Discover Water

Research

Modeling of water level trends and characterizing potential influencing factors in Lake Baringo in Kenya

Doreen Jelagat Kimtai[1] · Godfrey Ouma Makokha[1] · Arthur W. Sichangi[2]

Received: 31 January 2024 / Accepted: 3 July 2024
Published online: 06 August 2024

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, which has 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 to conserve the water basin effectively, and a plan should be drawn to re-delineate the new riparian buffer.

Keywords LULC · DAHITI · Cellular automata · MOLUSCE · Riparian buffer · Siltation

Abbreviations

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

✉ Doreen Jelagat Kimtai, doreenkimtai@gmail.com | [1]Department of Science and Informatics, Taita Taveta University, P.O Box 635-80300, Voi, Kenya. [2]Institute of Geomatics, GIS & Remote Sensing, Dedan Kimathi University of Technology, Private Bag, Nyeri 10143, Kenya.

1 Introduction

Lakes are critical 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, from the destruction of property and agriculture when it floods; the road becomes inaccessible to 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]. As shown in Fig. 1, the Lake has a surface area of 130 km^2 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].

Lake variability has been studied from time to time all over the world as it has a very significant impact on water resources management [18, 32, 34, 45–47]. Mark B. Abbott & Lesleigh Anderson [1] show that the causes of such fluctuations include climatic change [14, 23, 29, 35, 50, 77], activities within the tectonic plates, erosion at the outlet or inlet [38, 55, 64], and human activity [5, 7, 10, 17, 41]. Research in western Lake Victoria by Brown [13] shows that land cover, topography, and climate significantly influence the region's streamflow and wetland extents. These fluctuations significantly impact the ecosystem [26, 54], community, and biodiversity [7, 20, 33]. The effects that the water basin feels from the lake fluctuations can be mitigated by effective planning that can only be achieved by forecasting the probable water levels for the future [40]. Many models have been used in predicting water levels not limited to machine learning, arithmetic, spatial analysis, and GRU model [16, 30]. Lake Baringo, being that it lacks a physical outlet, is presumed to have an underground water outlet as it's a freshwater lake [49]; several research has been done to show the relationship between groundwater and lake water [36, 76, 78].

From the above research, it is duly noted that there is a lack of spatial research in the region due to a lack of ground data, limited comprehensive models that integrate various factors that influence water level fluctuations, and the need to localize the prediction research as many research has been done everywhere except for Lake Baringo. Using satellite imagery, the study intends to check the effects of human activities in the water basin using land use land cover, the intensity of soil erosion, the impact of rainfall, and land surface temperature on the lake. The water level and the factors that influence the water level are correlated, and using the MOLUSCE tool, a prediction of the future water level is obtained.

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. The specific objectives of the study are to determine the Lake's water fluctuations for the years 1990, 2000, 2010, and 2020 using AWEI and DAHITI tools, to characterize the probable factors affecting changes in water level in Lake Baringo and to predict water level in the year 2030 later using MOLUSCE tool.

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. 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 far above the current 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 conserving and managing water resources.

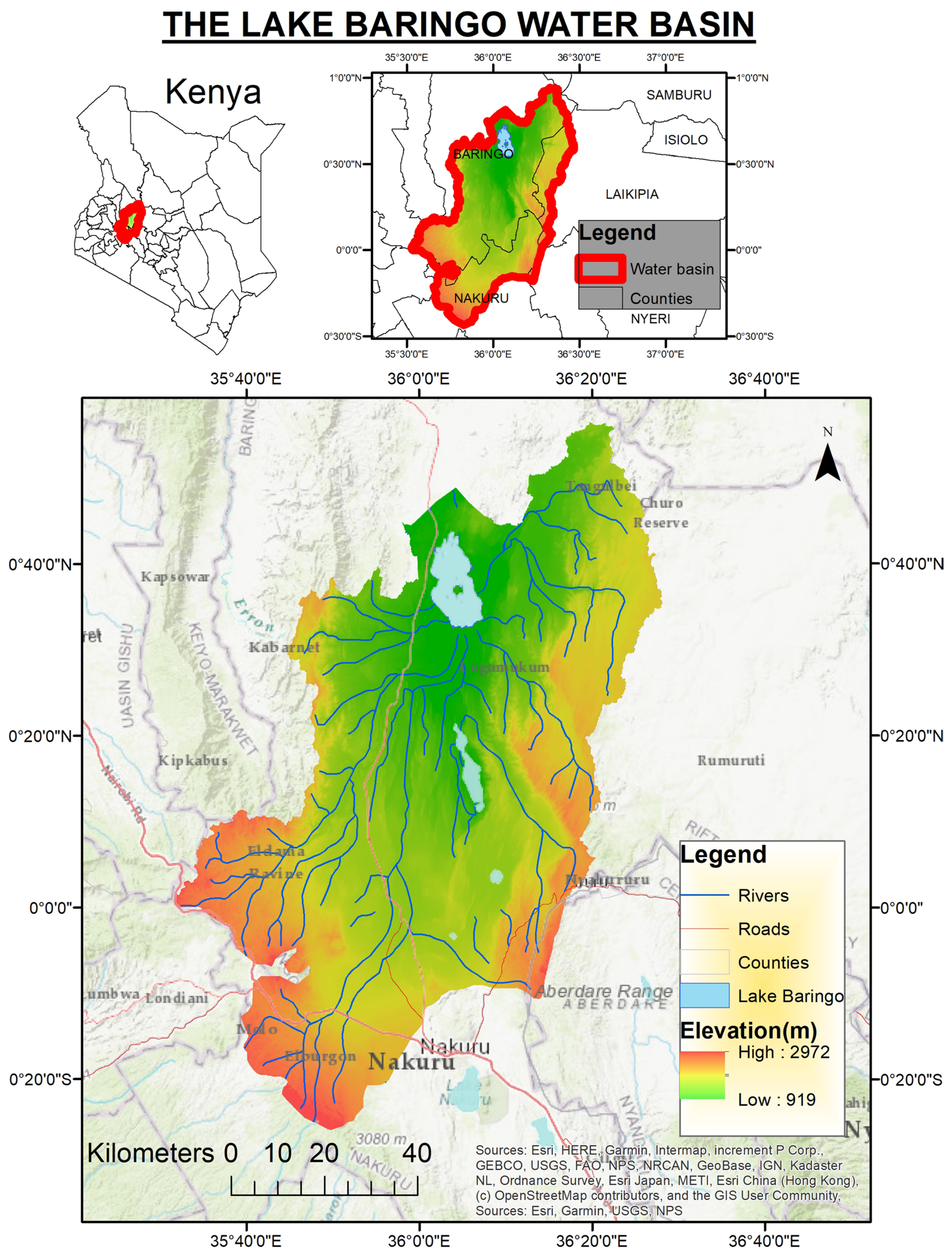


Fig. 1 Lake Baringo Water Basin showing the DEM, river, Lake Baringo, and the ESRI topographical map as the Base Map

2 Methodology

2.1 Methods

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, as well as to clean 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 lake's water level and surface area were determined using AWEI, which was then correlated with the water level from the DAHITI website [61]. Using satellite images, land use land cover, rainfall, and land surface temperature maps were drawn. In contrast, soil erosion maps were obtained from the RUSLE model, which utilizes land use land cover, slope, rainfall, soil, and topographical maps. Finally, the 2030 water level prediction was made using an automatic neutral network and cellular automata in the Qgis MOLUSCE tool. Sensitivity analysis of the predicted output is then done for accuracy checks.

2.1.1 Data collection

The data used in this study are DEM; the digital elevation maps that were acquired from ALOS PALSAR, metrological data; the precipitation and humidity obtained from CHIRPS, and topographical maps from Kenya Survey offices, Landsat satellite images from the USGS website, and water level data that was obtained from the DAHITI website, as shown in Table 1. The satellite images obtained were for between January and March since these months are the dry months and there are fewer clouds, which helped with the data quality.

2.1.2 Software

The data were clipped, cleaned, merged, overlayed, and processed using ArcGIS, Quantum GIS, ENVI, ERDAS Imagine, Google Earth, R studio, Geodata, Microsoft Excel, and Global Mapper.

2.2 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 [3, 42]. This tool improves the accuracy of extracting water bodies in areas including shadows and dark surfaces compared to other methods that fail

Table 1 Characteristics of satellite imagery used for the study

Data	Resolution	Sensor	Year	Source	Date acquired	Date analysed
DEM	12.5 m	SAR		ALOS PALSAR	16.03.2022	16.03.2022
LANDSAT 4	30 m	TM	1990	USGS	6.04.2022	26.05.2022
LANDSAT 5	30 m	TM	2010	USGS	6.04.2022	27.05.2022
LANDSAT 7	30 m	ETM +	2000	USGS	6.04.2022	28.05.2022
LANDSAT 8	30 m	OLI	2020	USGS	6.04.2022	29.05.2022
PRECIPITATION	0.05^0		1990–2020	CHIRPS	8.9.2022	1.10.2022
SOIL DATA	5*5 arc minutes			FAO	21.10.2022	21.10.2022
WATER LEVEL	< 10 m	Sentinel-3A, Jason-2& ENVISAT (MERIS)	2008–2020	DAHITI	13.12.2022	13.12.2022

to classify water correctly [47]. The formula for this index is shown in Eq. 1. 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 [15].

$$AWEI = 4 * (green - SWIR2) - (0.25 * NIR + 2.75 * SWIR1) \tag{1}$$

where the SWIR is Short-wave infrared, and the NIR is Near-infrared [42].

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) [60]. 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 [37]; 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 made, 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 [21].

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 [9]. 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 comparing precipitation and water fluctuation 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 [68]. The formula in Eq. 2 is used to calculate it:

$$E = C\,factor * LS\,factor * P\,factor * K\,factor * R\,factor \tag{2}$$

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 [44]. The atmospheric reflectance, NDVI, brightness temperature, and land surface emissivity were obtained using Landsat data from the split window method [56], as in Eq. 3.

$$T_S = BT_{10} + \left(2.946 * \left(BT_{10} - BT_{11}\right)\right) - 0.038 \tag{3}$$

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 forests 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, an accuracy assessment and post-classification were performed to check the accuracy of the LULC [77].

