# Modeling of Water Level Trends and Characterizing Potential Influencing Factors in Lake Baringo in Kenya

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**Research Article**

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**Posted Date:** March 8th, 2024

**DOI:** https://doi.org/10.21203/rs.3.rs-3913496/v1



**Additional Declarations:** No competing interests reported.

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*Article*

# MODELING OF WATER LEVEL TRENDS AND CHARACTERIZING POTENTIAL INFLUENCING FACTORS IN LAKE BARINGO IN KENYA

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Received: date / Accepted: date

**Abstract**
Water plays a significant role in every sector of the ecosystem. The fluctuation of the water levels in lakes is influenced by natural and man-made factors within the water catchment. Lake Baringo, having no visible outlet, has been rising drastically, causing panic among native communities and businesses on the shores of the lake. Using GIS and Remote Sensing, this study intends to analyze the changes in water lakes using the Automatic water extraction index (AWEI), determine the causes of the fluctuation using Land use land cover, land surface temperature, soil erosion, and siltation in the lake basin and the lake respectively, precipitation, and later predict of the water level for the year 2030 using the MOLUSCE tool. The tool utilizes an artificial neural network and cellular automata to analyze land use and land cover conveniently. It was found that the lake's water level has been increasing drastically over the years, and the leading causes of the fluctuations were increased rainfall and human activities within the water basin. There are visible increased human activities within the water basin, such as agriculture, deforestation, settlement, and urbanization. It was also found that there will be a further increase in water level in 2030. With all the above results, it is recommended that better policies be made for the effective conservation of the water basin, and a plan should be drawn to re-delineate the new riparian buffer.

**Keywords** Land Use Land Cover· DAHITI· Cellular automata· Lake Baringo· Water Level.

**List of Abbreviation**
ALOS PALSAR- Advanced Land Observing Satellite Phased Array Type L-band Synthetic Aperture Radar
AWEI - Automatic Water Extraction index
CHIRPS -Climate Hazards Center InfraRed Precipitation with Station data
DAHITI- Database for Hydrological Time Series of Inland Waters
DEM - Digital Elevation Model
FAO - Food and Agriculture
LULC - Land Use Land Cover
MOLUSCE -Modules for Land Use Change Simulations
USGS- U.S. Geological Survey

**Availability of Data and Material**
The datasets generated during this study are available in the USGS website: https://earthexplorer.usgs.gov/, Climate Hazards Center (U.C. Santa Barbara) website: https://data.chc.ucsb.edu/products/CHIRPS-2.0/, and FAO website; https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/en/

**Competing Interest**

The authors declare that they have no competing interests.

**Funding**

The project was self-funded since none of the authors received any financial support from any organization for data collection, processing, analysis, or drawing of the manuscript.

**Author's Contribution**

All the authors contributed to the study conception and design, material preparation, data collection, analysis and the drafting of the manuscript as Doreen Jelagat Kimtai did them under the supervision of Dr. Godfrey Ouma Makokha and Dr. Arthur Wafula Sichangi.

## 1 Introduction

Lakes play a critical role in the world's biodiversity as they are habitats, resources for consumption, industrialization, and recreation [19]. The fluctuation in lake water levels has affected the community in a big way, either directly or indirectly. It has directly affected the community through the destruction of property and agriculture when it floods; the road becomes inaccessible, and people and animals die due to drowning [26]. There is an urgent need for greater comprehension of the underlying patterns of natural variability of water resources and evaluation of their implications for water resource management and conservation due to the ever-increasing human demand for water and the growing unpredictability of the climate [39]. Lake Baringo is one of the most important lakes in the Rift Valley of Africa [52], as it is a freshwater lake in the Great Rift Valley, providing water for consumption, fishing, industries, and recreation. It is also among northern Kenyan Rift Valley lakes [29]. The Lake as shown in Fig. 1 has a surface area of 130 km2 and an elevation of 970 m. Its inlets are the rivers Ol Arabel, Perkerra, and Molo, but it has no visible outlet as it is assumed to have an underground outlet through the faults of the Rift Valley [49].

The causes of the fluctuation of water levels in Rift Valley lakes are siltation, the increase in rainfall, changes in land use, land cover, siltation, and tectonic forces [1]. Many theories are said to have caused the rise in water level in Lake Baringo, not limited to the increase in population, leading to people encroaching into forests and riparian lands for settlement and agriculture. Owiti and Oswe [54] research shows that deforestation, urbanization, pollution, and other activities are known to increase the carbon dioxide in the atmosphere, leading to climate change. Agriculture on the riparian lands and in the forests exposes the soil, and when it rains, causing a lot of erosion, the sedimentation over time then fills the lake siltation, displacing the water; therefore, it seems that the water has increased in volume, but that's not the case [20]. Apart from human activities in the lake basin, other factors lead to water fluctuations, like tectonic forces and increased precipitation, and the water level changes can be on both sides, either rising or drying up [41]. There are some theories that the causes of the rise in water levels of the lakes in the Rift Valley are siltation, the increase in rainfall in recent years, changes in land use and land cover, and tectonic forces in the Rift Valley [55].

Much research has been done on the study of the water levels in Lake Baringo. There's a need to analyze how the inflow rivers affect the water quality of the Lake, analysis of the topographical conditions between Lake Baringo and Lake Bogoria, and the potential flow paths in the event of an overflow. There is also a need to determine the effect of tectonic forces on the lake water level. In this study, we will analyze the causes of the fluctuations in the water level in Lake Baringo and predict the water level in the year 2030. Studying the fluctuations of water levels and their causes is very important as it leads to efficient resource management and encourages the development of conservation measures. These factors were then used to predict future water levels and provide data to draw the lake's management plans.

Additionally, predicting water level fluctuations is crucial for sustainable water supply planning, flood control, water resource management, shoreline maintenance, and the overall sustainability of lakes. The research's data and output will help researchers develop a program automatically delineating riparian buffers as they will be a certain distance above the highest watermark. It will also be a stepping stone for those who study water quality and its effects on the ecosystem, formulating effective plans for conservation and the management of the water resource.

The study aims to extract the water levels, characterize the probable factors that led to the changes in Lake Baringo, and predict the possible water level for the year 2030. At the same time, the specific Objectives are to determine the Lake's water fluctuations for the years 1990, 2000, 2010, and 2020 using AWEI and DAHITI data, to characterize the probable factors affecting changes in water level in Lake Baringo and to predict water level in the year 2030 using MOLUSCE tool.

A multidisciplinary approach and integration of diverse data sources are used to model water level trends and characterize probable causes impacting water levels in Lake Baringo, Kenya. The main steps in doing this analysis are data gathering and assembling historical Lake Baringo water level information. A lengthy time series dataset is ideal for capturing seasonal and long-term patterns. The data collected include satellite images from Landsat [4], meteorological data [26], soil data [22], and water level data from the DAHITI website [60]. Preparation and quality assurance were done to ensure the obtained data's correctness and consistency, clean it, and pre-process it. Align all datasets to a constant period, then remove any outliers or missing values. This process is essential for accurate analysis. The data, especially the Landsat data, were pre-processed by radiometric and geometric corrections. The mosaic, layer stacking, co-registration, and resampling were done to improve the output of the processed data [15].

The data is then used to get the Land use land cover, land surface temperature, soil erosion, precipitation analysis, and evapotranspiration. Exploratory data analysis was conducted on the water level data to find fundamental trends, seasonal fluctuations, and long-term trends. The data was then plotted, and graphs were drawn to understand better how water levels fluctuate. After this, statistical methods like time series analysis or linear regression were applied to measure the long-term patterns in water levels.

In this study, the water lateral extent was obtained from satellite data using the automatic water extraction index and the correlations between the surface area obtained from the AWEI and the water level obtained from the DAHITI database. According to Schwatke et al. [61], the surface area time series of DAHITI is a continuous dataset that spans from 1984 to almost the present. To obtain water level information from wetlands, reservoirs,

and other inland water bodies, DAHITI also uses satellite altimetry. Based on a combination of water surface area and water level time series, the volume changes of DAHITI are determined. A hypsometry model is computed using the novel modified Strahler approach based on the dependence of these two variables.
Studying water levels in lakes and their causes is important to the community and the academic world as it helps in adaptive resource management, understanding the global water cycle, assessing the health of lake ecosystems, protecting water resources, and managing water levels. The fluctuations in lake water levels are influenced by various factors such as climate change, population growth, urbanization, water consumption, industrialization, and irrigation. The prediction of water levels is further helpful for future planning.

