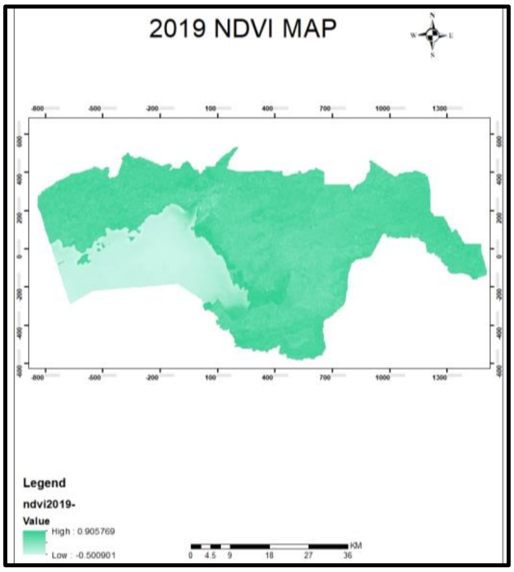


Figure 10. 2019 NDVI.

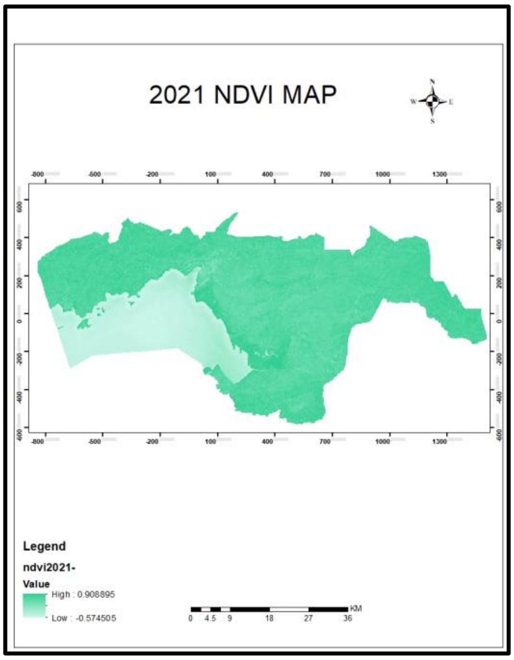


Figure 11. 2021 NDVI.

Normalized Difference Vegetation Index (2019) Map

Vegetation with higher spectral reflectance is located along the shores of the lake. This vegetation is growing along the wetlands and floodplains where inlet rivers enter the lake; river Sondu and river Nyando. The forest is located on the east side of the conservancy. Areas between Nyandiwa and Dunga beach are vegetated as well.

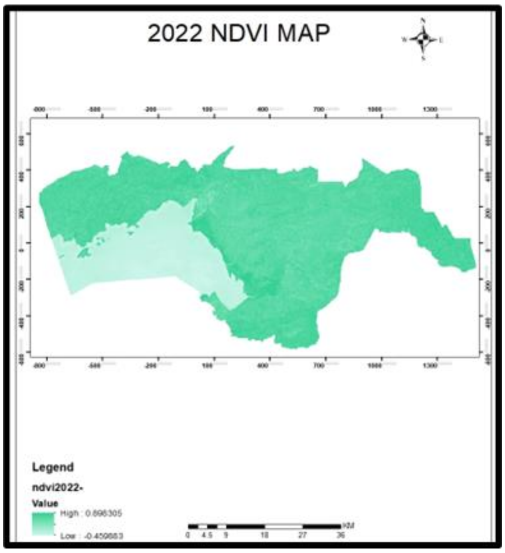


Figure 12. 2022 NDVI.

Normalized Difference Vegetation Index (2021 and 2022) Map

High reflectance vegetated areas remain to be along the shores of the lake and likewise along rivers. This vegetation has a higher spectral reflectance than the rest of the high area of Kisumu County. Vegetation cover is reduced than the preceding years due to flooding experienced in this year as the lake reclaims the land. As and more land is under water.

Normalized Difference Water Index

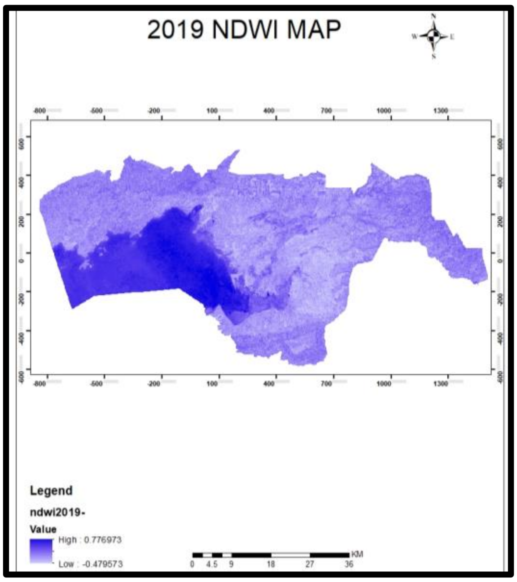


Figure 13. NDWI 2019.

Normalized Difference Water Index is a remote sensing derived index estimating the leaf water content. It makes use of reflected near-infrared radiation and visible green light to enhance the presence of water features while eliminating the presence of soil and terrestrial vegetation features. The ranges from 2019 to 2022 range from 0.776973 being the highest water reflected and the lowest being -0.439419.

NDWI Map support presence of long rains in the year 2019 as there was more vegetation growing as a result. There are a lot of vegetation growing along the rivers and the shores of the lake. Osodo has vegetation with the most water content. Areas classified as water areas have a pixel value of more than one, with areas with a pixel value of less than zero classified as non-water areas.

Normalized Difference Water Index (2019) Map.