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 [30] 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, the LULC for 2020 was projected. 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, the LULC data from 2010 to 2020 was employed 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 [58]. 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. This study used artificial neural networks and cellular stomata to predict 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 [10]. Lake Baringo is a special case as it has no visible outlets. It is presumed that since it is a freshwater lake, it has underground water outlets, so it is necessary to study its outlet and know the relationship between the water level, siltation, and underground water resources in the water basin [76, 80].

This process is shown in the Fig. 2;

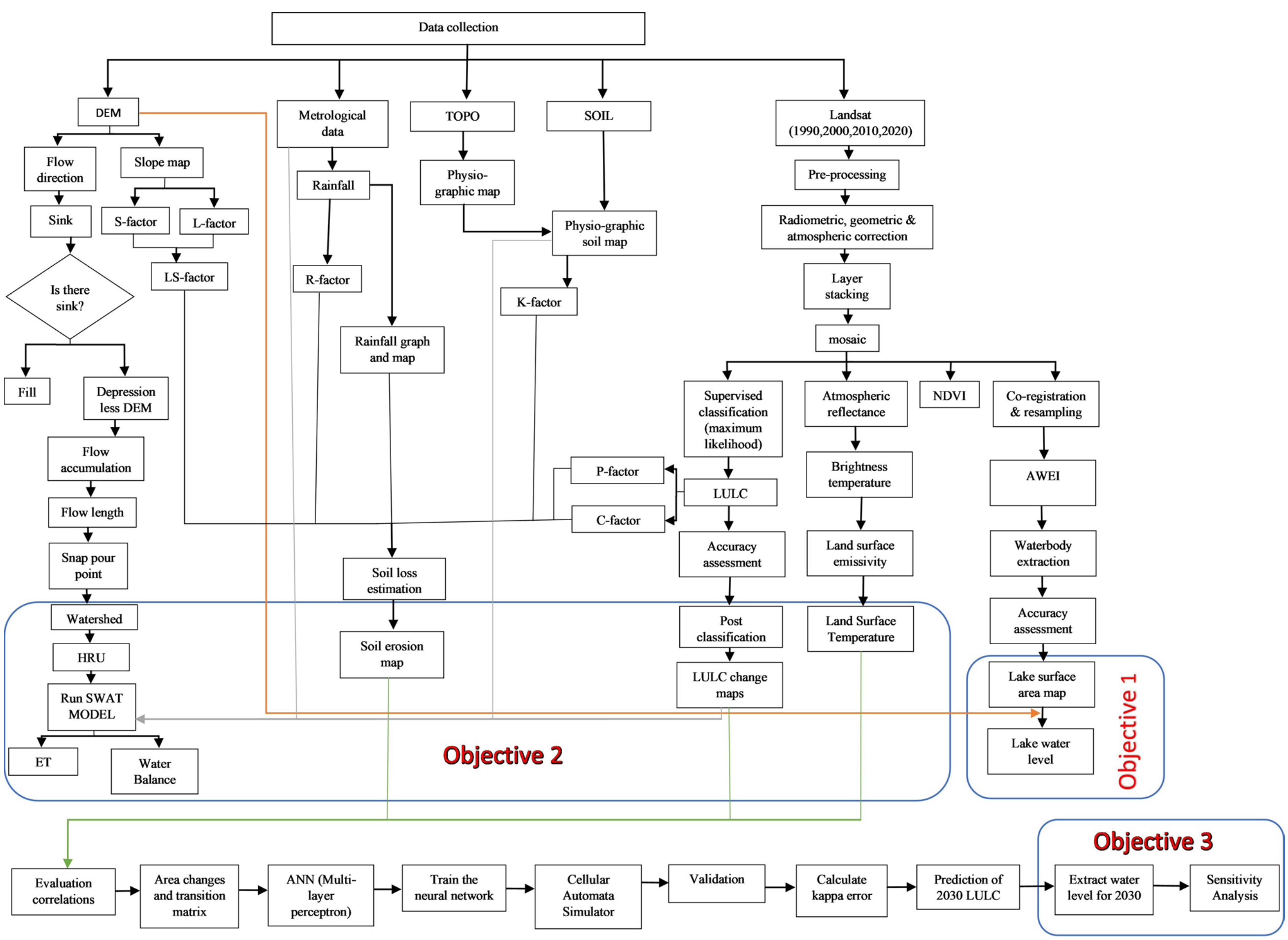


Fig. 2 Flow Chart Methodology for remote sensing and GIS analysis

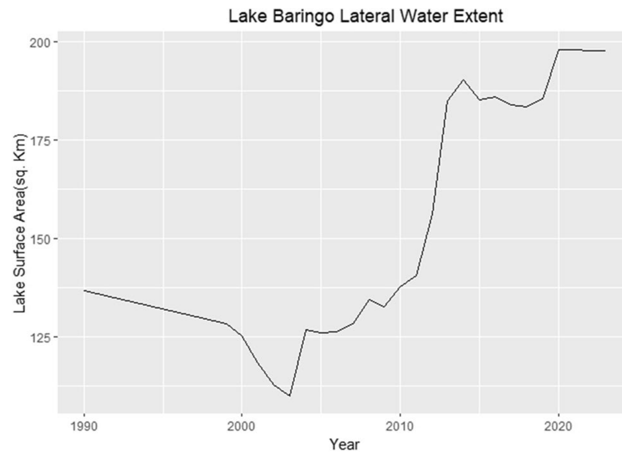


Fig. 3 Lake Baringo Water Surface Area from the year 1990 to 2020

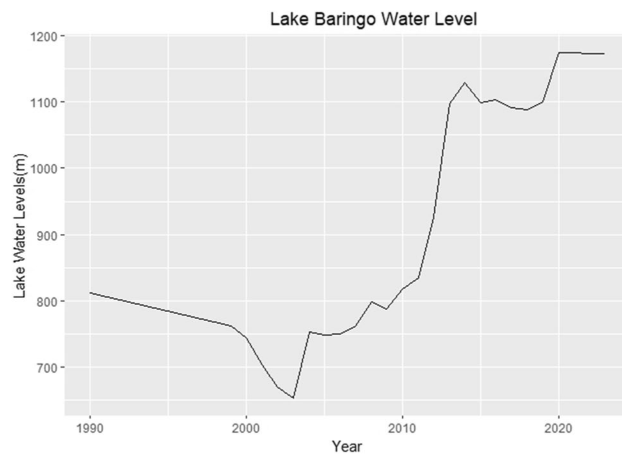


Fig. 4 Lake Baringo Water Level from the year 1990 to 2020

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. 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 Fig. 3, 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. There has been a visible instantaneous increase in water lateral extent from 2003 to 2020, as confirmed by the lake's rise in water levels.

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 Fig. 4. It is demonstrated that the water level was 820 m in 1990, which further decreased to 740 m 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 522 m level increase is visible from 2003 to 2020, backed by the data from the water lateral extent difference of 88 square kilometres. It is also to be noted that from 1990 to 2023, the lowest water level in Lake Baringo was witnessed in the same year, as shown in the lateral water extent of the Lake; Fig. 5.

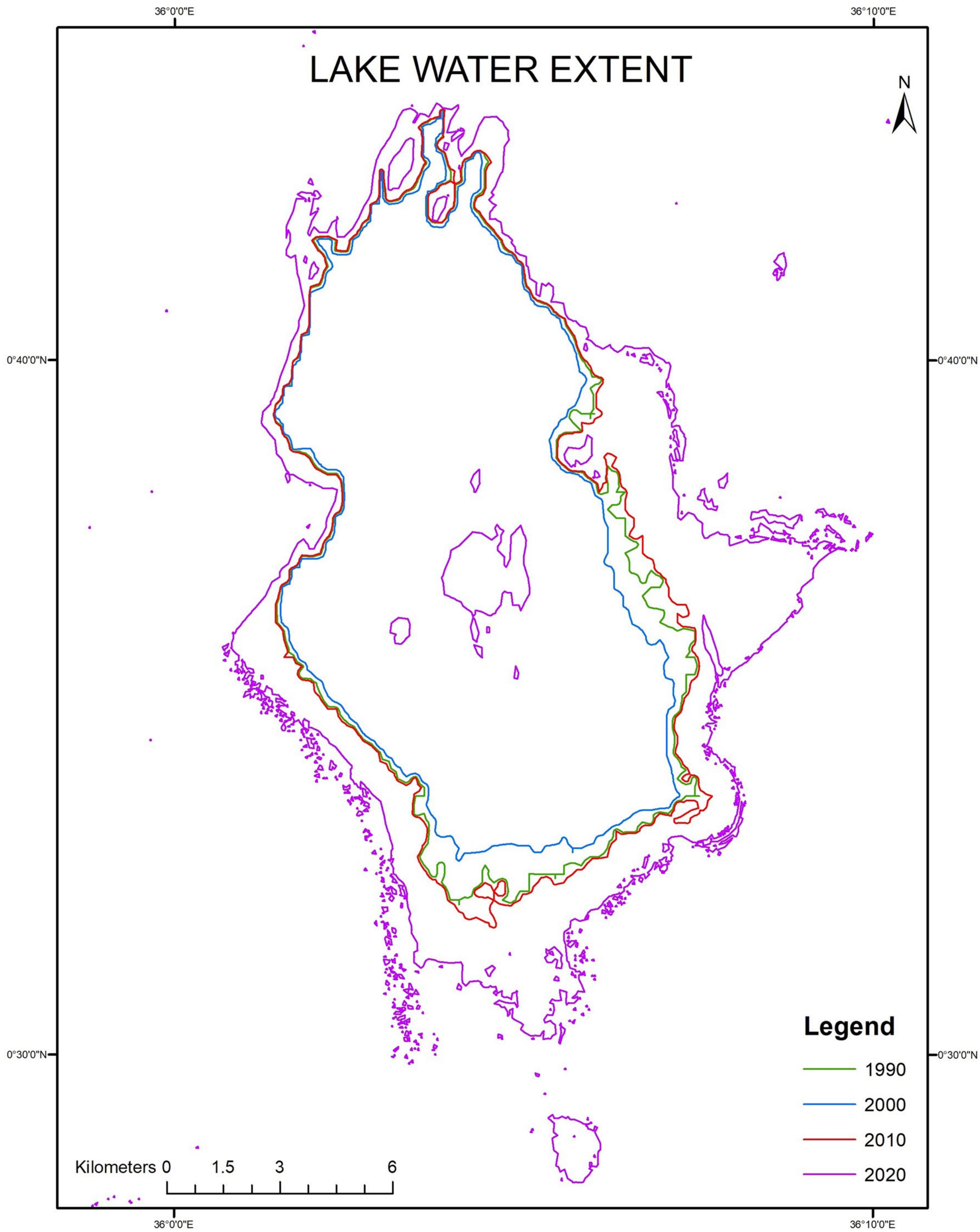


Fig. 5 Lake Baringo Lateral Water Extent for 1990, 2000, 2010, and 2020

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 size of bare land rose significantly, 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 graphical representation of the land use land cover is clearly shown in Figs. 6 and 7, respectively;