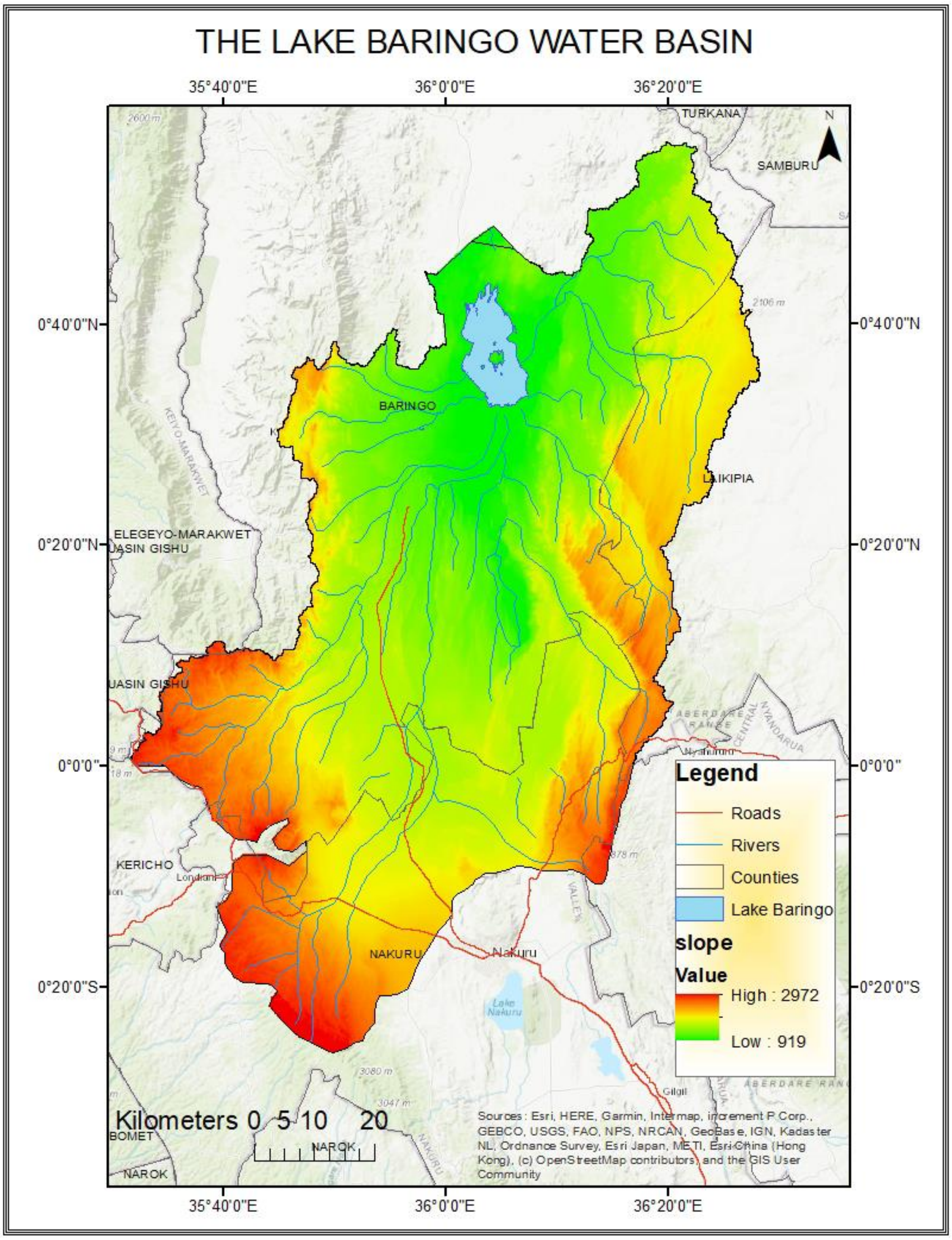



**Fig. 1;** Lake Baringo Water Basin showing the DEM, river, Lake Baringo, and the ESRI topographical map as the Base Map

## 2 Methods

The lake's water level and surface area were determined using AWEI, which was then correlated with the water level from the DAHITI website. Land use land cover, land surface temperature, and soil erosion were obtained from the RUSLE model. Finally, the 2030 water level prediction was done using an automatic neutral network and cellular automata.

### 2.1 Data

The data used in the above processes are DEM, metrological data, topo maps, Landsat, and water level, as shown in table 1 below.

**Table 1;** Characteristics of satellite imagery used for the study

| DATA | RESOLUTION | SENSOR | YEAR | SOURCE |
|---|---|---|---|---|
| DEM | 12.5 m | SAR | | ALOS PALSAR |
| LANDSAT 4 | 30 m | TM | 1990 | USGS |
| LANDSAT 5 | 30 m | TM | 2010 | USGS |
| LANDSAT 7 | 30 m | ETM+ | 2000 | USGS |
| LANDSAT 8 | 30 m | OLI | 2020 | USGS |
| PRECIPITATION | $0.05^0$ | | 1990-2020 | CHIRPS |
| SOIL DATA | 5*5 arc minutes | | | FAO |
| WATER LEVEL | < 10m | Sentinel-3A,Jason-2& ENVISAT (MERIS) | 2008-2020 | DAHITI |

### 12.2 Data Processing and Analysis

Using Landsat data from the USGS for 1990, 2000, 2010, and 2020, the lake water surface area was extracted using the automatic water extraction index (AWEI) since it gives better accuracy than other water indices. This tool improves the accuracy of extracting water bodies in areas including shadows and dark surfaces compared to other methods that failed to classify water correctly [47]. The formula for this index is shown below. Still, these need to be done after the satellite images have been pre-processed, radiometric, geometric, and atmospheric corrections done, layer stacking, mosaicking, co-registration, and resampling have been done.

$AWEI=4 * (green - SWIR2) - (0.25 * NIR + 2.75 * SWIR1)$ [42] ………………………………………….. (1)

The output of AWEI is the lake water surface area, while the water level was obtained from the Database for Hydrological Time Series of Inland Waters (DAHITI). The ratio was calculated using the lake water surface area and the water level from DAHITI, giving a water level graph.

The DEM data from ALOS PALSAR was used to delineate the water basin; this was done by processing the flow direction and establishing whether there were sinks. If there is no sink, a depression-less DEM is created; if there are sinks, a fill needs to be done. From the depression-less DEM, flow accumulation was created, a flow length was drawn, the snap pour points were drawn, and the water sub-basins were created with all these. The merging of sub-basins forms the Lake's water basin.

After the water basin has been delineated, the HRUs are drawn, and the SWAT model runs, getting the evapotranspiration maps and the water balance equation analyzed. The annual rainfall data collected from the CHRPS database was used to draw maps and graphs to show rainfall variation over the years. These graphs are essential when doing the comparison analysis on the relationship between the precipitation and the fluctuation of water in Lake Baringo.

The revised universal soil loss equation (RUSLE) model was used to calculate the amount of erosion within the Lake Baringo basin [12]. The above model was to determine the siltation level caused by soil erosion. The formula below is used to calculate it:

$E = Cfactor * LSfactor * Pfactor * Kfactor * Rfactor$……………………..……………………... (2)

Where the C-factor is the crop management factor, it was used to reflect the effects of crops, soil biomass, construction, and other activities on the basin. The LS factor is the slope length factor, which was used to calculate the erosion that occurs due to the slope of the Land. When the slope is steep, it is presumed to have a higher erosion rate than flat ground. The P-factor is the practice support factor used to analyze the effects of agricultural practices, such as strip cropping and terracing. With this, it can be differentiated between agricultural lands and rangelands. K-factor is the soil erodibility factor due to surface runoff; therefore, it only affects the topsoil. While the R-factor estimates erosion caused by rainfall, it is derived from rainfall data, usually in point data; it is converted to a polygon using ArcMap with the annual rainfall as the value. The amount of soil loss is to be identified for the years 1990, 2000, 2010, and 2020.

The land surface temperature (LST) of the water basin for the years of study was extracted from the processed Landsat data. The atmospheric reflectance, NDVI, brightness temperature, and land surface emissivity were obtained using Landsat data from the split window method [56], as shown in the equation below.

$T_S = BT_{10} + (2.946 * (BT_{10} - BT_{11})) - 0.038$……………………..………………………………... (3)

Where; $T_S$ Is Surface Temperature in degrees Celsius, $BT_{10}$ is Brightness Temperature Value in degrees Celsius at band ten and $BT_{11}$ is Brightness Temperature Value in degrees Celsius at band 11.

Land use land cover (LULC) is to be obtained from the Landsat data for 1990, 2000, 2010, and 2020. Using a level, I classification system, water, urban, agricultural lands, bare Land, range lands, and forest are extracted from the Landsat satellite images in Erdas Imagine using supervised classification [38]. The supervised classification uses a maximum likelihood classifier after the satellite images from Landsat have been pre-processed, radiometric, geometric, and atmospheric corrections are done, and layer staking and mosaic are done. After the LULC analysis, the accuracy assessment and post-classification were done to check the accuracy of the LULC.

Pearson correlation analysis was done to determine the relationship between the lake's water level with respect to the Land Use Land Cover (LULC), the Land Surface Temperature (LST), soil erosion, and rainfall. The output of the correlations is the graphs with the above variables as the primary vertical, the water level as the secondary vertical, and the years of study as the primary horizontal.

The water level was modelled using an artificial neural network and cellular automata to train the data using the MOLUSCE tool available in the QGIS open-source application. Based on the LULC data for 2000 and 2010, explanatory variables, and transition matrices, we projected the LULC for 2020. The MOLUSCE plugin offers a kappa validation technique and comparison of actual and forecasted LULC images to validate the model and prediction accuracy. In the ANN learning process, 1000 iterations, a neighborhood value of 1 1 pixels, a learning rate of 0.001, 10 hidden layers, and 0.05 momentum were chosen to project the LULC for 2020. After obtaining satisfactory results from the model validation, we employed LULC data from 2010 and 2020 to forecast the LULC in 2030.

Sensitivity analysis determines how different values of an independent variable affect a particular dependent variable under a given set of assumptions. The MOLUSCE plugin did this to determine if the variables LST, rainfall, elevation, and siltation affect the prediction of water levels in the year 2030.

### 2.3 Limitations

Water level fluctuations in lakes are very dynamic and complex to analyze and forecast correctly, which is why different machine learning has been used. In this study, we can use artificial neural networks and cellular stomata to forecast the water level, and no other machine learning model was used to check the model's accuracy. There was also a challenge with the availability of ground data and spatial for the same period as when the analysis was to be done. Most of the data were initially recorded in files and books, and the data was not consistently collected, affecting the reliability of the available data. Systematic errors and biases in environmental models used to study water-level fluctuations can affect the reliability of model parameters and predictions. Due to financial constraints as the project was self-funded, tectonic forces, a significant factor assumed to have caused the water level fluctuation due to tectonic plates converging, were to be analyzed in this study.

This process is shown in the chart 1 below;