There is a lot more vegetation along the rivers than the preceding year. Visibly, hyacinth have reduced water content than the previous year.

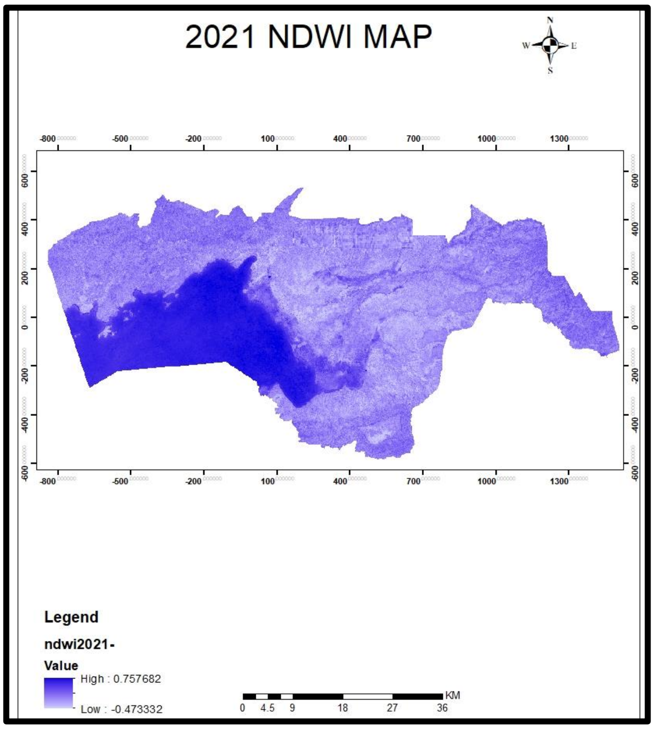


Figure 14. 2021 NDWI.

Normalized Difference Water Index year 2021 and 2022.

The year 2022 was less wet than the preceding two years. The NDWI maps were important in establishing the areas to be classified as vegetation areas.

Normalized Difference Built-Up Index Maps

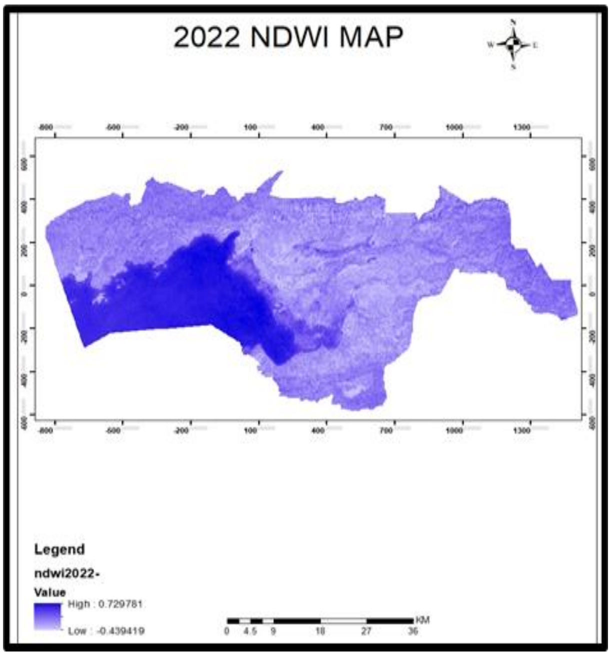


Figure 15. 2022 NDWI.

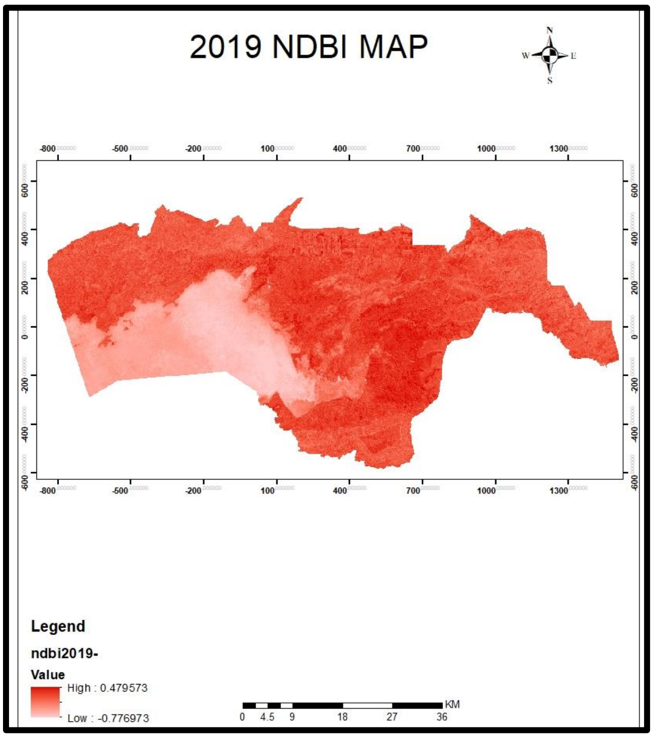


Figure 16. 2019 NDBI.

Normalized Difference Built-up Index uses the NIR and SWIR bands to emphasize manufactured built-up areas. NDBI values ranges between −1 and 1. The level of built-up reflectance was high in 2019 in Kisumu town and some other markets. The reflectance drastically reduced in 2021, and a worse reduction was in 2022. This followed the destruction of many beaches. the floods experienced in the year 2020 made many buildings to be under water.

Normalized Difference Built-Up Index Maps (2019)

High reflectance built up areas are Kisumu town and junction marketplaces like Ahero and Kombewa. This built up has a higher spectral reflectance than the rest of the rural areas of Kisumu County.