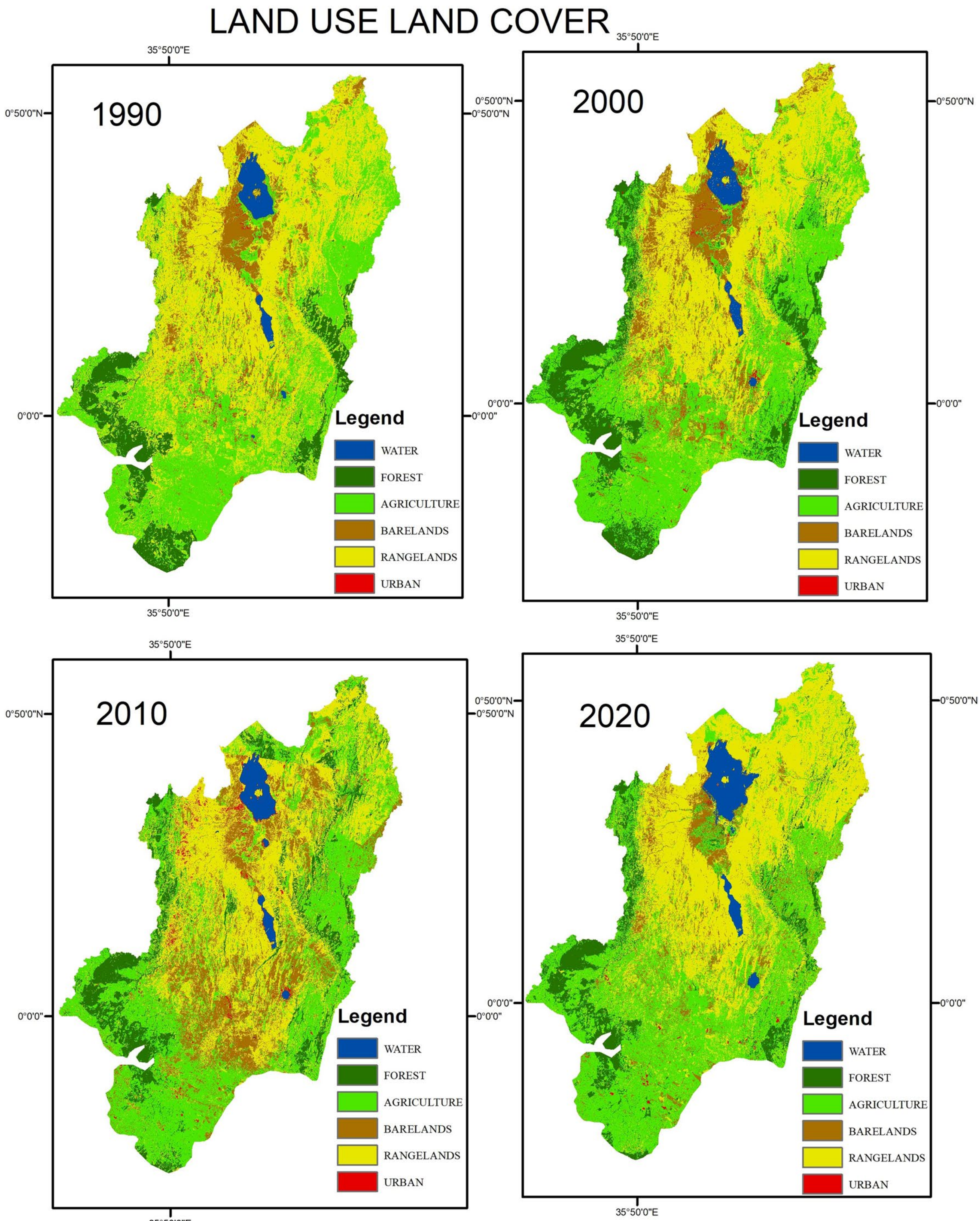


Fig. 6 Land Use Land Cover Maps for the years 1990, 2000, 2010, and 2020

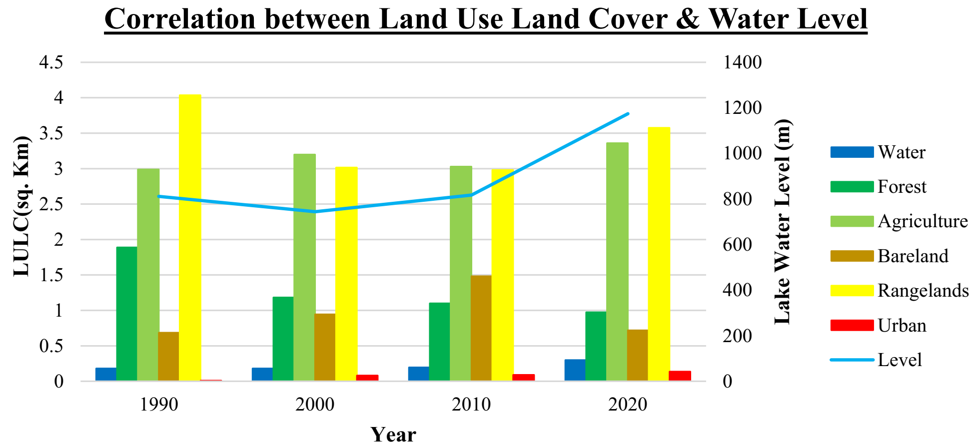


Fig. 7 Graph of the correlation between LULC and Water Level

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. The year's average rainfall in the water basin is clearly represented in Fig. 8. The basin receives different intensities of rainfall continuously around the year. The precipitation across the year is represented with the word ppt; hence, the six categories of rainfall with the light showers (ppt1) were represented by light blue, the heavy rainfall(ppt6) was represented by the darkest blue color in Fig. 9, it 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 1000 mm. In 1990, the rainfall measured a low of 896 mm 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.

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 Fig. 9. 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 774 m. 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.

Figure 10 shows the relationship between water level and soil erosion; since soil erosion varies with intensity across the water basin, the word rusle1 (rusle)representing the output of the RUSLE model was used to show the minimal levels of erosion. In contrast, rusle5 represents the highest intensity of soil erosion, such as excavations and landslides. It is shown that there is 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

