# Spatio-temporal modeling of lake's ecosystem and dynamism in response to changing environment. A case study of L. Olbolossat in Kenya

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## Abstract

Lakes' ecosystems are vulnerable to environmental dynamisms prompted by natural processes and anthropogenic activities happening in catchment areas. The present study aimed at modeling the response of Lake Olbolossat ecosystem in Kenya to changing environment between 1992 to 2022, and its future scenario in 2030. The study used temperature, stream power index, rainfall, land use land cover, normalized difference vegetation index, slope and topographic wetness index as datasets. A GIS-ensemble modeling approach coupling the analytical hierarchical process and principal component analysis was used to simulate the lake's extents between 1992–2022. Cellular Automata-Markov chain analysis was used to predict the lake extent in 2030. The results revealed that between 1992–2002, the lake extent shrunk by about 18%; between 2002–2012, the lake extent increased by about 13.58%; and between 2012–2022, the lake expanded by about 26%. The spatial temporal changes exhibited that the lake has been changing haphazardly depending on prevailing climatic conditions and anthropogenic activities. The comparison between the simulated and predicted lake extents in 2022 produced Kno, Klocation, KlocationStrata, Kstandard, and average index values of 0.80, 0.81, 1.0, 0.74, and 0.84, respectively, which ascertained good performance of generated prediction probability matrices. The predicted results exhibited there would be an increase in lake extent by about 13% by the year 2030. The research findings provide baseline information which would assist in protecting and conserving the lake Olbolossat ecosystem which is very crucial in promoting tourism activities and provision of water for domestic and commercial use in the region.


## Introduction

A lake ecosystem, also known as the Lacustrine system, comprises of biotic (living) plants, animals, and microorganisms and are surrounded by land masses (Wetzel et al., 2001). Lakes are crucial natural resources and carbon gas emitters that contain fresh or saltwater, especially in arid regions, serving as essential sources for consumption, fishing, irrigation, power generation, transportation, recreation, and various agricultural and industrial purposes (Downing et al., 2006). Lake ecosystem dynamism refers to the continual changes and fluctuations within the structure, function, and components of a lake environment (Grant et al., 2021). Globally, lakes are undergoing changes in response to climate change and human activities (Zheng et al., 2021). Climate change induces alterations in temperature, precipitation patterns, and extreme weather events, impacting lake dynamics worldwide. Warmer temperatures lead to changes in water temperature, affecting the water levels (et al., 2018). Altered temperature regimes influence the distribution and behavior of species, impacting the ecosystem balance (Woolway et al., 2020). Additionally, changes in precipitation patterns can result in altered water levels and flow rates in lakes. Increased precipitation can lead to higher inflows, potentially causing flooding, while decreased precipitation may lead to droughts and lower water levels (Kraemer et al., 2020). Destruction of wetlands and vegetation along the shores reduces the lake's ability to filter pollutants and provide habitat for various species thus contributing to reduced water levels (Maua et al., 2022).

Hampton et al. (2018) examined the impacts of climate change on Lake Baikal, the world's deepest and oldest freshwater lake. It showed that warming temperatures and changes in ice cover duration altered the lake's ecosystem, affecting phytoplankton productivity, zooplankton dynamics, and fish populations. A study by IPCC (2021) emphasizes how rising temperatures alter thermal stratification, ice cover duration, and precipitation regimes in lakes, influencing their structure and function. Jeppesen et al. (2010) provides a comprehensive look at the impacts of climate change on lakes globally, focusing particularly on shallow lakes and encompassing various ecological perspectives. Climate change, is also characterized by alterations in temperature and regional weather patterns, which largely impacts the hydrological cycle (Kundzewicz, 2008; Abbass, 2022). The escalated temperatures attributed to climate change cause increased evaporation rates from oceans, lakes, and soil surfaces, thereby augmenting moisture entering the atmosphere and potentially influencing precipitation patterns (Bolan et al., 2024). The intensified evaporation can exceed incoming water in regions experiencing heightened temperatures, contributing to lake depletion (Smith et al., 2019). Tian et al., (2019) assessed the spatial temporal characteristics which influence the ecological water levels of lake Dongting in China. Furthermore, alterations in precipitation patterns induced by climate change modify the frequency, intensity, and distribution of rainfall (Wang et al., 2020). The study by Smith et al. (2019) underscores how rising temperatures impact evaporation rates and precipitation patterns, thereby affecting the water balance of lakes.