Normalized Difference Built-Up Index Maps (2019).

Normalized Difference Built-Up Index Map (2021)

Built areas are reduced than the preceding years due to flooding experienced in the year 2020 as the lake claims the land. Many beaches were flooded and destroyed; people were displaced from their homes. This led to a steady reduction of built areas from the previous year, 2019

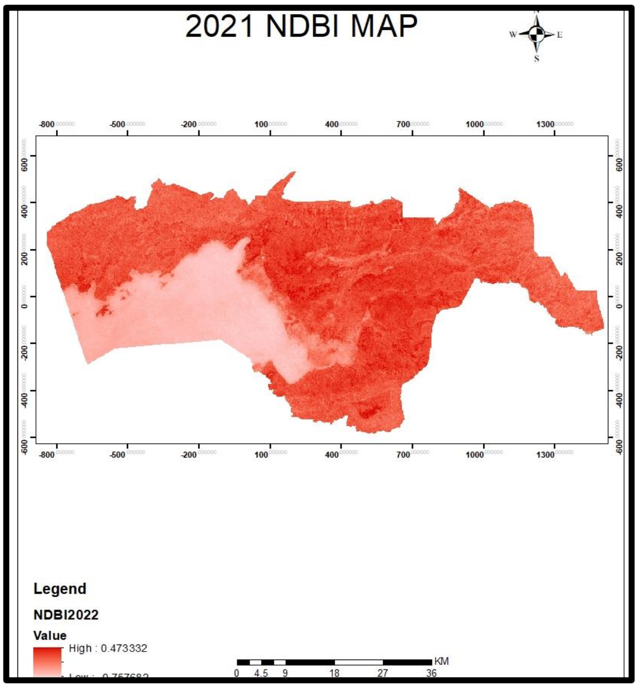


Figure 17. 2021 NDBI.

Normalized Difference Built-Up Index Maps (2021 and 2022).

Built areas are reduced than the preceding years due to flooding experienced in the year 2020 as the lake claims the land. Many holiday resorts and homes were submerged.

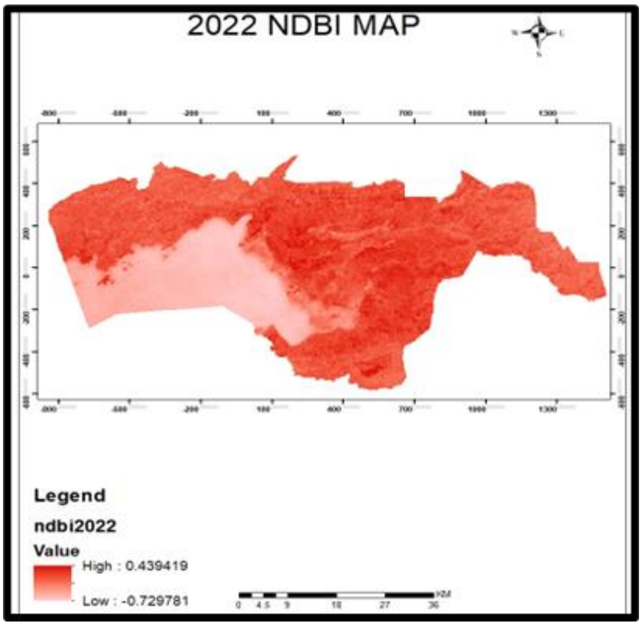


Figure 18. 2022 NBI.

Image Classification

It is a method of assigning pixels for the different classes with similar pixel classified as one class. Distinct classes are made up of pixel with the same properties. Kisumu county Classification Study adopted a supervised classification of different classes. The classes identified for classification are as follows:

1) water
2) built-up
3) herbaceous
4) roads
5) bare land
6) woody_vegetation

Distribution of Land Use Land cover on Lake Victoria and Environs

Table 2. Land classes coverage.

Value	2019	Area Prop.	2021	Area Prop.	2022	Area Prop.
Water	559258200	20.8%	584175600	21.8%	583134300	21.7%
Built-up	126221400	4.7%	190736100	7.1%	80011800	3.0%
herbaceous	1248071000	46.5%	1362137400	50.8%	1239657000	46.2%
Roads	177093000	6.6%	73032300	2.7%	155682000	5.8%
Bare land	23552100	0.9%	18925200	0.7%	40279500	1.5%
Woody Vegetation	548579700	20.4%	453769200	16.9%	584010900	21.8%

Value	2019	Area Prop.	2021	Area Prop.	2022	Area Prop.
Total	2682775400		2682775800		2682775500	