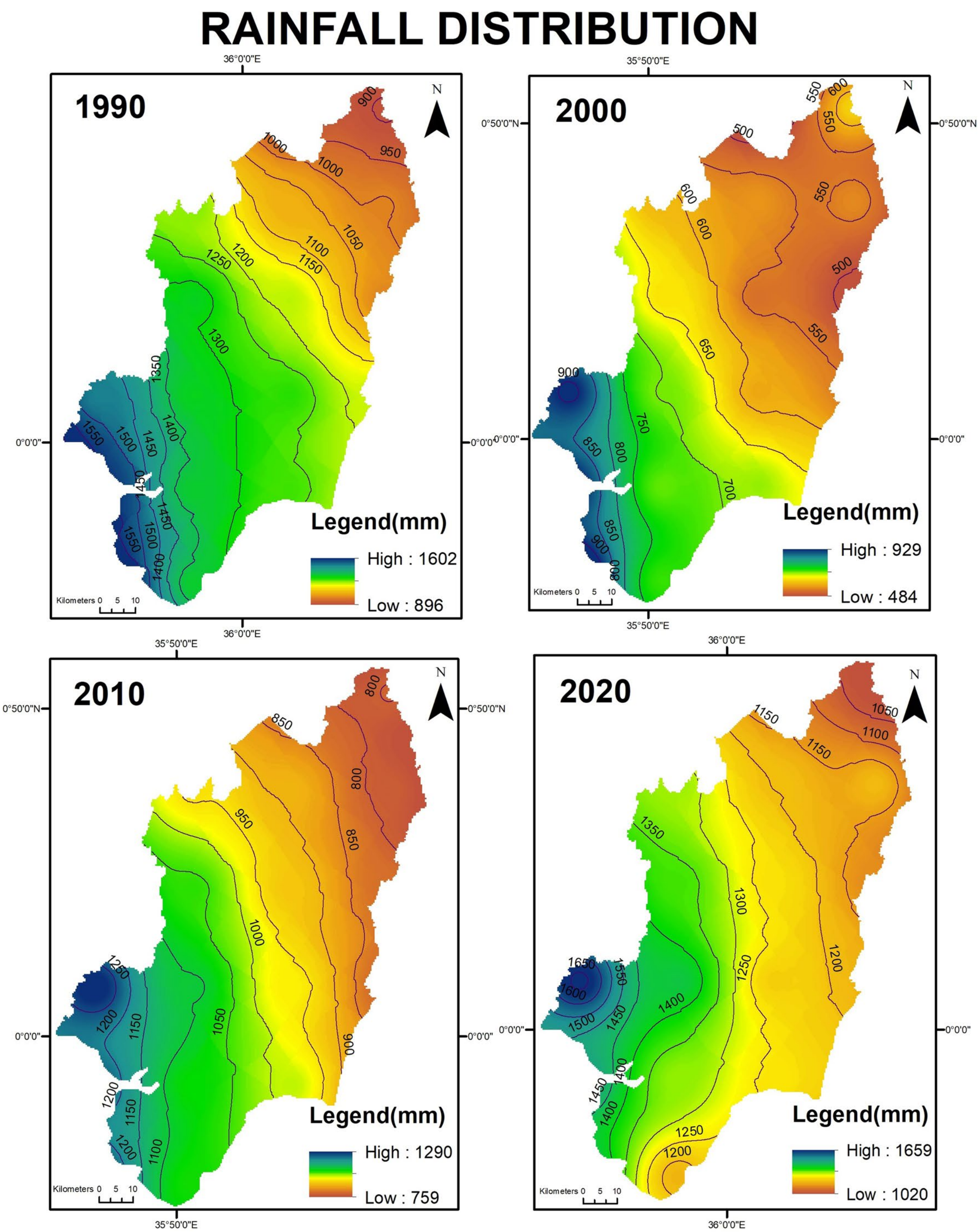


Fig. 8 Rainfall Maps for the years 1990, 2000, 2010, and 2020

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.

There is also a relationship between soil erosion and precipitation. Typically, soil erosion increases with increased rainfall due to surface runoff. From Fig. 8, despite the year 1990 having an average rainfall of 1223 mm, the average soil erosion in the water basin was 7.6 t/y, while in 2000, the precipitation reduced to 694 mm, and there was an increase in soil erosion to 26 t/y. In 2010, the rainfall was 1002 mm while the soil erosion was 36 t/y. Finally, in 2020, the rainfall was at its highest at 1328 mm, while the soil erosion was at its highest at 54.6 t/y. It is clearly

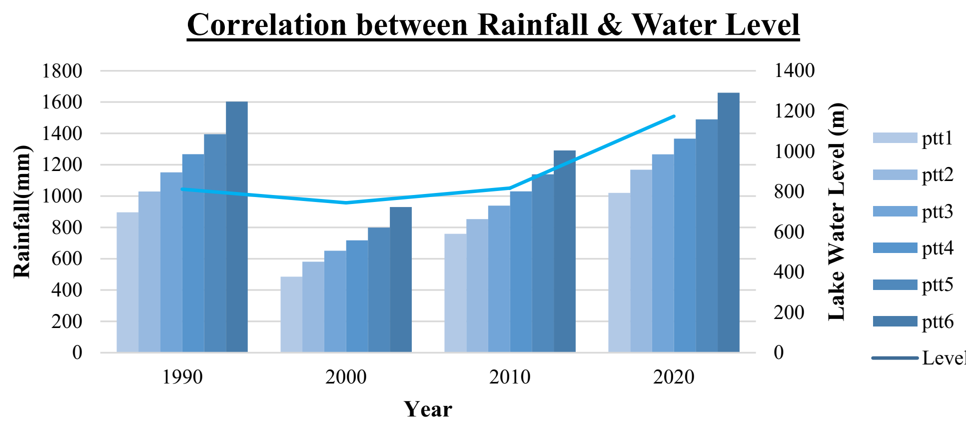


Fig. 9 Graph of the correlation between Rainfall and Water Level

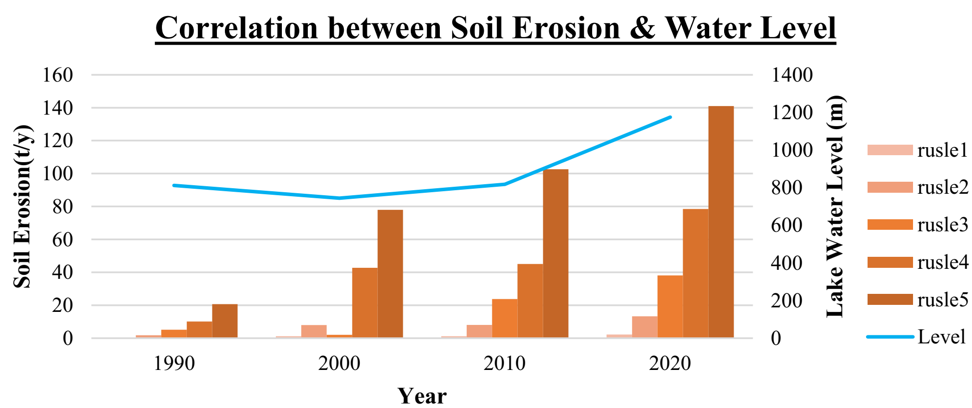


Fig. 10 Graph of the correlation between Soil Erosion and Water Level

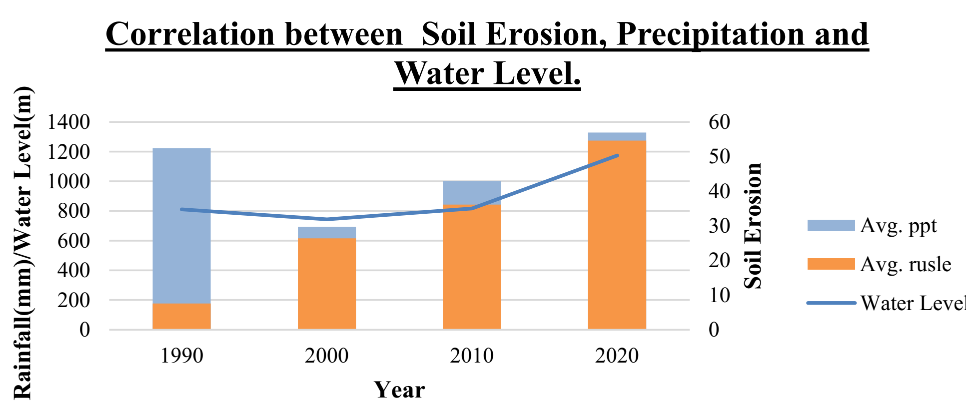


Fig. 11 Graph of the correlation between Soil Loss, precipitation, and Water Level

shown from the graph in Fig. 11 that the soil has been increasing constantly over the years despite the variability of precipitation in the water basin.

The years 1990, 2000, and 2010 had relatively average amounts of soil losses, measuring a high range between 77 and 102 t/yr, while in the year 2020, soil erosion was at its highest of 140 t/yr, as shown in Fig. 12. These results indicate that this is directly proportional to the increased rainfall and human activities within the water basin. Soil

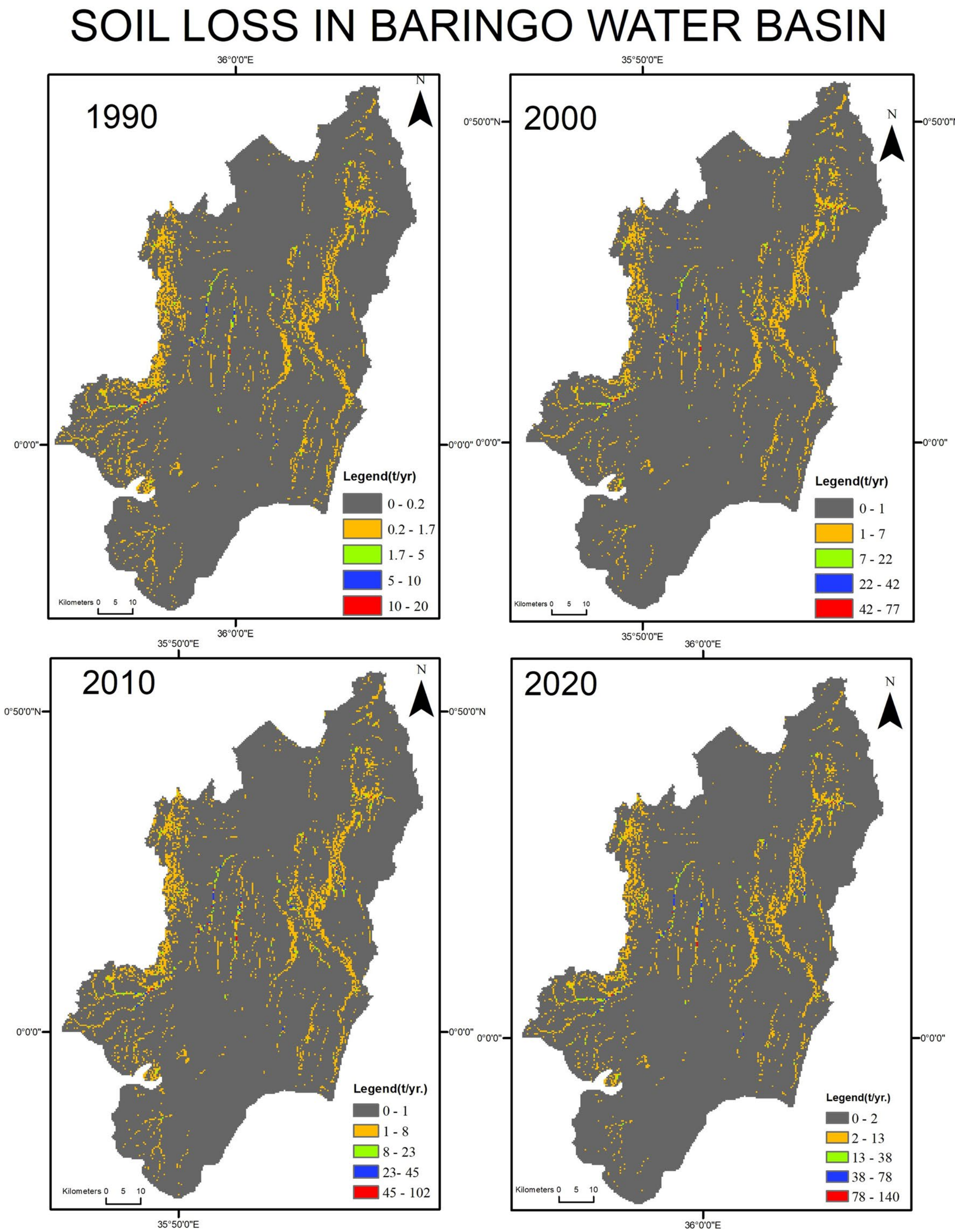


Fig. 12 *Soil Erosion* Maps

erosion has increased drastically since 1990, as shown in the Fig. 10. However, despite 2000 having the least amount of water in the Lake and the precipitation level being low, 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 temperature is where the incoming solar energy interacts with and warms the ground or the surface of the canopy in vegetated regions and 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.