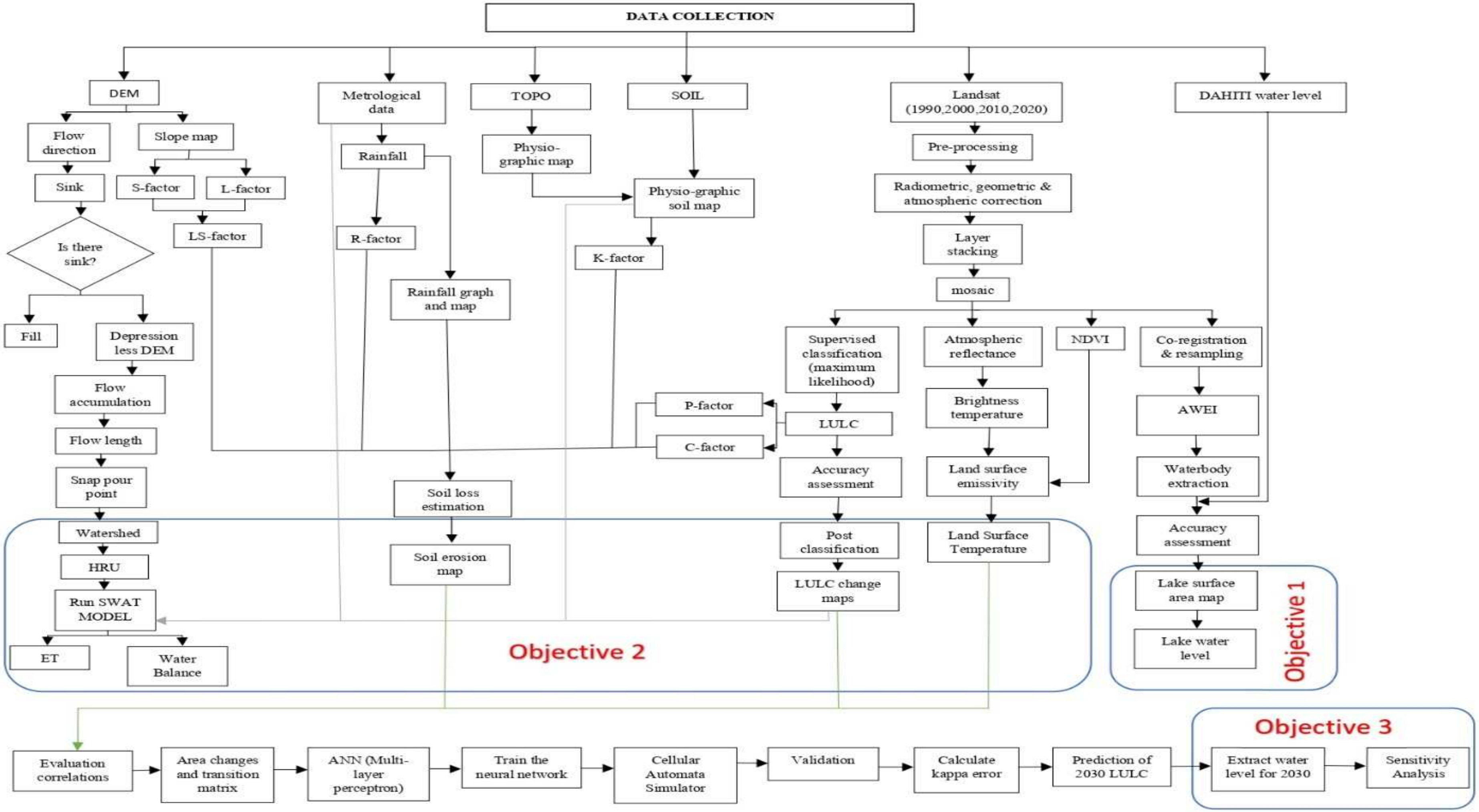
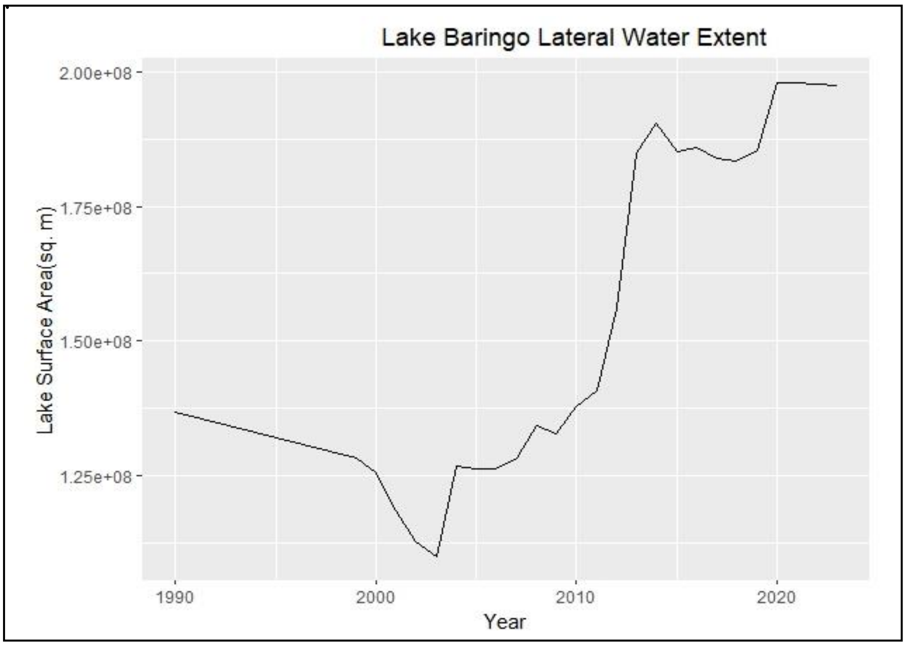



**Chart 1;** Flow Chart Methodology for remote sensing and GIS analysis

**3. Results**

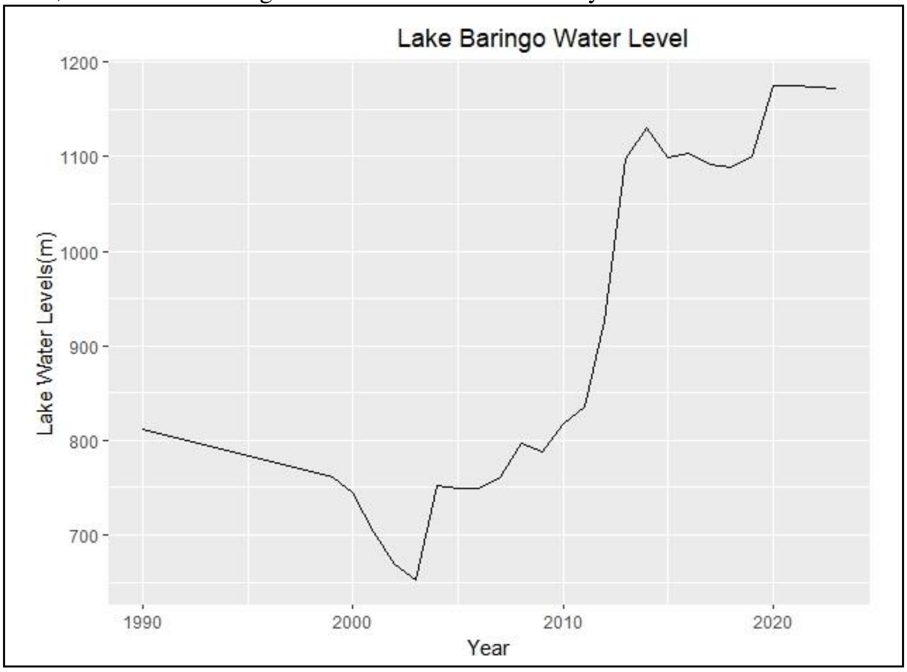
**3.1 Fluctuation of Lake water levels**

The research on modelling the water level trends of the lake and analyzing the factors causing the fluctuations was successful. The output is displayed as maps, charts, and graphs with clear descriptions.




**Graph 1;** Lake Baringo Water Surface Area from the year 1990 to 2020

The accuracy assessment for the water extraction index showed that the extracted surface area of the Lake was close to a perfect replica of the ground data obtained from Google Earth and other high-resolution images. The output of the AWEI gives the surface area as shown in graph 1 below, showing that the lateral water extent had been reducing from the year 1990 to the year 2003, it started increasing to the year 2014, dropping slightly to 2018, and it made the highest water extent mark in the year 2020.




**Graph 2;** Lake Baringo Water Level from the year 1990 to 2020

A correlation between the water surface area and the data obtained from the Database for Hydrological Time Series of Inland Waters (DAHITI) website, the Water Level Time Series (Altimetry), gives the water level as shown in graph 2 above. It is demonstrated that the water level was 820 m in 1990, which further decreased to 740m in 2000. There was a drastic further decrease and increase respectively between 2000 and 2004. It is clearly shown that there was a further increase in water level in 2014, which again dropped and later increased to 1180 m in 2020. The lateral water extent of the Lake is shown in Fig 2 below;

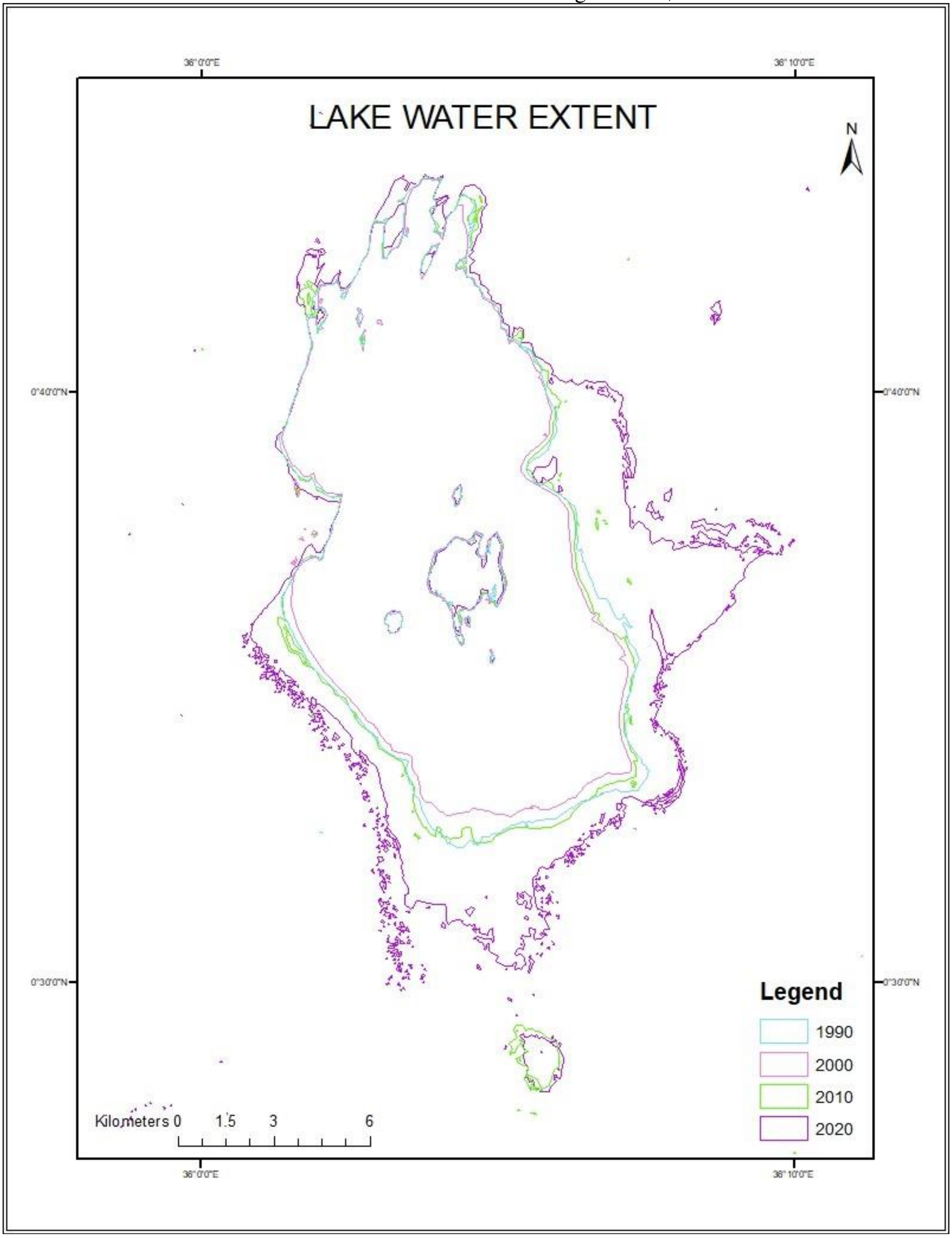



**Fig. 2;** Lake Baringo Lateral Water Extent for the years 1990, 2000, 2010, and 2020

**3.2 Land Use Land Cover**

Water levels have risen over time, with the year 2020 significantly having the highest increase ever seen, with a 65.58% increase from 1990. Forest cover has decreased by 48.43% in 2020 compared to 1990. Agricultural land is seen to increase continuously but dropped in 2010. 2020 marked the highest increase in agricultural activities, with a 12.41% increase compared to 1990. Between 1990 and 2010, the amount of bare Land significantly rose, but between 2010 and 2020, it decreased by 51.5%. After declining year after year, the rangelands increased in 2010. It can be seen through a comparison of the years 1990 and 2020 that there has been a decline of 11.39% between 2020 and 1990. The visual representation of the land use land cover is clearly shown in Figure 3 and graph 3 below;