In Africa context, Sharma et al. (2020) explains how climate variability leads to changes in water levels, biodiversity shifts, and altered trophic interactions, impacting the ecological balance of these lakes. Mavuti et al. (2015) assesses the specific threats posed by climate change to African lakes, offering insights into adaptation strategies. Tierney et al. (2010) observed a decrease in phytoplankton productivity in Lake Tanganyika attributed to climate change. Warmer temperatures have altered the lake's thermal structure, leading to reduced mixing and decreased nutrient availability, impacting the productivity of phytoplankton, the base of the aquatic food web. Odero et al. (2021) focused on Lake Victoria in Kenya and examined the impacts of climate change induced factors such as altered rainfall patterns and increased temperatures affect the lake's water levels and quality, and their impacts on fisheries and local communities. Climate change has influenced Lake Victoria's ecosystem, contributing to the decline of native fish species (Ogutu-Ohwayo et al., 2016). Changes in temperature and rainfall patterns have affected water levels and quality, impacting the habitat and food availability for native fish (Ohwayo et al., 2018). Harper et al. (2004) explains how climate change impacts on Lake Naivasha have been observed to affect water levels and quality. Shifts in precipitation patterns and temperatures have influenced the lake's hydrology, altering water inflow, which in turn affects the abundance and distribution of species, particularly impacting the diverse bird populations that depend on the lake (Haig et al., 2019).

Moreover, the anthropogenic activities such as urbanization, agriculture, and deforestation, have been noted to alter land cover, nutrient inputs, and hydrological processes. A study by Capenter et al. (2021) highlights the impacts of land-use changes on nutrient loading, eutrophication, and habitat degradation in lakes. Additionally, Li et al. (2018) in Asian lakes, demonstrate how land-use changes cause sedimentation, nutrient runoff, and algal blooms, affecting the water quality and ecological balance of these lakes. Scavia et al. (2014) explains the anthropogenic activities like agricultural runoff containing phosphorus and nitrogen, have led to harmful algal blooms and eutrophication in Lake Erie in North America. Ochumba et al. (2012) explains the human activities, such as the introduction of invasive species and the extensive use of herbicides to control water hyacinth, have had detrimental effects on Lake Victoria's ecosystem. These actions altered the lake's biodiversity, affecting native species and the overall ecological balance. Odada et al. (2014) shows how deforestation, agricultural practices, and urbanization, have contributed to sedimentation and nutrient loading in Lake Malawi. These activities have led to changes in water quality, affecting the lake's ecosystem and biodiversity. Hecky et al. (2010) explains how Lake Victoria has experienced severe eutrophication due to anthropogenic activities, such as agricultural runoff, deforestation, and industrial discharge. Increased nutrient input, especially phosphorus and nitrogen, has led to algal blooms, loss of biodiversity, and a decline in water quality. Moreover, Harper et al. (2004) explains how anthropogenic activities, including agricultural practices and rapid urbanization around Lake Naivasha in Kenya, have resulted in habitat degradation, pollution from agrochemicals, and altered water levels. These activities have affected the lake's ecological health, including shifts in species composition, water quality issues as well as decrease in the extent of the lake. Pálmai et al. (2023) explains how the Lake Nakuru has faced anthropogenic pressures, notably from urbanization, agriculture, and untreated sewage inflows. These activities have led to increased nutrient levels, eutrophication, and algal blooms, impacting the lake's biodiversity, including its iconic flamingo population.