Land surface temperature is a continuous variable that is not the same throughout the lake basin; with this in mind, it seemed fit to have variable extends of the LST in a year. As shown in Fig. 13, in 1990, the water basin experienced the lowest LST value of – 5 k represented by lst1 in the graph, while the highest LST, represented by lst6, was 45.8 k. With the above explanations, LST is a measure of global warming, if there is any. As shown in Fig. 14, 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 – 6 k and a high of 39 k. The lake water level was also at its lowest, making the relationship between LST and water level ambiguous.

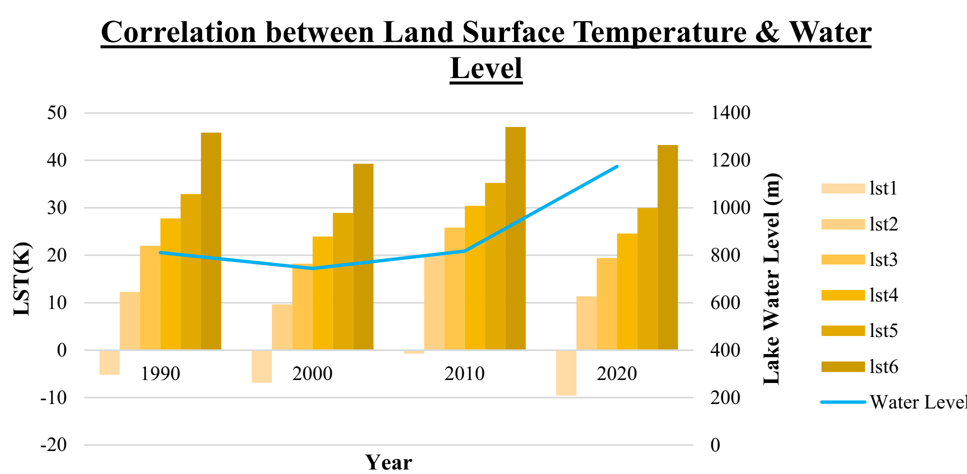
The correlation between land surface temperature and water levels is now direct, as in the year 2000, the water levels were at their overall lowest, and the land surface temperature was also at its lowest. It should also be considered that when the water level was at its highest in 2020, the LST registered a low of – 9 k compared to – 6 k in 2000, as shown in Fig. 13.

Despite having the lowest range of low LST, the largest region in 2020 experienced a low LST. Figures 6 and 14 show that most forested areas, agricultural areas, and water bodies experienced a lower LST, while the rangelands and bare Land experienced a high of 47 k. 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, reducing 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.

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. 13 Graph of the correlation between LST and Water Level



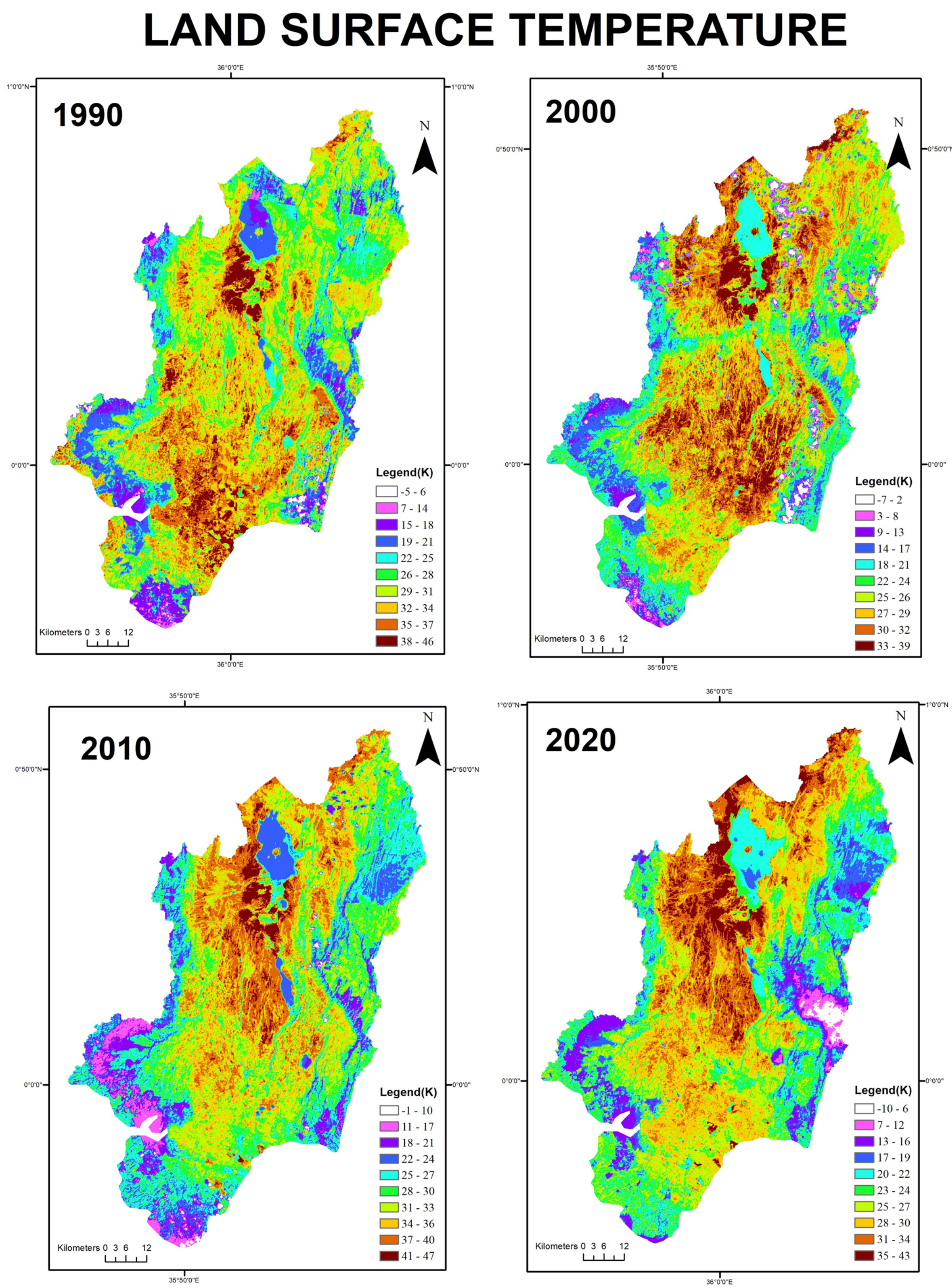


Fig. 14 *Lake Baringo Basin LST Maps* for 1990, 2000, 2010, and 2020

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

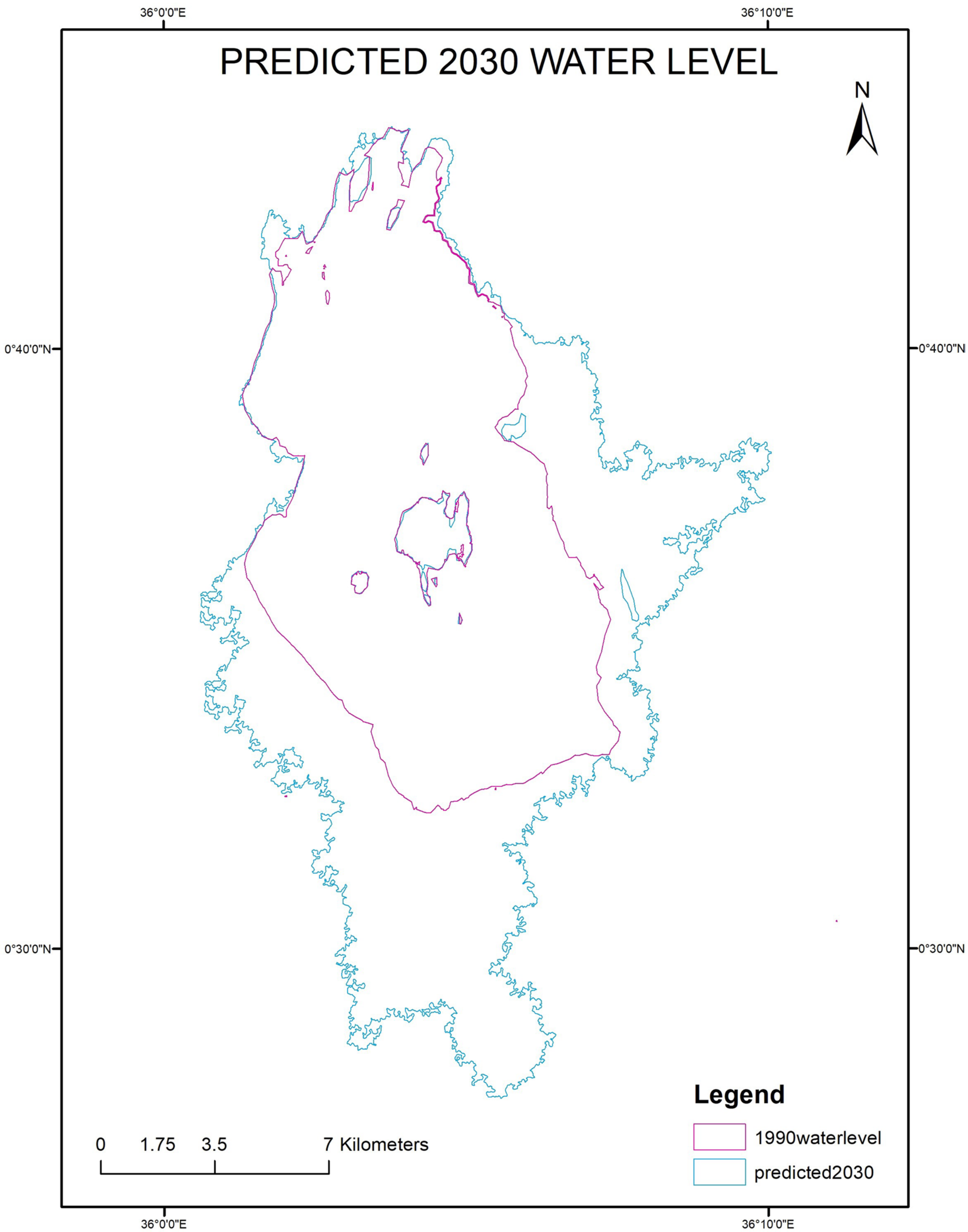


Fig. 15 The Lake Water extent for the year 1990 and the Predicted Lake Water Extent for 2030