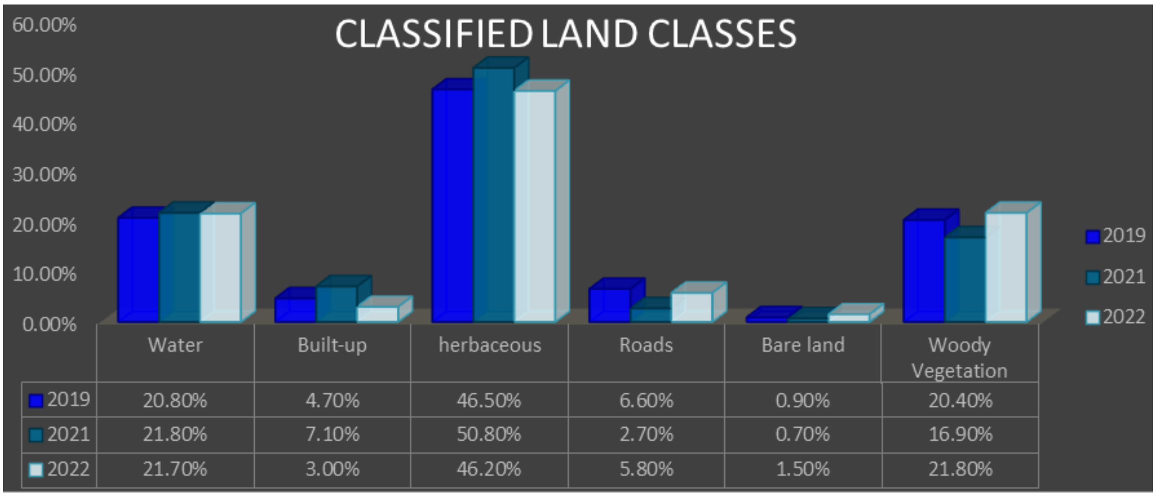


Figure 19. *Classified land classes.*

Land Use & Land cover classes of Lake Victoria & Environs.

Results from table 1 and figure 24 clearly show the change in land cover and use. From the supervised classified classes, for 2019, which was the onset of flooding, water coverage was at approximately 21%. This is not alarming as compared to the following years.

Classification for 2021 shows some concern on the water coverage concern. The water coverage surpasses the one on 2019. This follows the 2020 long rains which led to the areas around the lake basin flooding. Roads drastically reduced in coverage which may be because they were covered under water or were destroyed.

For 2022 classification, the water coverage had either reduced or at the same level as it was in 2021. Many roads came back to surface but the built up has highly reduced. This might be since the flooding invaded people's houses, the houses collapsed with time leaving many homeless.

Land Use Land Cover of Lake Victoria & Environs

Flooding because of the increased lake volume has been witnessed since 2019 to date. There was a significant increase from 2019 to 2021 due to heavy rains received in 2019 and 2020. The lake is still showing signs of claiming the land.

Classification of sentinel 2 images from 2019 to 2022 especially the 2022 image depict increasing water level in the county. This is possibly because of the of the heavy rainfall that are received in the catchment areas of the lake's inlet rivers. Most of these rivers are also responsible for the down the shore flooding because of the high-water volume which makes them burst their banks. Built up areas have reduced due to flooding which destroyed the buildings.

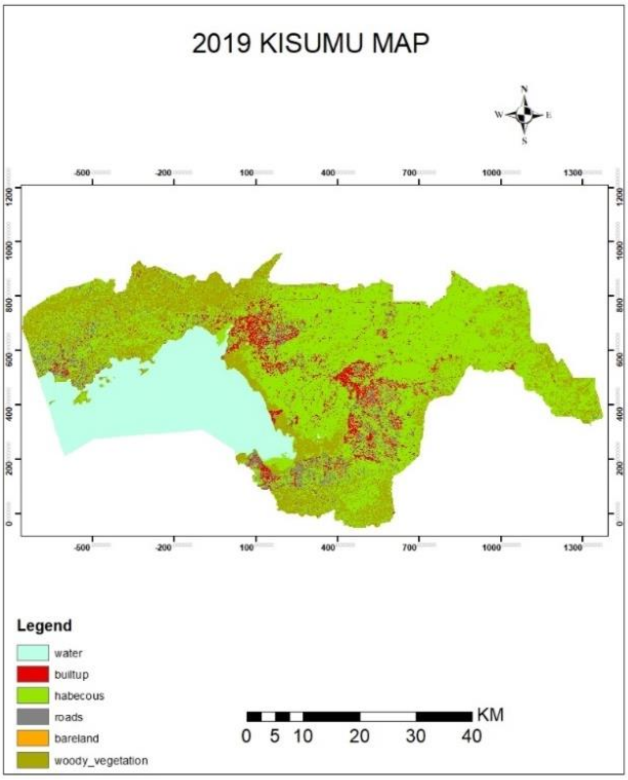


Figure 20. *2019 landcover map.*

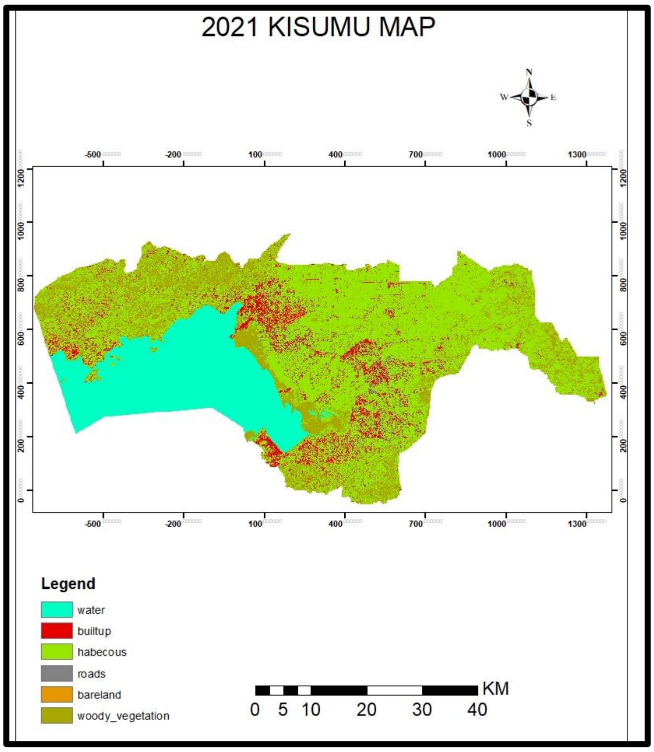


Figure 21. 2021 landcover map.

Land Use Land Cover Map of Lake Victoria & Environs (2019).