Different methods have been implemented to simulate the effects of climatic, geomorphological and anthropogenic variables on lake extent. Some have employed geographic information systems techniques (GIS) and remote sensing technologies because of their ability to explore spatial, spectral and temporal aspects of the causing factors (Zhao et al., 2018). The Hydrologic Engineering Centre-Hydrologic Modelling System (HEC-HMS) being a numerical model (computer software) simulates the behavior of watersheds, channels, and water-control structures to predict flow, stage, and timing. Precipitation and evaporation from watersheds are represented by the HEC-HMS simulation techniques. A study by Kaberia et al. (2023) used the HEC-HMS model to predict the sediment loads in the upper Ewaso Nyiro river basin. Also, Natarajan et al. (2019) used the HEC-HMS model to simulate the effects of extreme surface runoff in an urban development area. Sengul et al. (2022) used the HEC-HMS model to predict snowmelt runoff for water supply and flood control issues in the Euphrates River basin. The study by Chathuranika et al. (2022) carried out the comparison between the HEC-HMS model and the Soil Water Assessment Tool (SWAT) model in run-off estimation. Msaddek et al. (2020) used the model to define how land use land cover changes simultaneously influence the hydrological capabilities of a river in Morocco. The Hydrological Engineering Center River Analysis System (HEC-RAS) model is used to simulate the scenarios of flooding in rivers and also identify the flood risks of the river when precipitation rate is at maximum. Pradhan et al. (2022) used the HEC-RAS model to simulate the flood inundation, flow velocity and water depth in India. Besides, Singh et al. (2023) used the HEC-RAS model for flood risk assessment in Hasden River basin in India. Ramly et al. (2016) used the HEC-RAS model to simulate flash floods in order to predict the hazard in Teirang River, Pahang, Malaysia for better flood preparedness and minimizing of flood damages.

The geographic information systems (GIS) coupled with the analytical hierarchical process

(AHP) model are used to determine the relative importance of criteria influencing lake expansion or depletion. These criteria are prioritized based on their contributions, as identified through the AHP pairwise comparison matrix (Gharizadeh et al., 2020). The AHP is commonly employed for its straightforward method of assigning relative weights to causal factors, despite its being subjective (Kulimushi et al., 2021). Additionally, the principal component analysis (PCA) is an unbiased multivariate model frequently used to reduce data dimensionality among causal factors. Its advantage lies in its insensitivity to measurement units of input variables (Keyantash and Dracup, 2004), although it has the drawback of excluding domain knowledge (Gharizadeh et al., 2020)

The current study aimed at assessing the influence of climatic, anthropogenic, and geomorphological variables on the extent of Lake Olbolossat. To achieve this, a GIS-ensemble modelling approach was employed, integrating the Analytical Hierarchy Process (AHP) and principal component analysis (PCA). This approach was designed to alleviate the subjectivity associated with AHP and concurrently reducing data dimensionality using the PCA approach. The research outcomes are anticipated to offer insights into mitigation strategies that can be implemented to minimize the impact of environmental changes on the lake ecosystem.

# Methodology

**Description of the study area.**

Lake Olbolossat is an alkaline lake in the flood plain of Aberdare Ranges Nyandarua county and is bordered by Ndaragwa, Ol’Kalou, and Ol’Jorok sub-counties. It is located approximately 195 km from Nairobi at around latitude

0° 9' 49" S, and longitude 36° 26' 40"E (Zakaria et al., 2013). It has an approximate area of 43.3 squares kilometers. Figure 1 shows the lake Olbolossat basin, Kenya water basins and Nyandarua county basin where Lake Olbolossat lies. It is the source of the famous Thompson Falls in Nyahururu which is a tourist attraction site thus generating revenue for the County government.

The region has a favourable climate throughout the year. The region around Lake Olbolossat has a tropical climate due to its proximity to the equator. The climate is semi-humid, and wet and is largely influenced by the local topography because of the surrounding highlands. Mean annual rainfall ranges between 400-1000mm (Zacharia et al., 2013). Rainfall peaks are between April-June and October to November. The mean annual temperature is 23.5º C with monthly variations between 10º C and 28º C on the extreme. (Kiama et al., 2021).