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 that checks persistent classes and produces 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, as shown in Fig. 15.

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 downloaded from the DAHITI website. The data is then correlated to determine the lake water level for

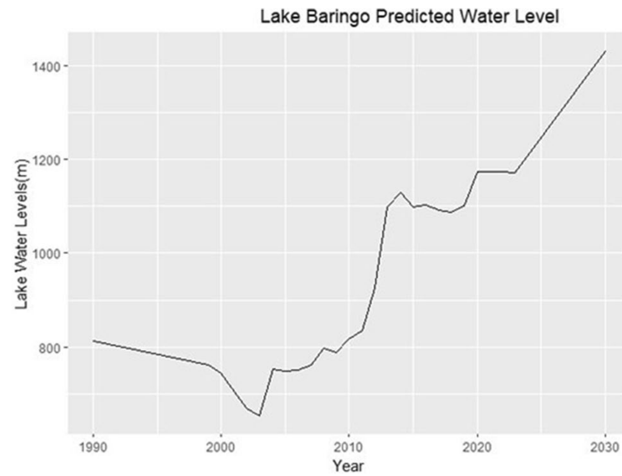


Fig. 16 Graph of Water level from 1990 to the year 2030

2030, as shown in Fig. 16. The output 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.

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 significantly impacting the model's results. 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 process 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 Fig. 17. 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.

4 Discussions

The research results have shown a recent increase in Lake Baringo's water level from 2003, the highest level being in 2020 and the lowest in 2003. The increase is due to human activities within the lake basin, such as urbanization, agriculture, and deforestation, thereby increasing soil erosion in the water basin. The research also shows a direct relationship between water level and rainfall, with an inverse relationship between land surface temperature. The MOLUSCE predicting tool shows that the water level will increase even further in 2030.

The water level in the lake decreased from 1990 to 2003, marking it as the lowest it has ever been. There was and still is an increase in the water level since the year 2003 and 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.

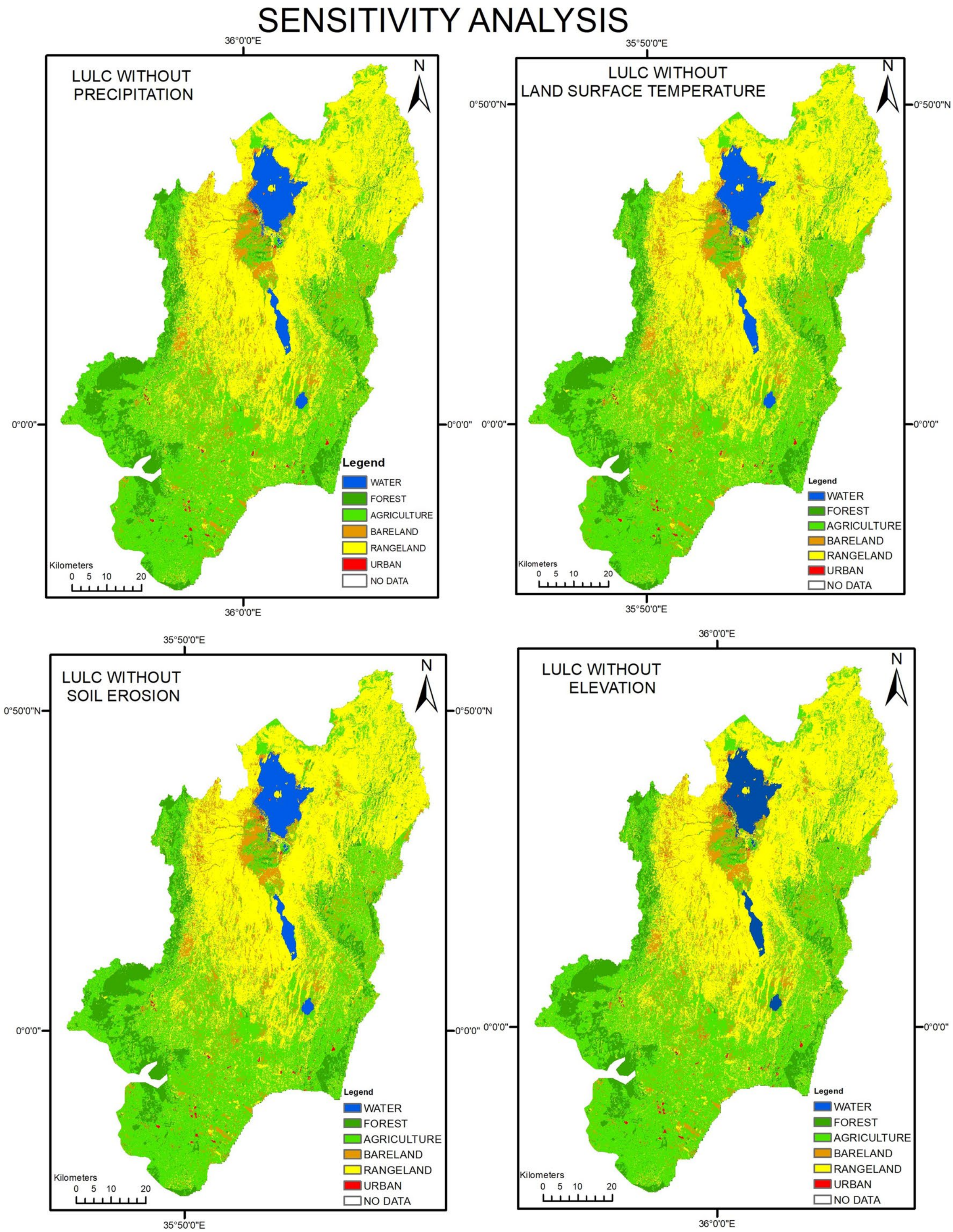


Fig. 17 Sensitivity Maps for predicted LULC without precipitation, LST, soil erosion, and Elevation

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.

Humans can either be creators or destroyers, and their activities within this lake basin, alongside natural factors like rainfall, have been shown to impact the Lake Baringo basin significantly. It is shown that in the basin, urbanization, agriculture, and deforestation have been increasing year after year as the water levels rise. 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. When Versace [66] examined the Glenelg Hopkins landscape, he determined that land cover influences water quality and quantity. 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.

The study shows that climatic changes greatly affect water levels as the increase in rainfall and the decrease in land surface temperature have led to increased water levels in Lake Baringo. The 522 m level increase is visible from 2003 to 2020, backed by the data obtained from the water lateral extent difference of 88 square kilometres. It is also to be noted that from 1990 to 2023, the lowest water level in Lake Baringo was witnessed in the same year when rainfall was at its lowest. 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. Rainfall affects not only the water level in lakes but also the water quality since, 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.

With the increase in rainfall, there is an increase in soil erosion due to surface runoff and vice versa. Still, the Lake Baringo case study is not a typical day-to-day encounter since even in 2003, when rainfall greatly reduced, soil erosion in the basin still increased. This incident is due to other contributing factors, such as human activities, and natural factors, such as winds. It should be noted that the results show a direct relationship between soil erosion and lake water levels, considering that Lake Baringo has no visible outlet and utilizes underground water outlets. The study by Tufa et al. [64] 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 erosion 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 prediction of water levels for Lake Baringo shows that there will be a further increase in the year 2030. The research is seconded by Herrnegger et al. [78], who modeled the probability of Lake Baringo with a freshwater lake, merging with Lake Bogoria, a salty water lake. The same incident happened when Lake Baringo merged with Lake 92.

The study of the factors affecting the water levels in lakes goes beyond being beneficial to academic circles as it is a blueprint for decision-making and policy formulation in resource management and conservation. The resources are not only tied down to water but also land survey, land use, urban planning, mining, agriculture, wildlife and environmental conservation.

However, there were a few challenges that need to be addressed by future researchers. Data contrasts: the research was mainly done using satellite images as there is no historical ground for accuracy assessment. Due to financial constraints, all the satellite images used in the study are free and publicly available data to the public. However, you must use high-resolution satellite images in your research for better and highest-quality policy-making output. The time factor was also not a luxury, and there is a need for more studies on the outlet for Lake Baringo, its effects on the underground water resources, and the effects of tectonic activities on the water level.

In summary, this study has shown the factors that caused the fluctuations of water levels in Lake Baringo are human activities, climatic and topographical changes. This research offers valuable insight for governments in decision-making and policy formulation and is a stepping stone for future researchers on sustainable water resource management and environmental conservation.

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 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. The 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.

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 has no visible water outlets, as underground outlets are assumed to be used. 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.