Land Use Land Cover of Lake Victoria & Environs 2021 and 2022

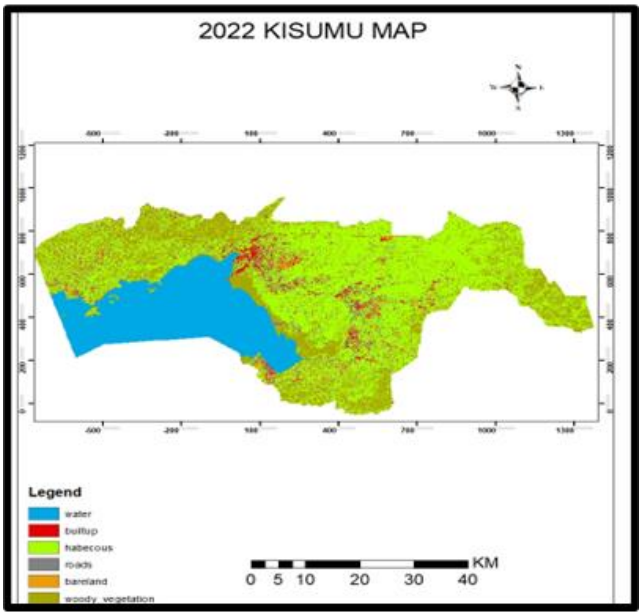


Figure 22. 2022 landcover map.

Land Use Land Cover Map of Lake Victoria & Environs (2021 and 2022).

Table 3. 2019 accuracy assessment.

	water	built-up	herbaceous	roads	bare land	Woody_vegetation	Total User
Water	30	0	0	0	0	2	32
Built-up	0	47	6	0	24	1	78
herbaceous	0	0	189	1	0	4	194
Roads	5	0	0	112	1	0	118
bare land	0	2	3	0	85	0	90
Woody_vegetation	0	0	0	0	2	173	175
TOTAL PRODUCER	37	49	197	113	112	180	687

A pivot table was generated using the columns, ground truth and classified values. A confusion matrix table is generated which allows for calculation of user's accuracy, producer's accuracy and overall accuracy of each of the classification map.

The classification was well done depending on the user's percentage accuracies which were 92.9% for 2021 classification, 97.26% for 2022 classification and 94.12% for 2019 classification. This indicates that most class points were accurately classified. This important as it validates the spatial location of the classified classes for accurate analysis. Calculations of how the accuracies were obtained for the classifications are as shown below.

Accuracy Assessment on Land Use Land Cover Map 2021

Accuracy assessment 2021

Overall Accuracy

Correctly classified values = 32+47+189+112+85+173= 638

Total value =687

Overall Accuracy (638/687) *100= 92.8675%

User's Accuracy.
water (30/32) × 100 = 93.75%
built-up (47/78) × 100 = 60.2564%
herbaceous (189/194) × 100 = 97.4227%
roads (112/118) × 100 = 94.9152%
bare land (85/95) × 100 = 89.4737%
woody_vegetation (173/175) × 100 = 98.8571%
Producer's Accuracy.
water (30/37) × 100 = 81.0810%
built-up (47/49) × 100 = 95.9183%
herbaceous (189/197) × 100 = 95.9391%
roads (112/113) × 100 = 99.1150%
bare land (85/112) × 100 = 75.8928%
woody_vegetation (173/180) × 100 = 96.1111%
Accuracy Assessment on Land Use Land Cover Map 2022
Accuracy assessment on the 2022 Land Use Land cover map

Table 4. *2021 accuracy assessment.*

	water	built-up	herbaceous	roads	bare land	Woody_vegetation	Total User
Water	86	0	0	0	0	0	86
built-up	0	37	0	0	11	2	50
herbaceous	0	0	300	0	0	0	300
Roads	0	0	0	105	0	0	105
bare land	0	0	1	2	112	0	115
Woody_vegetation	0	0	8	0	0	211	219
TOTAL PRODUCER	86	37	309	107	123	213	875

Overall Accuracy
Correctly classified values =300+105+112+211+37+86= 851
Total value =875
Overall Accuracy (851/875) *100= 97.25714%
User's Accuracy.
water (86/86) × 100 = 100%
built-up (37/50) × 100 = 74%
herbaceous (300/300) × 100 = 100%
roads (105/105) × 100 = 100%
bare land (112/115) × 100 = 97.3913%
woody_vegetation (211/219) × 100 = 96.3470%
Producer's Accuracy.
water (86/86) × 100 = 100%
built-up (37/37) × 100 = 100%
herbaceous (300/309) × 100 = 97.0873%
roads (105/107) × 100 = 98.1308%
bare land (112/123) × 100 = 91.0569%
woody_vegetation (211/213) × 100 = 99.0610%
Accuracy Assessment on Land Use Land Cover Map 2019
Accuracy assessment on the 2019 Land Use Land cover map

Table 5. *2022 accuracy assessment.*

	water	built-up	herbaceous	roads	bare land	Woody_vegetation	User Total
Water	218	2	0	0	0	0	220
built-up	0	94	4	1	7	1	107
herbaceous	1	0	263	0	3	5	272
Roads	0	0	5	66	1	2	74
bare land	0	2	4	0	35	0	41
Woody_vegetation	1	0	16	0	0	205	222
TOTAL PRODUCER	220	98	292	67	46	213	936

Overall Accuracy

Correctly classified values = 218+94+263+66+35+205=881

Total value =936

Overall Accuracy (881/936) *100= 94.1239%

User's Accuracy.

water (218/220) × 100 = 99.0909%

built-up (94/107) × 100 = 87.8505%

herbaceous (263/272) × 100 = 96.6912%

roads (66/74) × 100 = 89.1892%

bare land (35/41) × 100 = 85.3658%

woody_vegetation (205/222) × 100 = 92.3423%

Producer's Accuracy.

water (218/220) × 100 = 99.0909%

built-up (94/98) × 100 = 95.9184%

herbaceous (263/292) × 100 = 90.0685%

roads (66/67) × 100 = 98.5074%

bare land (35/46) × 100 = 76.0870%

woody_vegetation (205/213) × 100 = 96.2441%

A statistical table was generated from land change classification maps which shows changes in area coverage of the in a gap of a year. The differences in land cover over the years is clearly shown.