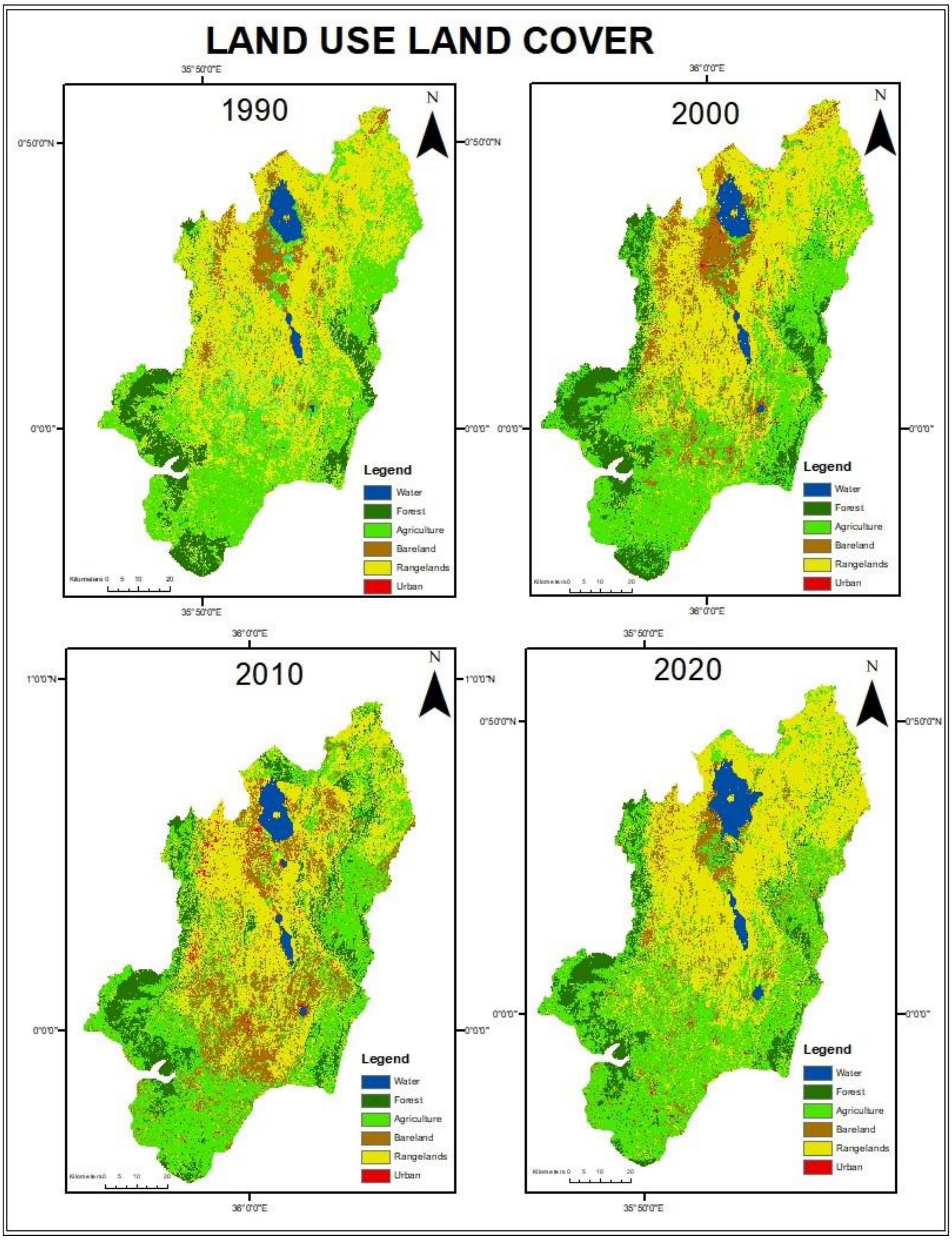
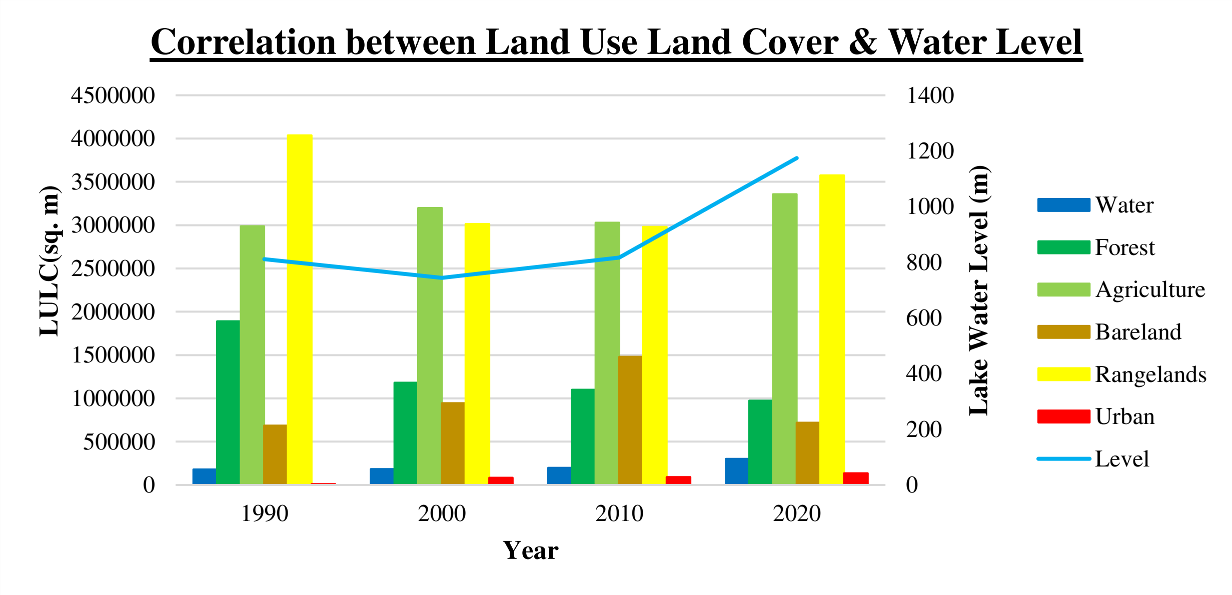


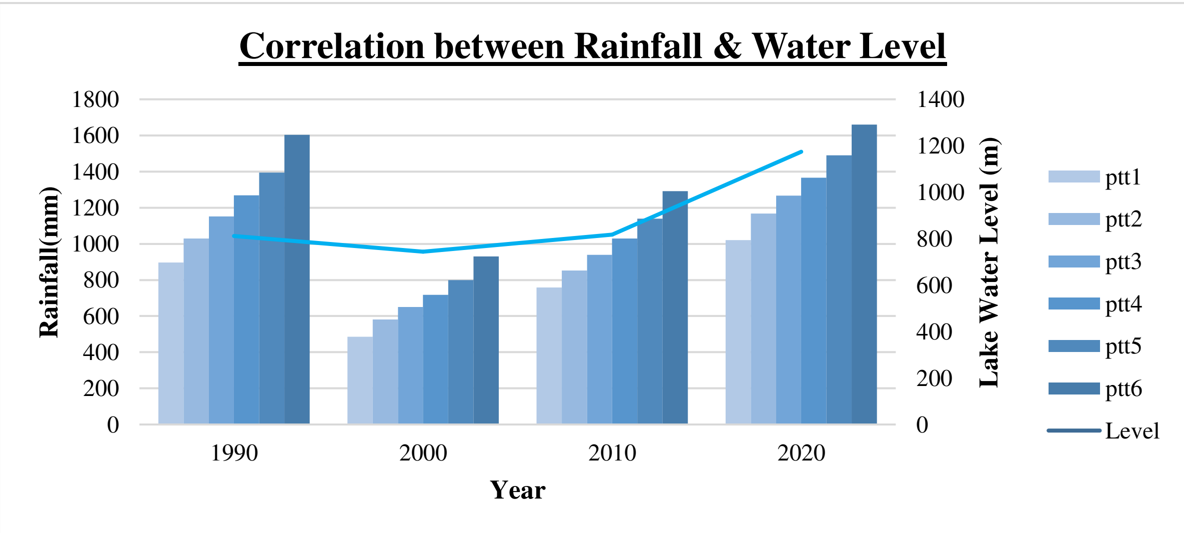

**Fig. 3;** Land Use Land Cover Maps for the years 1990, 2000, 2010, and 2020




**Graph 3;** Graphs of the correlation between LULC and Water Level

### 3.3 Precipitation

Kenya has its maximum rainfall in April and May each year, and the dry months are December to March, but some of the years, like 2020, had an averagely high rainfall for the whole year. Light showers or moderate humidity are expected for the year's remaining months. Figure 4 shows that 2020 had the highest low and highest high of 1020 mm and 1659 mm, respectively, double the rainfall received in 2000. Rainfall in the basin has been different yearly, but it usually reaches 1000mm. In the year 1990, the rainfall measured a low of 896mm and a high of 1602 mm; in 2000, it was a high of 929 mm and a low of 484 mm; and in 2010, it had a low rainfall of 759.13 mm. These rainfall amounts have a direct relationship with the water level as shown in the graph 4 below.