The soils in Nyandarua County are volcanic and vary in mineral composition from one region to another. These soils are generally fertile and well-draining, making them suitable for agriculture for subsistence or commercial purposes (Gichuki et al., 2000). Soils around Ol' Kalou have poorly drained clay soils. The region is fairly plain because it is surrounded by the Aberdare Ranges. It is located in the Great Rift Valley, which is a major geological feature of East Africa. The Great Rift Valley is an active tectonic feature caused by the movement of tectonic plates (Mathenge et al., 2014). The geological setting and soil types around Lake Olbolossat play a crucial role in shaping the surrounding ecosystem and influencing the land use patterns in the region. These factors also impact the lake's water quality and contribute to the rich biodiversity found in and around the lake (Zacharia et al.,2013). However, geological and environmental conditions might change over time, so ongoing monitoring and research are necessary to maintain the health and sustainability of Lake Olbolossat.

**Dataset description.**

The research utilized various datasets to evaluate and forecast the impacts of climatic, geomorphological, and anthropogenic factors on the lake's extent. These datasets encompassed variables such as slope, stream power index (SPI), land use land cover (LULC), soils data, plan curvature, aspect, topographic wetness index (TWI), normalized difference vegetation index (NDVI), bareness soil index, rainfall, and temperature. Landsat imageries were processed to extract LULC, soil bareness index and NDVI. Other key components used were slope, SPI, aspect, basin delineation and TWI which were extracted from a 30m digital elevation model obtained from the United States Geological Survey. Soil types were derived from attributes of soil data obtained from the Kenya Soil Survey (KSS), and gridded rainfall data were sourced from the Climate Hazards Group Infrared Precipitation with station data (CHIRPS). Gridded temperature data were acquired from Africa Grid. The software and hardware used were ARCGIS, ERDAS and Terrset. A summary of the datasets used in the study are presented in Table 1.

Table 1
Datasets used for assessing and predicting the lake extent.

| DATA SOURCE | SOURCE | SPECIFICATION | RELEVANCE |
|---|---|---|---|
| Landsat Imagery (1992,2002,2002,2012) | USGS | 30m spatial resolution (Raster) | Extraction of Land uses land cover, Normalized difference vegetation Index and Bareness index, |
| Digital Elevation Model (DEM) | USGS | 30m spatial resolution (Raster) | Used to extract slope, aspect, Topographic wetness index, Plan curvature, and Lineaments. |
| Soil | Kenya Soil Survey (KSS) | 250 m spatial resolution (Shapefile) | Used to extract soil types |
| Rainfall | Chirps | 0.25*0.25 resolution (Raster) | Used to determine the rainfall trends. |
| Temperature | Africa Grid | 0.25*0.25 resolution(raster) | Simulate evapotranspiration using Thornthwaite model |

# Methodology workflow

This study adopted the methodology shown in Fig. 2.

# Data pre-processing and harmonization

Landsat images underwent preprocessing using remote sensing aimed to rectify distortions arising from characteristics of the imaging system, imaging conditions, and data gaps. Radiometric corrections were applied to eliminate atmospheric errors, including cloud cover, atmospheric haze, and image scanline noise. Geometric correction involved geo-referencing and projecting the images onto the Arc 1960, Universal Transverse Mercator (UTM), zone 37S coordinate system to improve data overlay. Band combination was done through layerstacking. Additionally, all other datasets were constrained to the specified spatial extent of the study area, and raster datasets were resampled using the bi-linear interpolation method to achieve a 30m spatial resolution. Furthermore, vector datasets, were rasterized to ensure data uniformity before processing. After reclassification and standardization, they were subjected to the AHP and PCA models.

# Data Analysis Extraction of land use land cover

Landsat images for the years under investigation were corrected, clipped to the area of interest and then used to extract variables like LULC, bareness soil index and NDVI which are part of the input variables to explore the effects of lake dynamism in response to the changing environment.

The maximum likelihood supervised classifications algorithm was used to extract the land use land cover (LULC) from the pre-processed multispectral Landsat images for 1992, 2002, 2012 and 2022. The classification algorithm generated six categories of LULC namely: bareland, grassland, forest, built-up area, cultivated fields, and waterbody. The extracted LULC were used in the Markov chain analysis model to predict the future scenario of the lake.