From Table 6, where change was between 2019 to 2021, water area coverage had a percentage change of 4.4554%. This therefore, lead to road coverage change of -58.7605% this has made accessibility to places difficult.

From Table 7, which is about 2021 to 2022 change, shows a percentage change of -0.17825% for water coverage and -58.051% for built cover which shows the built areas are under great threat despite the water level reducing.

Table 8 shows land cover change between 2019 to 2022. Water coverage percentage was 4.269245% and -36.61% change for built coverage. This a clear indication that majority of people were displaced from the homes and many businesses closed down.

Table 6. *2019-2021 land change.*

Land Use Land Cover change (2019-2021)

LULC Classes	2019	2021	Diff	% change
Water	559258200	584175600	24917400	4.455438
built-up	126221400	190736100	64514700	51.11233
herbaceous	1248071000	1362137400	114066400	9.139416
Roads	177093000	73032300	-104060700	-58.7605
bare land	23552100	18925200	-4626900	-19.6454
Woody_vegetation	548579700	453769200	-94810500	-17.2829

Table 7. *2021-2022 land change.*

Land Use Land Cover change (2021-2022)

LULC Classes	2021	2022	Diff	%change
Water	584175600	583134300	-1041300	-0.17825
Built up	190736100	80011800	-110724300	-58.051
herbaceous	1362137400	1239657000	-122480400	-8.99178
Roads	73032300	155682000	82649700	113.1687
Bare land	18925200	40279500	21354300	112.8353
woody_vegetation	453769200	584010900	130241700	28.70219

Table 8. *2019-2022 land change.*

Land Use Land Cover change (2019-2022)

	2019	2022	Diff	%change
Water	559258200	583134300	23876100	4.269245
Built up	126221400	80011800	-46209600	-36.61
Herbaceous	1248071000	1239657000	-8414000	-0.67416
Roads	177093000	155682000	-21411000	-12.0903
Bare land	23552100	40279500	16727400	71.02297
woody_vegetation	548579700	584010900	35431200	6.458715