**Graph 4;** Graph of the correlation between Rainfall and Water Level

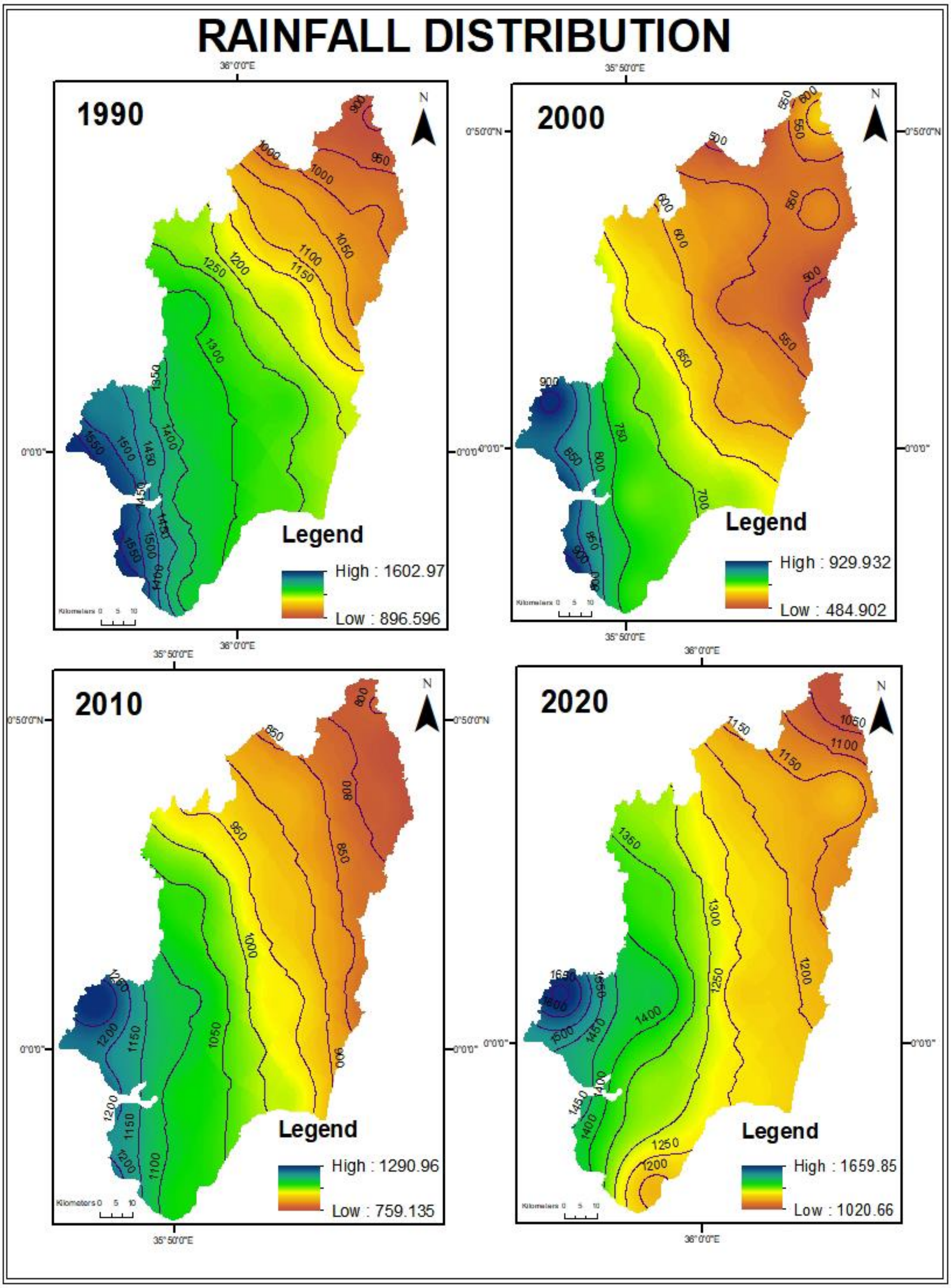


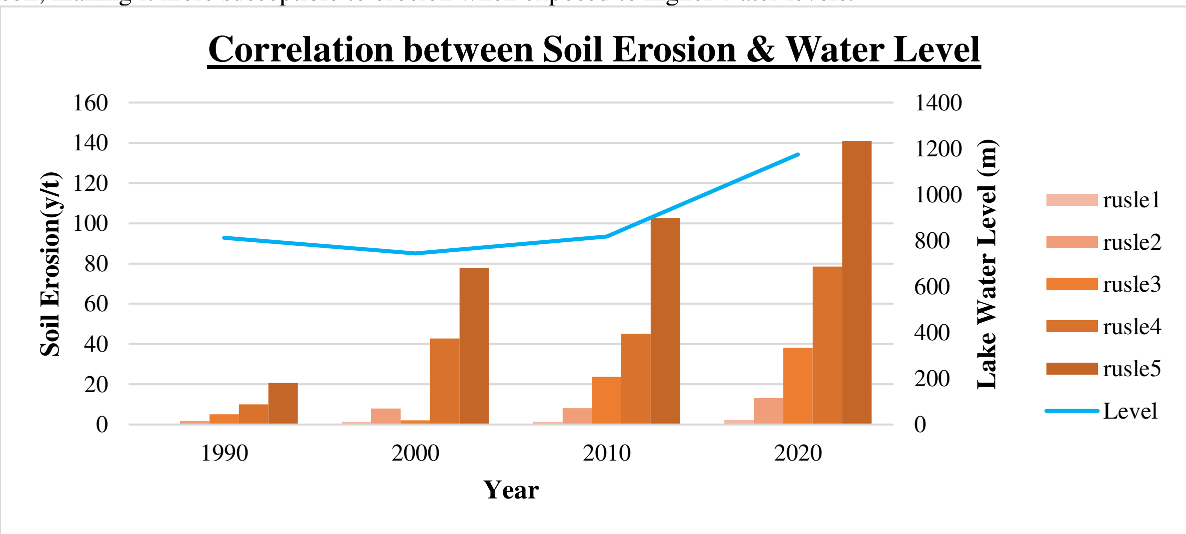

**Fig. 4;** Rainfall Maps for the years 1990, 2000, 2010, and 2020

Precipitation and water level go hand in hand, especially when there is high surface runoff, as Hartmann et al. [27] discussed. There was a direct relationship between water level and precipitation, as shown in graph 5, since the highest water level that has ever been witnessed in the Lake Baringo water basin was in the year 2020, when the rainfall measured 1659 mm, while the least precipitation level was in the year 2000, at an average of 706 mm, which coincidentally marked the lowest water level at 774m. These results show a direct relationship between the water level and the precipitation. As the precipitation increases, the water level increases, and vice versa. This correlation between rainfall and water level is crucial for understanding the hydrological dynamics of Lake Baringo. It highlights the significance of rainfall patterns in maintaining the water balance and overall health of the lake ecosystem. Additionally, monitoring and analyzing these trends can aid in predicting future water levels and implementing effective water management strategies.

### 3.4 Soil Erosion

The model soil erosion probability zones within the lake basin were generated by overlaying the Land use land cover maps, soil maps, slopes, and rainfall maps using the weighted index overlay method. It is clearly shown that the erosion level is highest in slopy areas where agriculture is practiced; there is little to no soil loss in rangelands and forested regions. Bare Land, on the other hand, had negligible soil erosion, which is alarming, and more research needs to be done to check it. It should also be noted that soil loss is more concentrated in the river channels, noting that most erosion within the lake basin is caused by water rather than by wind.

Graph 5 below shows a direct relationship between the water level and the soil erosion level, as the water level was at its highest in 2020 while the soil erosion levels, especially in the agricultural area, were high, too. These results suggest that the increase in soil erosion can be attributed to the higher water levels caused by human activities such as deforestation and agricultural practices. These activities contribute to the destabilization of the soil, making it more susceptible to erosion when exposed to higher water levels.