# Extraction of topographic attributes from DEM

Topographic features which represent the physical appearance of the area of study such as slope, stream power index, aspect and topographic wetness index (TWI) were extracted from the 30m spatial resolution DEM. The slope, aspect and stream power index were extracted using Arc hydro tool which is a spatial extension tool of ArcGIS software.

# Extraction of Bareness soil index

The Landsat images were utilized in ArcMap software's raster calculator to derive the bare soil index for the years 1992, 2002, 2012, and 2022 using equations 1 and 2. The bareness soil index (BSI) was obtained by the combination of the blue, red, near infrared and shortwave infrared bands to capture soil variation. These spectral bands are used in a normalized manner. The shortwave infrared (SWIR) and red spectral bands are used to quantify the soil mineral composition while the blue and near infrared (NIR) are used to enhance the presence of vegetation (Zhao et al. 2005). Bareness soil index ranges from − 1 to 1 (Diek et al., 2017; Salas et al., 2023).

$$BSI\_L8 = \frac{(\mathrm{Band6} + \mathrm{Band4}) - (\mathrm{Band5} + \mathrm{Band2})}{(\mathrm{Band6} + \mathrm{Band4}) + (\mathrm{Band5} + \mathrm{band2})}(1)$$

$$BSI\_L5 = \frac{(\mathrm{Band5} + \mathrm{Band3}) - (\mathrm{Band4} + \mathrm{Band1})}{(\mathrm{Band5} + \mathrm{Band3}) + (\mathrm{Band4} + \mathrm{band1})}(2)$$

# Extraction of normalized difference vegetation index

The landsat images were used to obtain the normalized difference vegetation index using equations 3 and 4. The raster calculator was used to achieve the maps for the years 1992, 2002, 2012 and 2022. The normalized difference vegetation index quantifies the health and density for vegetation with the range being − 1 to 1 where the − 1 shows the less vegetative areas like water bodies and 1 show the areas that are highly vegetative (Assefa et al., 2021; Huang et al., 2021).

$$NDVI for Landsat 8 and 9 = \frac{(\mathrm{Band5} - \mathrm{Band4})}{(\mathrm{Band5} + \mathrm{Band4})}(3)$$

$$NDVI for Landsat 5 to 7 = \frac{(\mathrm{Band4} - \mathrm{Band3})}{(\mathrm{Band4} + \mathrm{Band3})}(4)$$

# Reclassification of the contributing factors

Reclassification of contributing factors was based on the Saaty nine-weighted scale as presented in Table 2 (Sharma, 2018). Additionally, the study adopted the criteria provided in Table 3 to reclassify the causal factors influencing the changes in lake extent.

Table 2
Saaty nine-point weighted scale for ranking the factors (Sharma, 2018)

| Scale | Meaning | Related flood's vulnerability level |
|---|---|---|
| 1 | Equal importance | Very Low |
| 3 | Moderate importance | Low |
| 5 | Important | Moderate |
| 7 | Very Strong importance | High |
| 9 | Extreme importance | Extremely high |
| 2, 4, 6, 8 | Intermediate values between adjacent scales | |

Table 3
Criterion table

| Factors | Criteria scales and scores in parentheses () | | | | | | Source |
|---|---|---|---|---|---|---|---|
| Slope | (˚) | 0–3(9) | 3–8(7) | 8–15(5) | 15–25(3) | 25–87(1) | Kanwal et al. (2016) |
| LULC | level | Waterbody (1) | Forests (2) Grasslands (3) | Bareland (5) | Built up areas (7) | Cultivated Fields (9) | Penki et al. (2022) |
| Topographic wetness index | level | < 2.8 (1) | 2.8–4.2(3) | 4.2-6.0 (5) | 6.0-8.2(7) | > 8.2(9) | Penki et al. (2022) |
| NDVI | level | < -0.02 (9) | -0.02-0.30(7) | 0.3–0.4(5) | 0.40-0.5(3) | > 0.5(1) | Kanwal et al. (2016) |
| Soil Texture | level | Sandy (1) | Loamy (3) | Clayey (5) | Very Clayey (7) | | Tugen and Thug (2003) |
| Aspect | | -1 (1) | 0 to 22.5(3) | 22.6 to 67.5 (5) | 67.5 to 112.5 (7) | 112.5-360 (9) | Kanwal et al. (2016) |
| Plan Curvature | Degrees | -4 to-1 (1) | -1 to 0 (3) | 0 to 1 (5) | 1 to 3(7) | 3–87 (9) | Kanwal et al. (2016) |
| Stream Power index | degrees | -6 to 0(1) | 0 to 5 (3) | 5 to 10(5) | 10–16 (7) | > 16 (9) | Kanwal et al. (2016) |
| Temperature | Degree Celsius | < 0 to 16(1) | 16 to 18 (3) | 18 to 21 (5) | 21 to 30 (7) | > 30 (9) | Kanwal et al. (2016) |
| Precipitation | mm | < 0 to 90(1) | 90 to 140(3) | 140 to 180 (5) | 180 to 220(7) | > 220(9) | Penki et al. (2022) |