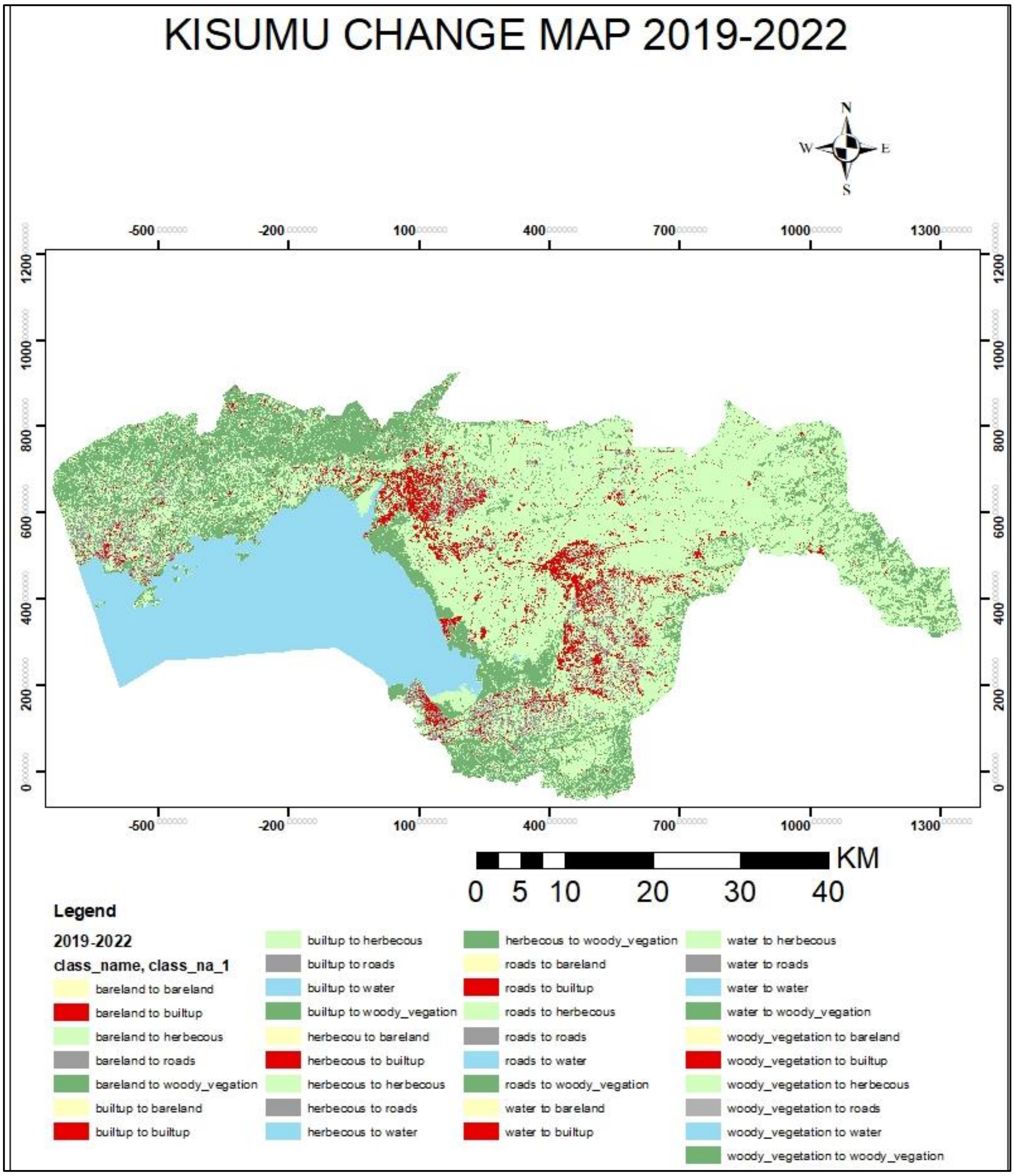


Figure 23. *2019-2022 change map.*

The 2019-2021 Land Use Land Cover Change Map of Lake Victoria & Environs

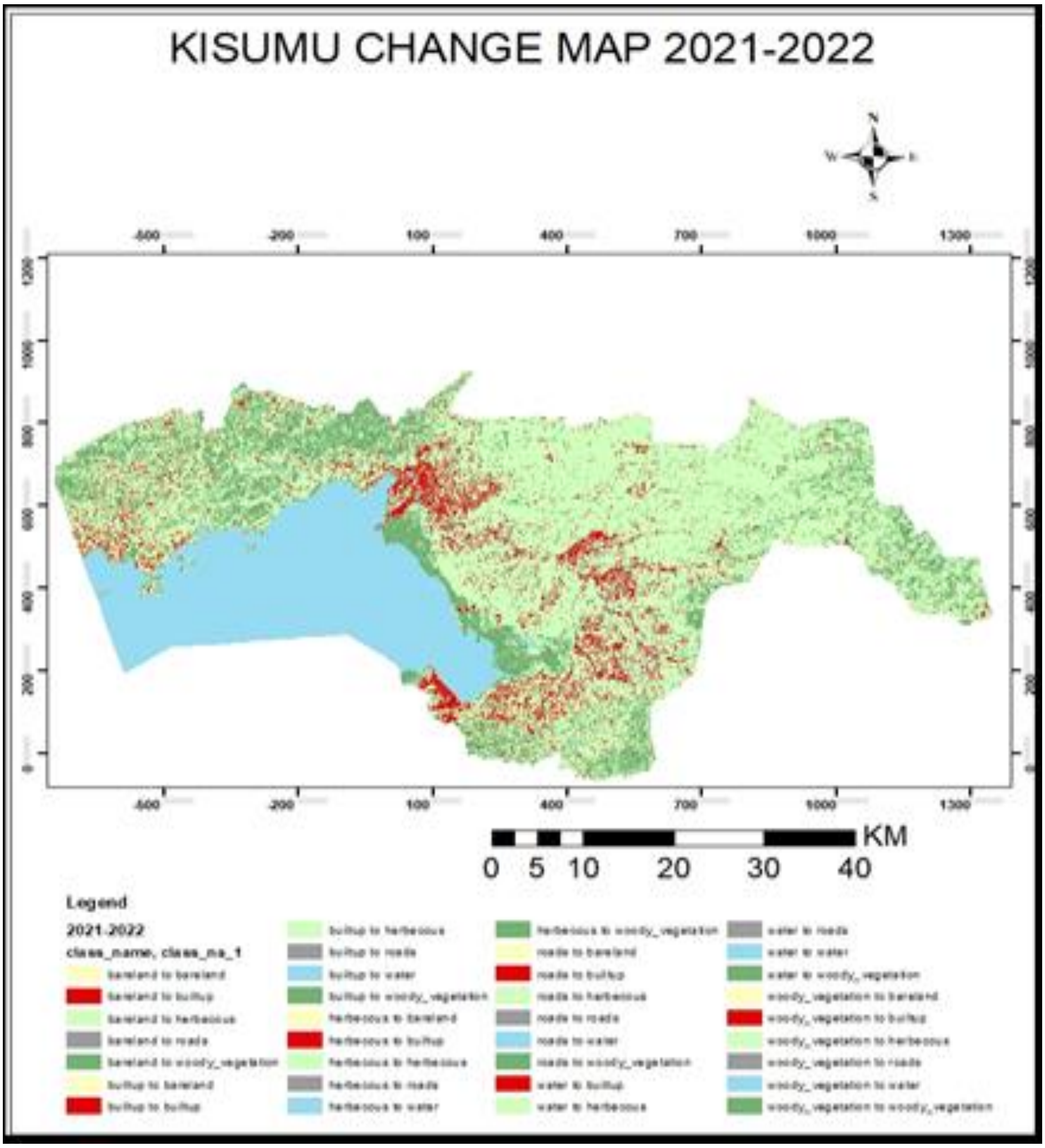


Figure 24. *2021-2022 change map.*

2019-2022, 2021-2022 Land Use Land Cover Change Map of Lake Victoria & Environs.

3. Conclusion and Recommendations

The classification of Kisumu County has revealed that the lake is claiming the land. People who live and get their livelihood along the shores of the lake, like farming, fishing and businesses were highly affected by the flooding. Most impact was felt along the developed shores where activities such as sand harvesting and wood logging are major activities. Previously carried studies have found that the lake is expanding at a very high rate. In this study alike, the areas covered under water have increased following the flooding that have occurred in the previous years. Even though the water coverage has reduced, it has not gone back to its original state.

This study contributes to other primary research conducted using satellite observation providing insights into expansion of the lake. Classification accuracies for the different years are suitable enough as all of them are 90% and over.