**Graph 5**; Graphs of the correlation between Soil Loss and Water Level

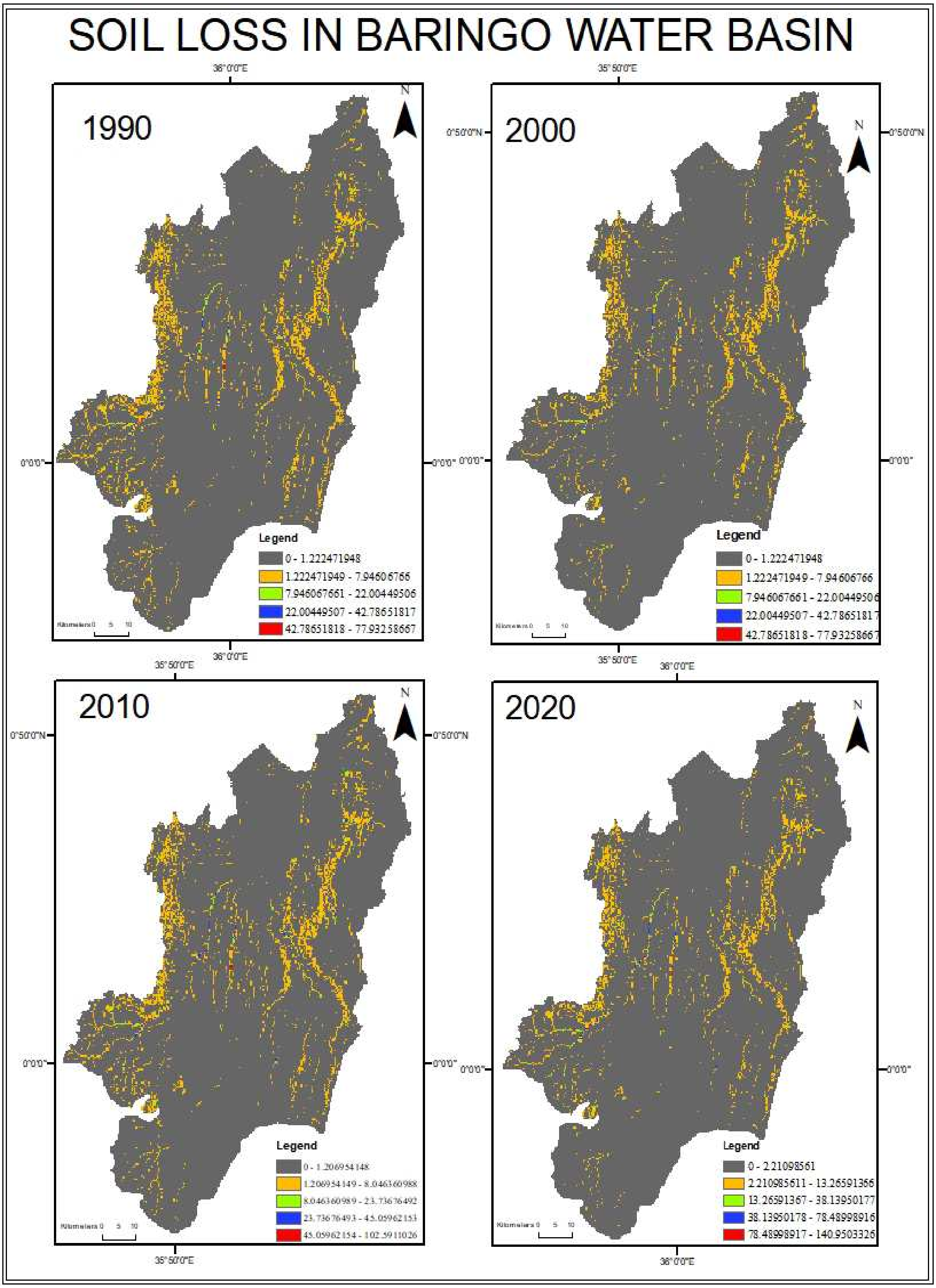


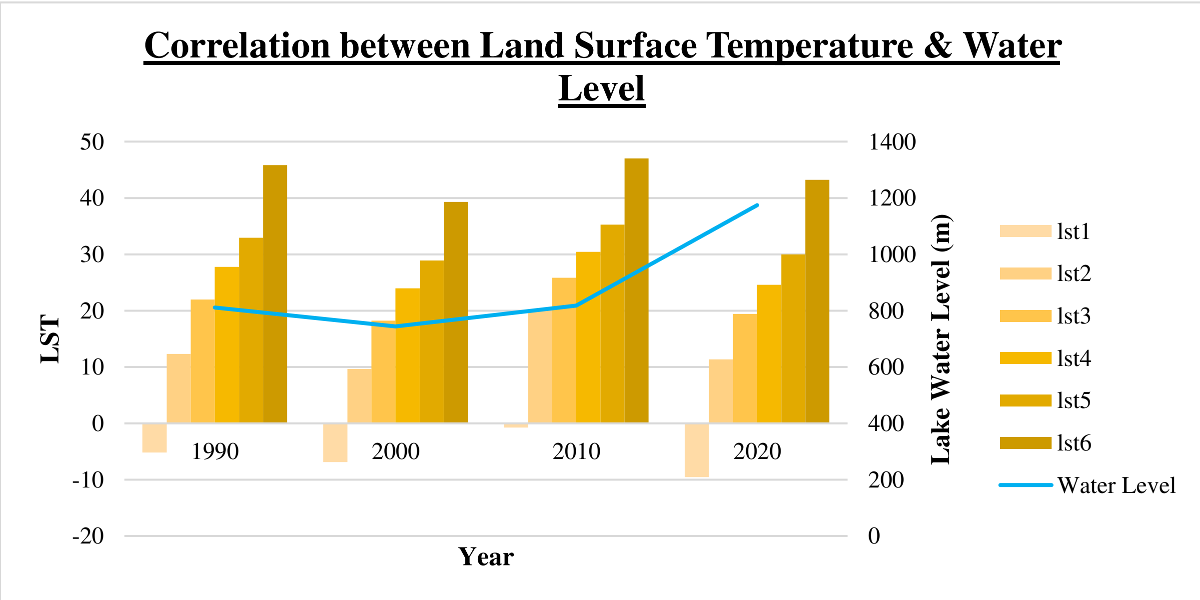

**Fig. 5;** *Lake Baringo Basin Soil Loss* Maps for 1990, 2000, 2010, and 2020.

The years 1990, 2000, and 2010 had relatively average amounts of soil losses, measuring a high range between 77 t/yr and 102 t/yr, while in the year 2020, soil erosion was at its highest of 140 t/yr, as shown in Fig 5 below. These results indicate that this is directly proportional to the increased rainfall and human activities within the water basin. Soil erosion has increased drastically since 1990, as shown in the graph below. However, despite 2000 having the least amount of water in the Lake and the precipitation level being low, as shown above, there was a higher erosion than in 1990, which is said to be due to human activities like deforestation, agricultural practices, and settlements.

**3.5 Land Surface Temperature**

The radiative skin temperature of the Land that results from solar radiation is known as the land surface temperature (LST). The land surface where the incoming solar energy interacts with and warms the ground, or the surface of the canopy in vegetated regions, is where LST detects the emission of thermal radiation. The temperatures of bare soil and plants combine to form LST. Due to this characteristic, LST is sensitive to changing surface conditions and a reliable indication of energy partitioning at the Land surface-atmosphere interface.

With the above explanations, LST is a measure of global warming, if there is any. As shown in the maps above, the land surface temperature in 2020 was the coldest, considering a lot of precipitation. But using the other years, like 2000, where the rainfall was at its lowest, it is funny enough that there was a low of -6k and a high of 39k. The lake water level was also at its lowest, making the relationship between LST and water level ambiguous.




**Graph 6**; Graph of the correlation between LST and Water Level

The correlation between land surface temperature and water levels is now direct, as in the year 2000, the water levels were at their overall lowest, and the land surface temperature was also at its lowest. It should also be considered that when the water level was at its highest in 2020, the LST registered a low of -9 k compared to -6 k in 2000.

Despite having the lowest range of low LST, the largest region in 2020 experienced a low LST. With respect to figure 3 above, figure 5 below shows that most forested areas, agricultural areas, and water bodies experienced a lower LST, while the rangelands and bare Land experienced a high of 47k. Mwaka et al.'s [44] study discovered a significant inverse relationship between LST and lake water levels in Lake Baringo. Their research using remote sensing data and statistical analysis showed that lake water levels tend to decline when land surface temperatures rise. This connection is explained by the possibility that increasing LST may result in higher evaporation rates, which will reduce the Lake's water level. These results emphasize the need for conservation efforts and methods to lessen the effects of climate change on this essential water resource and are significant. The results indicate that the overall temperature fluctuations varied significantly across different regions and land types. It is crucial to analyze the factors contributing to these variations, such as vegetation cover, land use patterns, and local climate conditions, to understand the complex dynamics of land surface temperature changes.

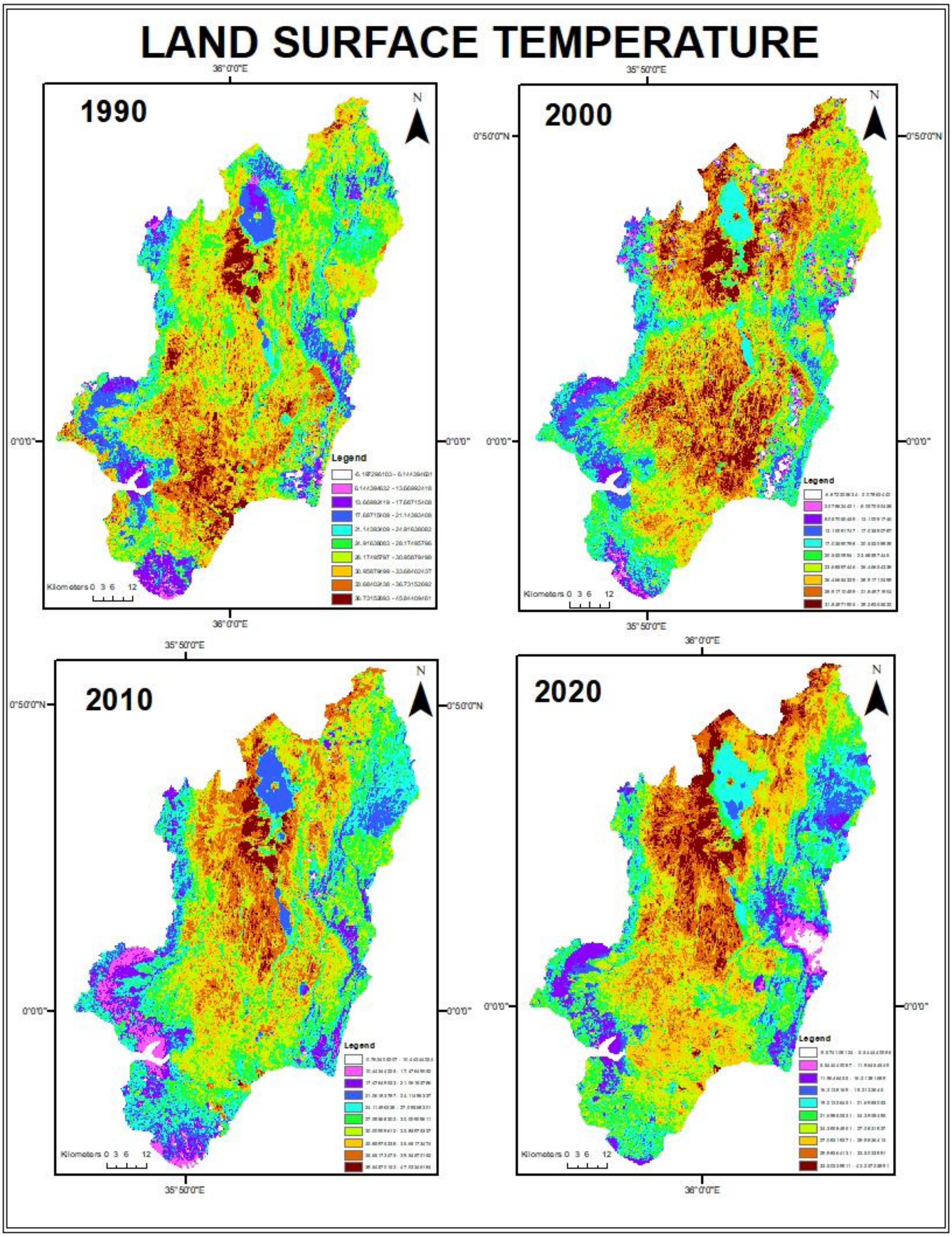



**Fig. 5;** *Lake Baringo Basin LST Maps* for 1990, 2000, 2010, and 2020.

**3.6 Prediction Model of the Water Level at 2030**

Using the MOLUSCE plugin, the predicted water surface area is found after the initial input of the model used is LULC for 1990, with the final input for the data training in 2010. The parameters used for the predictions are DEM, LST, precipitation, and soil loss map of 2020. A correlation analysis using the Pearson coefficient gives the class statistics and transition matrix.