Author 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 W. Sichangi.

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.

Data availability The datasets generated during this study are available on 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/

Declarations

Competing interests The authors declare that they have no competing interests.

References

1. Abbott, B. M., & Anderson, L. (2009). Lake-Level Fluctuations | SpringerLink. https://doi.org/10.1007/978-1-4020-4411-3_121
2. AbrahamNadew TB. Impact of land use land cover dynamics on water balance, Lake Ziway Watershed, Ethiopia. Hydrol: Curr Res. 2018;9(4):1–15.

3. Acharya TD, Subedi A, Lee DH. Evaluation of water indices for surface water extraction in a landsat 8 scene of Nepal. Sensors. 2018;18(8):2580. https://doi.org/10.3390/s18082580.
4. Acker J, Williams R, Chiu L, Ardanuy P, Miller S, Schueler C, Vachon PW, Manore M. Remote sensing from satellites☆. In: Elias SA, editor. Reference module in earth systems and environmental sciences. Amsterdam: Elsevier; 2014.
5. Aloo PA. Effects of climate and human activities on the ecosystem of Lake Baringo, Kenya. New York: Springer; 2002. p. 335–47.
6. Aretxabaleta AL, Ganju NK, Butman B, Signell RP. Observations and a linear model of water level in an interconnected inlet-bay system. J Geophys Res: Oceans. 2017;122(4):2760–80. https://doi.org/10.1002/2016JC012318.
7. Avery, S. (2020). *Kenya's Rift Valley lakes have been this high before. But there's cause for concern*. The Conversation. http://theconversation.com/kenyas-rift-valley-lakes-have-been-this-high-before-but-theres-cause-for-concern-147476
8. Baker B, Aldridge C, Omer A. Water: availability and use. Starkville: Mississippi State University Extension; 2016. p. p3011.
9. Balasubramanian, A., & Nagaraju, D. (2015). *The Hydrologic Cycle*.
10. Bergner A, Strecker M, Trauth M, Deino A, Gasse F, Blisniuk P, Duehnforth M. Tectonic and climatic control on the evolution of rift lakes in the Central Kenya Rift, East Africa. Quat Sci Rev. 2009;28:2804–16. https://doi.org/10.1016/j.quascirev.2009.07.008.
11. Bhatt R, Hossain A. Concept and consequence of evapotranspiration for sustainable crop production in the era of climate change. In: Bucur D, editor. Advanced evapotranspiration methods and applications. London: intechOpen; 2019.
12. Borrelli P, Alewell C, Alvarez P, Anache JAA, Baartman J, Ballabio C, Bezak N, Biddoccu M, Cerdà A, Chalise D, Chen S, Chen W, De Girolamo AM, Gessesse GD, Deumlich D, Diodato N, Efthimiou N, Erpul G, Fiener P, Panagos P. Soil erosion modelling: a global review and statistical analysis. Sci Total Environ. 2021;780:146494. https://doi.org/10.1016/j.scitotenv.2021.146494.
13. Brown, S. C. (2015). *Assessing spatio-temporal hydrologic variability: A case study in western Victoria*. https://typeset.io/papers/assessing-spatio-temporal-hydrologic-variability-a-case-1jf98115t3
14. Camberlin P, Gitau W, Planchon O, Dubreuil V, Funatsu BM, Philippon N. The major role of water bodies on diurnal precipitation regimes in Eastern Africa. Int J Climatol. 2018;38(2):613–29. https://doi.org/10.1002/joc.5197.
15. Chignell, S. (2017). A survival guide to Landsat pre-processing. https://www.academia.edu/33297238/A_survival_guide_to_Landsat_preprocessing
16. Cho M, Kim C, Jung K, Jung H. (2022). Water Level Prediction Model Applying a Long Short-Term Memory (LSTM)–Gated Recurrent Unit (GRU) Method for Flood Prediction. https://www.mdpi.com/2073-4441/14/14/2221
17. Coe MT, Foley JA. Human and natural impacts on the water resources of the Lake Chad basin. J Geophys Res: Atmospheres. 2001;106(D4):3349–56. https://doi.org/10.1029/2000JD900587.
18. Cohen AS, Talbot MR, Awramik SM, Dettman DL, Abell P. Lake level and paleoenvironmental history of Lake Tanganyika, Africa, inferred from late Holocene and modern stromatolites. GSA Bull. 1997;109(4):444–60. https://doi.org/10.1130/00167606.
19. Doi H, Katano I, Negishi J, Sanada S, Kayaba Y. Effects of biodiversity, habitat structure, and water quality on recreational use of rivers. Ecosphere. 2013;4:102. https://doi.org/10.1890/ES12-00305.1.
20. El-Noshokaty, D. (2017, October 17). *Big Lake, Big Problems*. International Reports. https://www.kas.de/en/web/auslandsinformationen/artikel/detail/-/content/grosser-see-grosse-probleme
21. Ficher K, Pereira D, Almeida A, Oliveira J. Water basin delimitation in a relief transition region. Floresta e Ambiente. 2019. https://doi.org/10.1590/2179-8087.101017.
22. Fuamba M, Branger F, Braud I, Batchabani E, Sanzana P, Sarrazin B, Jankowfsky S. Value of distributed water level and soil moisture data in evaluating a distributed hydrological model: application to the PUMMA model in the Mercier catchment (6.6 km2) in France. J Hydrol. 2019;569:753–70. https://doi.org/10.1016/j.jhydrol.2018.12.035.
23. Gadissa T, Nyadawa MO, Behulu F, Mutua B. The effect of climate change on loss of lake volume: case of sedimentation in central rift valley basin, Ethiopia. Hydrology. 2018;5(4):67. https://doi.org/10.3390/HYDROLOGY5040067.
24. Garrison PJ, LaLiberte GD, Ewart BP. The importance of water level changes and shoreline development in the eutrophication of a shallow, seepage lake. Proc Acad Natl Sci Phila. 2010;160:113–26.
25. Garelick S, Russell JM, Dee S, Verschuren D, Olago DO. Atmospheric controls on precipitation isotopes and hydroclimate in high-elevation regions in Eastern Africa since the last glacial maximum. Earth Planet Sci Lett. 2021;567:116984. https://doi.org/10.1016/j.epsl.2021.11698.
26. Gownaris NJ, Rountos KJ, Kaufman L, Kolding J, Lwiza KMM, Pikitch EK. Water level fluctuations and the ecosystem functioning of lakes. J Great Lakes Res. 2018;44(6):1154–63. https://doi.org/10.1016/j.jglr.2018.08.005.
27. Hartmann H, Snow JA, Su B, Jiang T. Seasonal predictions of precipitation in the Aksu-Tarim River basin for improved water resources management. Global Planet Change. 2016;147:86–96. https://doi.org/10.1016/j.gloplacha.2016.10.018.
28. Hecky RE, Bugenyi FWB. Hydrology and chemistry of the African Great lakes and water quality issues: problems and solutions. SIL Commun. 1992;23(1):45–54. https://doi.org/10.1080/05384680.1992.11904007.
29. Herrnegger M, Stecher G, Schwatke C, Olang L. Hydroclimatic analysis of rising water levels in the great rift valley lakes of Kenya. J Hydrol: Region Stud. 2021;36:100857. https://doi.org/10.1016/j.ejrh.2021.100857.
30. Hyndman RJ. Forecasting: principles and practice. 2nd ed. Melbourne: Otexts; 2018.
31. Kassam, A. H., Fischer, G. W., Velthuizen, H. T. van, Mitchell, AJ. B., & Shah, M. M. (1992). *Agro-ecological land Resources Assessment for Agricultural Development Planning—A case Study of Kenya- Technical Annex 2*. http://www.fao.org/3/t0733e/T0733E05.htm#ch4.1
32. Kutyła S. Characteristics of water level fluctuations in polish lakes—a review of the literature. Environ Protect Natl Resour. 2014;25:27–34. https://doi.org/10.2478/oszn-2014-0011.
33. Katano I, Doi H, Negishi J, Sanada S, Kayaba Y. Effects of biodiversity, habitat structure, and water quality on recreational use of rivers. Ecosphere. 2013;4:102. https://doi.org/10.1890/ES12-00305.1.
34. Leira M, Cantonati M. Effects of water-level fluctuations on lakes: an annotated bibliography. Hydrobiologia. 2008;613:171–84. https://doi.org/10.1007/s10750-008-9465-2.
35. Li X, Zhang L, Yang G, Li H, He B, Chen Y, Tang X. Impacts of human activities and climate change on the water environment of Lake Poyang Basin, China. Geoenviron Disasters. 2015;2(1):22. https://doi.org/10.1186/s40677-015-0029-2.
36. Li Y, Yao J, Zhao G, Zhang Q. Evidence of hydraulic relationships between groundwater and lake water across the large floodplain wetland of Poyang Lake, China. Water Supply. 2017;18(2):698–712. https://doi.org/10.2166/ws.2017.150.