The strategy for flood management in Lake Victoria basin, therefore, must simultaneously address the present problems of the poor flood plain dwellers and the imperative future development of the entire fertile land that is prone to frequent flooding. The developmental planning must be pro-active and dynamic and take into consideration the likely multiplier or cascading effects on various other sectors of economy that may spread far and wide beyond the target areas. Finally, this research project aims to contributes to management efforts and prevention policies through mapping affected zones, informing future steps to be adopted in preventing cases of people carried away and killed due to flooding.

This study recommends for:

1. The previous dry lands that are now covered under water be used for rice farming as they are fertile, and the water is good for rice. Concerned organizations like Kenya Agriculture and Livestock Research Organization can partner with County Government of Kisumu. Individuals whose lands are taken for this exercise can be compensated.
2. Adoption of geospatial technology by the county government of Kisumu to identify suitable spots to put up buildings and roads along the shores. This is also important as it helps avoid destruction and loss of lives during flooding.
3. Designate wetlands as buffer between the lake and any other human activities. This can be achieved by having law enforcement.
4. Civic education for those living around the rising of lake as it helps make people understand essence of not living next to the shores despite it having many advantages.
5. The government to monitor and know the high, medium and low flood risk areas as it helps them to plan well for emergencies of floods.

Abbreviations

APFM	Associated Programme on Flood Management
GIS	Geospatial Information System
SWIR	Short Wave Infrared
NIR	Near Infrared
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
NDBI	Normalized Difference Built-Up Index

Conflicts of Interest

The authors declare no conflicts of interest.

References

[1] Colliers, J. (2021). *The Future of Africa: Challenges and Opportunities* (p. 421). Springer Nature.

[2] Okurut, T. O., Kipkore, W. K., & Mngube, F. M. (2006). Management of a shared lake ecosystem: a case study of Lake Victoria. In *Proceedings of the 11 th World Lakes Conference--Proceedings* (Vol. 1, pp. 75-81).

[3] Okayo, J., Odera, P., & Omuterema, S. (2015). Socio-economic characteristics of the community that determine ability to uptake precautionary measures to mitigate flood disaster in Kano Plains, Kisumu County, Kenya. Geoenvironmental Disasters, 2, 1-22.

[4] Colvin, R., Crimp, S., Lewis, S., & Howden, M. (2020). Implications of climate change for future disasters. *Natural Hazards and Disaster Justice: Challenges for Australia and Its Neighbors*, 25-48.

[5] Otieno, J., & Otieno, A. C. (2020). Effects of Changes of Lake Victoria Water Levels on Land Use Patterns, Covid-19 Pandemic and Food Security in Winam Gulf, Homa-Bay County, Kenya. *Land Science*, *2*(2), p67-p67.

[6] Mokua, M. A., & Aloo, P. (2020). Factors Influencing the Economic Performance of Women Fish Processors: The Case of Small Scale Omena Fish Processors in Lake Victoria-Homabay County, Kenya. *Eastern Africa Social Science Research Review*, *36*(2), 19-34.

[7] Geheb, K. I. M., & Binns, T. (1997). 'FISHING FARMERS'OR 'FARMING FISHERMEN'? THE QUEST FOR HOUSEHOLD INCOME AND NUTRITIONAL SECURITY ON THE KENYAN SHORES OF LAKE VICTORIA. *African Affairs*, *96*(382), 73-93.

[8] Khaki, M., & Awange, J. (2021). The 2019–2020 rise in Lake Victoria monitored from space: exploiting the state-of-the-art grace-for and the newly released ERA-5 reanalysis products. *Sensors*, *21*(13), 4304.

[9] Hirwa, H., Zhang, Q., Li, F., Qiao, Y., Measho, S., Muhirwa, F. & Itangishaka, A. C. (2022). Water accounting and productivity analysis to improve water savings of Nile River Basin, East Africa: from accountability to sustainability. *Agronomy*, *12*(4), 818.

[10] Mugo, R., Waswa, R., Nyaga, J. W., Ndubi, A., Adams, E. C., & Flores-Anderson, A. I. (2020). Quantifying land use land cover changes in the Lake Victoria basin using satellite remote sensing: The trends and drivers between 1985 and 2014. *Remote Sensing*, *12*(17), 2829.

[11] Omute, P., Corner, R., & Awange, J. L. (2012). The use of NDVI and its derivatives for monitoring Lake Victoria's water level and drought conditions. *Water resources management*, *26*, 1591-1613.RIAGA, G. O., MATI, E. K., & MAKUNGU, F. (2021). FLOODS AND IT'S EFFECTS ON CLASS ATTENDANCE IN DAY SECONDARY SCHOOLS IN NYANDO SUB-COUNTY IN KISUMU COUNTY, KENYA.

[12] Authority, T. M. (2019). Statement on the staus of Tanzania climate in 2019.

[13] Swallow, B. M., Sang, J. K., Nyabenge, M., Bundotich, D. K., Duraiappah, A. K., & Yatich, T. B. (2009). Tradeoffs, synergies and traps among ecosystem services in the Lake Victoria basin of East Africa. *Environmental science & policy*, *12*(4), 504-519.

[14] Mafuta, C., Westerveld, L., & Lake Victoria Basin Commission. (2017). Lake Victoria Basin: Atlas of our Changing Environment.

[15] Luborsky, L., Crits‐Christoph, P., McLellan, A. T., Woody, G., Piper, W., Liberman, B,... & Pilkonis, P. (1986). Do therapists vary much in their success? Findings from four outcome studies. *American Journal of Orthopsychiatry*, *56*(4), 501-512.