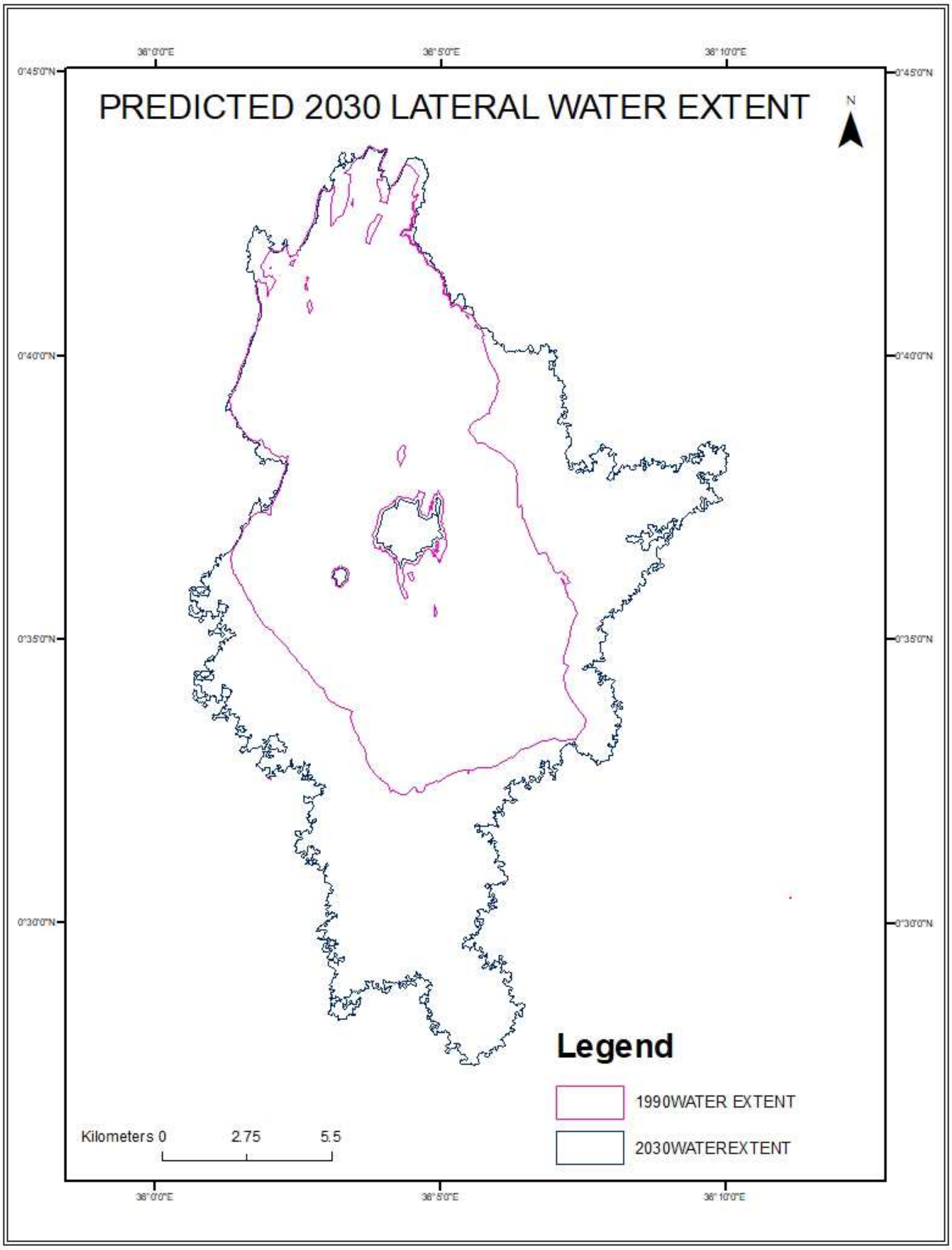
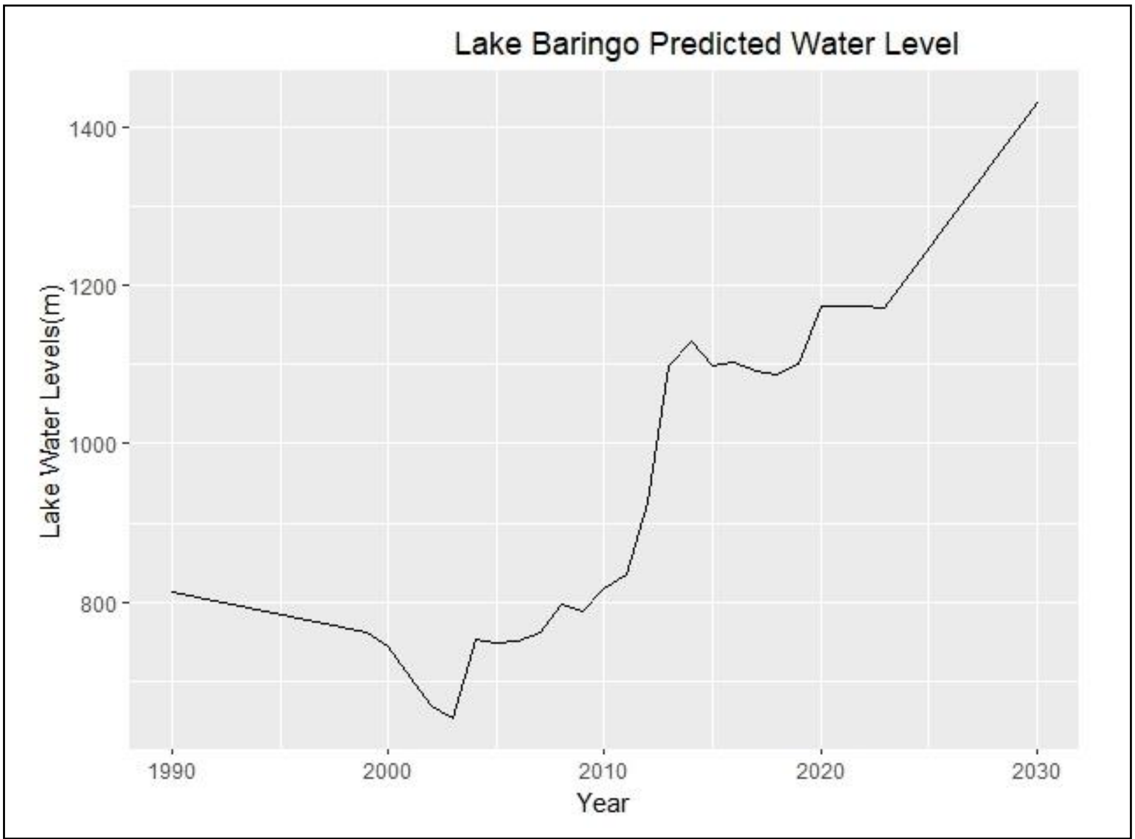



**Fig. 6;** The Lake Water extent for the year 1990 and the Predicted Lake Water Extent for 2030

The data that was used for training were randomly selected from 10000 samples. They were trained using an artificial neural network (multi-layer perceptron), with the following parameters: neighbourhood 1px, learning rate 0.1, maximum iterations 1000, momentum 0.05, and with that, an overall accuracy of -1.17058, a min validation overall error of 0.97237 and a current validation Kappa error of 0.45044. Using the cellular automata simulation and the parameter of 2020 as the calibration, the LULC for 2020 is predicted. The predicted map is then validated in 5 iterations using the classified LULC for 2020, creating a validation map checking persistent classes and producing a Kappa error of 0. 8975. Using the trained data, the LULC for the year 2030 is predicted, and the water surface area is extracted. The output was the lateral predicted water extent shown in figure 6 above.

The lake water level is then obtained by finding the ratio between the water surface area from 1990 to 2023 and the lake water level obtained from the DAHITI website. Using the relationship, the lake water level for 2030 can be determined and shown in the graph below. This indicates that the water level has been increasing drastically, and the water level in 2030 will have increased by 43.74% when the water level 1990 is used as the base.




**Graph 7;** Graph of Water level from 1990 to the year 2030

### 3.7 Sensitivity Analysis

Sensitivity analysis is a critical stage in modelling water levels and hydrological systems. It accomplishes several significant tasks. It is first helpful to pinpoint the crucial variables and inputs that significantly impact the results of the model. According to Saltelli et al. [58], sensitivity analysis enables modelers to concentrate their efforts and resources on the most important variables by quantifying the model's sensitivity to parameter changes. Examining how changes in inputs affect the model's predictions also helps determine the model's robustness and reliability. This is crucial to comprehending the model's constraints and error-proneness. According to Vrugt et al. [67], sensitivity analysis can also aid in the calibration and validation of models by directing the adjustment of ambiguous model parameters to match observed data better. In conclusion, sensitivity analysis ensures that hydrological models are reliable and accurate, offering crucial information for decision-making in the management of water resources and environmental planning.

Sensitivity analysis is a technique used to show how some of the parameters in the model change the output of the model. This study uses two modelling methods: artificial neural networks (ANNs) and cellular automata (CA) for spatial-temporal forecasting and simulation of land use changes. The two methods adjusted the model's input parameters and tracked how the results changed. The sensitivity analysis of the prediction model was done using the MOLUSCE plugin of QGIS, where the prediction was done with all the variables except one, as shown in figure 7 below. It is shown that the predicted LULC with Land surface temperature, DEM, and soil erosion without precipitation give almost the same value as the rest of the factors without DEM, Soil erosion, and land surface temperature, respectively. Using the predicted LULC, the water surface area is extracted and converted into water levels.