37. Luo Y, Su B, Yuan J, Li H, Zhang Q. GIS techniques for watershed delineation of SWAT model in plain polders. Proc Environ Sci. 2011;10:2050–7. https://doi.org/10.1016/j.proenv.2011.09.321.
38. Lwenya C, Yongo E. Human aspects of siltation of lake Baringo: causes, impacts and interventions. Aquat Ecosyst Health Manage. 2010;13(4):437–41. https://doi.org/10.1080/14634988.2010.524497.
39. Mishra KB, Kumar P, Saraswat C, Chakraborty S, Gautam A. Water security in a changing environment: concept, challenges and solutions. Water. 2021. https://doi.org/10.3390/w13040490.
40. Molinos JG, Viana M, Brennan M, Donohue I. Importance of long-term cycles for predicting water level dynamics in natural lakes. PLoS ONE. 2015;10(3):e0119253. https://doi.org/10.1371/journal.pone.0119253.
41. Munialo NA. The impact of human activities on the lake ecosystem: a case study of lake victoria shore, Nyando division, Kisumu District-Kenya. Uganda: Kampala International University; School of Engineering and Applied Science; 2012.
42. Mustafa M, Hassoon D, Hassan M, Abd M. Using water indices (NDWI, MNDWI, NDMI, WRI, and AWEI) to detect physical and chemical parameters by apply remote sensing and GIS techniques. 2017. Int J Res. https://doi.org/10.5281/zenodo.1040209.
43. Mutungwa DM. Effects of climate change and human activity on lake levels in the Kenyan rift (case study Naivasha). Nairobi: University of Nairobi; 2011.
44. Mwaka B, Mugo R, Isabirye M. Monitoring land surface temperature and lake water levels in Lake Baringo, Kenya, using satellite remote sensing. Int J Eng Technol. 2016;8(3):1602–11.
45. Nhu V-H, Mohammadi A, Shahabi H, Shirzadi A, Al-Ansari N, Ahmad BB, Chen W, Khodadadi M, Ahmadi M, Khosravi K, Jaafari A, Nguyen H. Monitoring and assessment of water level fluctuations of lake urmia and its environmental consequences using multitemporal landsat 7 ETM+ images. Int J Environ Res Public Health. 2020;17(12):4210. https://doi.org/10.3390/ijerph17124210.
46. Nicholson SE. Historical fluctuations of lake victoria and other lakes in the northern rift valley of East Africa. In: Lehman JT, editor. Environmental change and response in East African Lakes. Dordrecht: Springer, Netherlands; 1998. p. 7–35.
47. Nikraftar Z, Azizi A. Evaluation and analysis of urmia lake water level fluctuations between 1998–2006 using landsat images and topex altimetry data. 2015. Int Arch Photogramm Remote Sens Spatial Inf Sci. https://doi.org/10.5194/isprsarchives-XL-1-W5-549-2015.
48. Odada E, Olago D, Bugenyi F, Kulindwa K, Karimumuryango J, West K, Ntiba M, Wandiga S, Aloo P, Achola P. Environmental assessment of the East African Rift Valley lakes. Aquat Sci. 2003;65:254–71. https://doi.org/10.1007/s00027-003-0638-9.
49. Okech EO, Kitaka N, Omondi S, Verschuren D. Water level fluctuations in Lake Baringo, Kenya, during the 19th and 20th centuries: evidence from lake sediments. Afr J Aquat Sci. 2019;44(1):25–33. https://doi.org/10.4314/ajas.v44i1.
50. Olago DO, Raini J, Omuombo C, Ogonda G, Muli J, Okello C, Memo W, Onganga O. Lentic-lotic water system response to anthropogenic and climatic factors in Kenya and their sustainable management. Cham: Springer International Publishing; 2021.
51. Olaka L, Odada E, Trauth M. The sensitivity of East African rift lakes to climate fluctuations. J Paleolimnol. 2010. https://doi.org/10.1007/s10933-010-9442-4.
52. Omondi R, Ojwang W, Olilo C, Mugo J, Agembe S, Ojuok JE. Lakes Baringo and Naivasha: endorheic freshwater lakes of the rift valley (Kenya). In: Finlayson CM, Milton GR, Prentice RC, Davidson NC, editors. The wetland book: II: distribution, description, and conservation. Netherlands: Springer; 2018. p. 1349–60.
53. Onywere, S. M., Shisanya, C. A., Obando, J. A., Masiga, D. K., Irura, Z., & Mang, S. (2013). *Geospatial Extent of 2011–2013 Flooding from the Eastern African Rift Valley Lakes in Kenya and its Implication on the Ecosystems*. https://typeset.io/papers/geospatial-extent-of-2011-2013-flooding-from-the-eastern-6l8184t6s0
54. Owiti G, Oswe I. Human impact on lake ecosystems: the case of lake Naivasha, Kenya. Afr J Aquat Sci. 2010. https://doi.org/10.2989/AJAS.2007.32.1.11.148.
55. Parfait I, Sang J, Nyadawa M, Maina C. Sedimentation effect on the storage capacity in lake Nakuru, Kenya. J Sustain Res Eng. 2020;5(3):149–58.
56. Rooney G, Lipzig N, Thiery W. Estimating the effect of rainfall on the surface temperature of a tropical lake. 2018. Hydrol Earth Syst Sci Discussions. https://doi.org/10.5194/hess-2018-435.
57. Saah D, Tenneson K, Matin M, Uddin K, Cutter P, Poortinga A, Nguyen QH, Patterson M, Johnson G, Markert K, Flores A, Anderson E, Weigel A, Ellenberg WL, Bhargava R, Aekakkararungroj A, Bhandari B, Khanal N, Housman IW, Chishtie F. Land cover mapping in data scarce environments: challenges and opportunities. Front Environ Sci. 2019;7:150. https://doi.org/10.3389/fenvs.2019.00150.
58. Saltelli A, Annoni P, Azzini I, Campolongo F, Ratto M, Tarantola S. Variance-based sensitivity analysis of model output. Design and estimator for the total sensitivity index. Comput Phys Commun. 2008;180(3):253–62.
59. Scholten W. Agricultural development and water use in the central rift valley of Ethiopia: a rapid appraisal. Enschede: University of Twente; 2007.
60. Schwatke C, Dettmering D, Bosch W, Seitz F. DAHITI is an innovative approach for estimating water level time series over inland waters using multi-mission satellite altimetry. Hydrol Earth Syst Sci. 2015;19(10):4345–64. https://doi.org/10.5194/hess-19-4345-2015.
61. Schwatke C, Scherer D, Dettmering D. Automated extraction of consistent time-variable water surfaces of lakes and reservoirs based on landsat and sentinel-2. Remote Sens. 2019;11:1010. https://doi.org/10.3390/rs11091010.
62. Spigel RH, Coulter GW. Comparison of hydrology and physical limnology of the East African great lakes: Tanganyika, Malawi, Victoria, Kivu and Turkana (with reference to some North American Great Lakes). Milton Park: Routledge; 2019. p. 103–39.
63. Szesztay K. Water balance and water level fluctuations of lakes. Hydrol Sci Bull. 1974;19(1):73–84. https://doi.org/10.1080/02626667409493872.
64. Tufa BW, Senti ET, Gebrehiwot KA. Soil erosion, sediment yield, and conservation practices assessment on lake haramaya catchment. World J Agric Sci. 2014;2(7):186–93.
65. Van den Putte A, Govers G, Leys A, Langhans C, Clymans W, Diels J. Estimating the parameters of the Green-Ampt infiltration equation from rainfall simulation data: why simpler is better. J Hydrol. 2013;476:332–44. https://doi.org/10.1016/j.jhydrol.2012.10.051.
66. Versace. (2007). *Influence of land cover on water resources: A case study*. https://typeset.io/papers/influence-of-land-cover-on-water-resources-a-case-study-1yn02t842q
67. Vrugt JA, Gupta HV, Bastidas LA, Bouten W, Sorooshian S. Effective and efficient algorithm for multi-objective optimization of hydrologic models. Water Resour Res. 2008;44(9):W09417.

68. Wagari M, Tamiru H. RUSLE model based annual soil loss quantification for soil erosion protection: a case of fincha catchment, Ethiopia. Air, Soil Water Res. 2021;14:11786221211046234. https://doi.org/10.1177/11786221211046234.
69. Wainwright CM, Finney DL, Kilavi M, Black E, Marsham JH. Extreme rainfall in East Africa, October 2019–January 2020 and context under future climate change. Weather. 2021;76(1):26–31. https://doi.org/10.1002/wea.3824.
70. Wilcox DA, Nichols SJ. The effects of water-level fluctuations on vegetation in a Lake Huron wetland. Wetlands. 2008;28(2):487–501. https://doi.org/10.1672/07-129.1.
71. Yang X, Liu Z. Using satellite imagery and GIS for land-use and land-cover change mapping in an estuarine watershed. Int J Remote Sens. 2005;26(23):5275–96. https://doi.org/10.1080/01431160500219224.
72. Young N, Anderson R, Chignell S, Vorster A, Lawrence R, Evangelista P. A survival guide to Landsat pre-processing. Ecology. 2017;98:920–32. https://doi.org/10.1002/ecy.1730.
73. Zeman C, Rich M, Rose J. World water resources: trends, challenges, and solutions. Rev Environ Sci Bio/Technol. 2006;5:333–46. https://doi.org/10.1007/s11157-005-4089-8.
74. Zhang J, Zhu C. Time series analysis of water quality in hanjiang river. Nat Environ Pollut Technol. 2014;13(2):4.
75. Zhao X, Liu Y. Evapotranspiration partitioning and response to abnormally low water levels in a floodplain wetland in China. Adv Meteorol. 2016. https://doi.org/10.1155/2016/3695427.
76. Noori AR, Singh SK. Delineation of optimal locations for artificial groundwater recharge utilizing MIF and GIS in a semi-arid area. Environ Earth Sci. 2023. https://doi.org/10.1007/s12665-023-11338-8.
77. Noori AR, Singh SK. Rainfall assessment and water harvesting potential in an urban area for artificial groundwater recharge with land use and land cover approach. Water Resour Manag. 2023;37(13):5215–34.
78. Herrnegger, M., Kray, P., Stecher, G., Cherono, N., & Olang, L. (2023). On the potential cross-mixing of Lake Bogoria and Baringo in the Rift Valley of Kenya (GC8-Hydro-76). GC8-Hydro. Copernicus Meetings. https://doi.org/10.5194/egusphere-gc8-hydro-76
79. Victor N, Eric P, Kyeba K. The risk of flooding to architecture and infrastructure amidst a changing climate in lake Baringo, Kenya. Am J Clim Change. 2023. https://doi.org/10.4236/ajcc.2023.121005.
80. Singh, S. K., & Noori, A. R. (2020). Delineation of groundwater recharge potential zones for its sustainable development utilizing GIS approach in Kabul basin, Afghanistan. https://www.researchgate.net/publication/358005664_