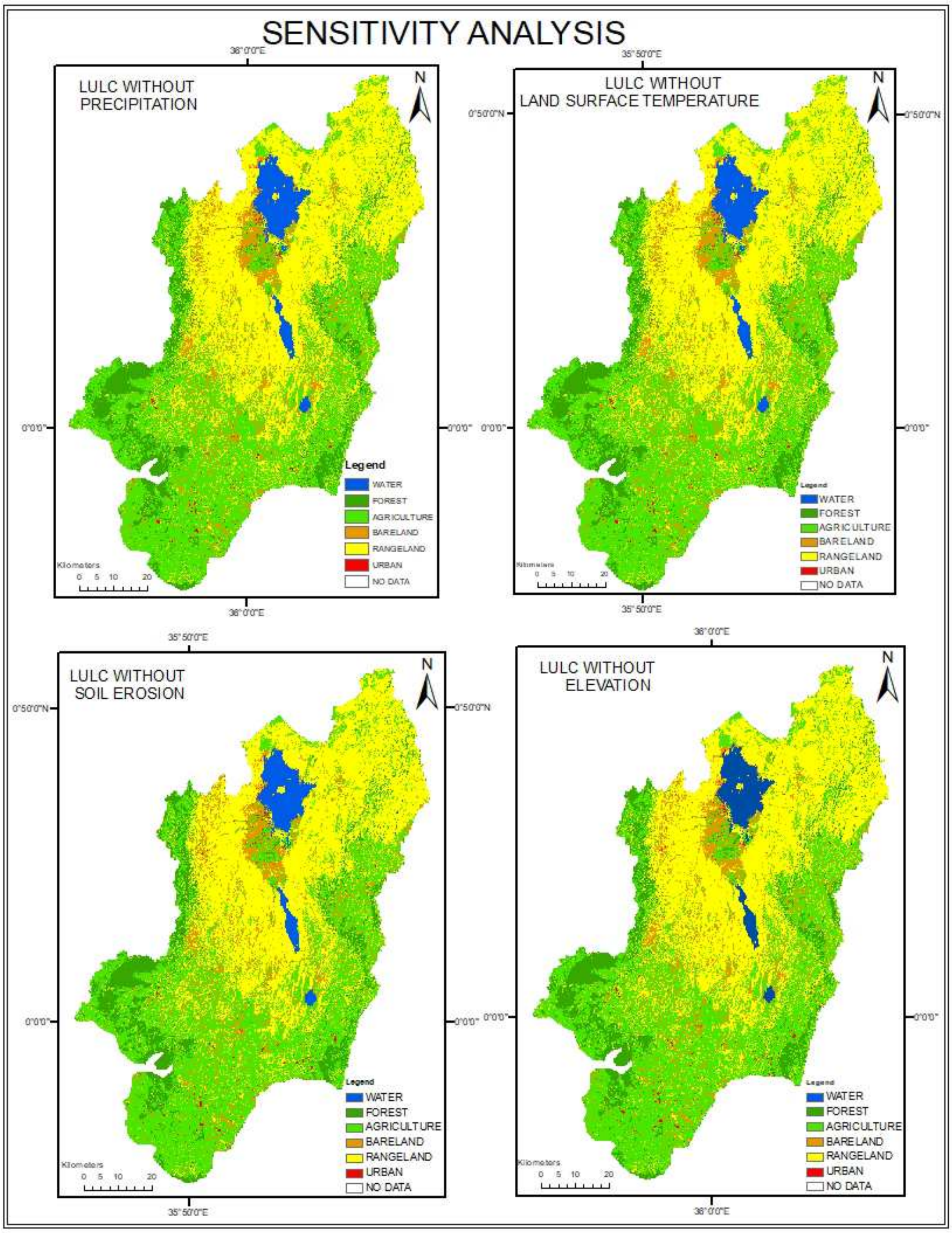



**Fig. 7;** Sensitivity Maps for predicted LULC without precipitation, LST, soil erosion, and Elevation.

## 4. Discussions

According to the research, the lake's water level has been increasing gradually, with 2020 being its climax. Human activities, including agriculture, deforestation, and urbanization or settlement, have been increasing, which has a direct relationship with soil erosion, which has been increasing as well. Rainfall was at its highest in 2020, and it has been constantly increasing over the years. The land surface temperature has had a different outcome from the rest as it has decreased as the rest of the factors increased. Using the MOLUSCE tool to predict was effective as it gave an output that the water level will increase further in 2030. After the prediction, the above factors were tested to see if there would be changes if a factor were held constant while the others were variables, but the results showed that the output of the water level would be the same. The research intended to find the cause of the water fluctuation in Lake Baringo, and siltation, rainfall, tectonic forces, human activities, and rainfall were some of the factors under speculation. The study found an increase in water level when forest cover was reduced and agriculture and settlement/urbanization increased; these results support the claim that human activities affect water level fluctuation. There has been a direct relationship between water level, rainfall, and siltation, which supports the theories.

The fluctuation of the water level in the lake is shown to be increasing drastically with a decrease in the year 2000, and this is supported by many other research, as shown below; Mutungwa,[43] found that the water level in Lake Naivasha has experienced significant variations in water levels over the past century, and this is attributed to both climate variations and human activities at the lake's shores. Due to the low water level in the year 2000 [5], there have been ecological changes due to human activities, and changes in climatic conditions resulted in extreme turbidity, high siltation, and low invertebrate life in the open waters.

Land use land cover has a significant impact on the water levels in lakes, as indicated by Abraham and Nadew [2]; their study found that the reduction of forested areas and the expansion of agriculture and built-up areas have had a significant impact on the water balance of Katar and Meki River Basins in Ethiopia. Then it rains, this has resulted in an increase in surface runoff in both river basins, which drain into lakes, causing siltation. When Versace [66] was examining the Glenelg Hopkins landscape, he determined that there is an influence of land cover on water quality and quantity. There is also research in western Lake Victoria by Brown [13] that shows that land cover, topography, and climate all play significant roles in influencing streamflow and wetland extents in the region.

The study done by Herrnegger et al. [29] finds that the increases in lake areas are significant, ranging from 21% for Lake Naivasha to an extraordinary 123% for Lake Solai, and attributes these changes to an increase in mean annual rainfall and minor changes in the water balance, rather than changes in catchment properties or underground permeability. According to Onywere et al. [53], the flooding in Kenya in Eastern African Rift Valley lakes has been unprecedented and is influenced by rainfall patterns and climatic cycles.

Soil erosion due to rainfall affects the lake water level, as discussed in the study by Tufa et al. [64], where he found that the Lake Haramaya Catchment has experienced severe degradation due to intensive cultivation, deforestation, and unwise utilization of land and water resources, leading to soil erosion. The average annual soil loss in the study area was estimated to be 24.315 tons/ha/year, primarily due to high rainfall erosivity. There was a direct relationship between rainfall and sediment yield.

The county and national governments will use the results of this study to create policies for effective conservation, i.e., agricultural policies that protect the forest and rangelands, to name a few. The results will also help the resettlement of the displaced people as most of them thought it would be a temporary thing, and after some time, the water will recede to its previous level, and they will go back home and to their farms. These will significantly help delineate the riparian buffer, zoning of plans, and other administrative purposes, as knowledge is power. After the spatial analysis has been made, the results obtained for each year need to be compared with ground retrieved data, which was lacking due to the storage of the files since soft copy data is not available and some of them were lost or not available at all. The correlation between lake water lateral extent and the DAHITI water was slightly affected since some years had no data available. All hydrological models have their errors during their execution, and there's a need to use other models to check the model error, but this was not done. Due to a lack of finances to study tectonic forces, they were not analyzed even though one of the significant theories that caused the fluctuation was the movement of tectonic plates. Most of the lakes in the Rift Valley were created due to faulting, and such movement has a significant role in the fluctuation of water levels.

Land use land cover classification using a supervised classifier can be a source of errors in the output first by inadequate data for training, or sometimes due to human error, some of the data can be classified wrongly, for example, classification of rock or whitish soil as urban. Since LULC was used in the analysis of most factors like soil erosion and the prediction model, such bias or error can affect the output of the whole model. Further research should be done on the effects of the tectonic forces on the lake water level as they play a significant role. After the causes of the fluctuation have been determined, there is also a need to research the effects of the fluctuations on the water quality and the ecosystem. With the lateral water extent results, the new riparian buffer can be delineated, gazetted, and later surveyed to make them official. The results of this research can be applied in many sectors, from using the data as the background of the resettlement maps to the delineations of the riparian buffer. It will be used in creating policies for agriculture and conservation within the water basin, and finally, this data is beneficial for effective spatial planning and zoning.

## 5. Conclusions

In conclusion, the study determined the water level fluctuations and found that the water level has been increasing over the years, with 2020 being the highest. Some of the causes of the water level fluctuation include human activities, which was indicated by the land use land cover, where the forest cover decreased while agricultural and urban areas increased. The water level was clearly shown to have increased as the rainfall increased. With the increase in agriculture without enforcing conservation policies plus the increased rainfall, soil erosion increased, and with the increased surface runoff, siltation has increased in the Lake. From the prediction model, the water level will increase by 43.74% when the water level 1990 is used as the base.

This research contributes to the existing body of knowledge and the community by encouraging open-source software like the MOLUSCE tool in QGIS. The research output can help the county and national government in decision-making, specifically in conservation, resettlement, and planning. Most of the studies that have been done in Lake Baringo are limited to the climatic causes of fluctuations and the potential of a cross mix of Baringo and Bogoria, to name a few. Still, this research fills the gap by analyzing all the causes of the fluctuation and predicting the lateral extent and the water level of the Lake. Our findings highlight several crucial factors that influence the growth in lake water levels, which aid in our understanding of this significant environmental occurrence. Because of climatic and precipitation pattern variations, our results could be inconsistent. Depending on the period and location of past studies, different meteorological conditions that impacted water levels may have been observed. Our findings are supported by the research that had been done by Herrnegger et al. [29], Olago et al. [50], Wainwright et al. [69], and Olaka et al. [51] showing a rise in Lake Baringo's water levels but is in contrast to earlier research by Scholten [59], Hassan et al., and (Gadissa et al., [23] finding that natural events resulted in a decline in water levels. This difference could be caused by analysis of several time and data sources. The results check the theories that were the basis of this research. The study's objectives were all achieved as the lake water level was determined to have increased, the factors that caused the water level to fluctuate were analyzed, and finally, the water level for 2030 was predicted to increase by 43.74% using 1990 as the base.

Despite the project being successful, the project will not go without challenges. Some include the lack of ground data to verify the spatially obtained data and financial constraints, as the study of the effects of the tectonic forces on the water level has not been analyzed even though Lake Baringo being in Great Rift Valley tectonic forces has a significant impact to the lakes. It should also be noted that the Lake does not have any visible water outlet as it is assumed to use underground outlets. Some unanswered questions that need to be investigated further are the effects of tectonic forces on the lake water level and the effects of siltation on the lake's underground water outlets. Further research avenues that need to be looked into is how the new riparian buffers are to be drawn and gazetted, especially since the riparian acts of Kenya do not give a definite demarcation where the riparian reserve for tidal rivers and Lake should not be less than 30 m from the high-water mark. The water quality of the Lake also has to be researched to determine the effects of the water fluctuations on the ecosystem. The dynamic change in water levels within lakes, a multifaceted phenomenon intricately influenced by climatic variability, hydrological dynamics, and anthropogenic interventions, underscores the complexity and interconnectedness of environmental factors shaping aquatic ecosystems.

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