# Lake extent mapping using multi-criteria decision evaluation approach

The extent of the lake was modelled using the Analytical Hierarchical Process (AHP) where reclassified slope, aspect, land use/land cover (LULC), stream power index, plan curvature, topographic wetness index, precipitation, temperature, bareness soil index, and normalized difference vegetation index were considered as factors. A pairwise comparison table, reflecting expert judgment, was created to determine the relative weights of each factor influencing the lake extent. Before conducting pairwise comparisons, the contributing factors were reclassified and standardized on a nine-point weighting scale (1 to 9) following Saaty (2003). Relative weights for the contributing factors were applied to obtain the consistency ratio. The scale facilitated comparisons between factors, as illustrated in Table 4. To address potential bias in criteria weighting resulting from the subjectivity of the AHP method, a consistency ratio was computed using Eq. 5 to assess the method's reliability (Gacu et al. 2022).

$$C.\,I. = \frac{\lambda\ \max - n}{n - 1} \tag{5}$$

Where C.I is the consistency index, n is the number of items being compared in the matrix, λ max is the largest eigen value. The consistency ratio should be 0.10 or below for accuracy purposes ( Mzuri et al., 2022).

Table 4
Pairwise comparison matrix for the contributing factors influencing lake extent.

| ID | layername | ndvi | temp | aspect | slope_ | TWI | curvature | rainfall | LULC | weight | CI |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **1** | **NDVI** | **1** | **2** | **2** | **3** | **4** | **5** | **7** | **9** | **0.31** | **0.03** |
| 2 | Temperature | 0.5 | 1 | 1 | 2 | 3 | 4 | 6 | 8 | 0.20 | 0.03 |
| 3 | Aspect | 0.33 | 1 | 1 | 2 | 3 | 3 | 5 | 7 | 0.18 | 0.03 |
| 4 | Slope. | 0.25 | 0.5 | 0.5 | 1 | 2 | 2 | 4 | 6 | 0.11 | 0.03 |
| 5 | TWI | 0.25 | 0.33 | 0.5 | 0.5 | 1 | 1 | 3 | 5 | 0.08 | 0.03 |
| 6 | Curvature | 0.17 | 0.25 | 0.33 | 0.33 | 0.5 | 1 | 2 | 4 | 0.06 | 0.03 |
| 7 | Rainfall | 0.14 | 0.17 | 0.25 | 0.25 | 0.33 | 0.55 | 1 | 3 | 0.04 | 0.03 |
| 8 | LULC | 0.13 | 0.17 | 0.14 | 0.17 | 0.33 | 0.5 | 0.5 | 1 | 0.02 | 0.03 |

Using the criteria weights generated in Table 4, the reclassified cause factors were integrated using the weighted overlay tool in ArcGIS to simulate the lake extent maps for 1992, 2002, 2012 and 2022. The simulated lake extent maps were reclassified into five levels (very low, low, moderate, high and extremely high) based on broad range of nine-point weighting scale and extracting the spatial extent of each category (Bagaram et al., 2016)

# Lake extent mapping using the Principal Component Analysis (PCA)

Principal component analysis (PCA) was conducted on the contributing factors, akin to those employed in the Analytic Hierarchy Process (AHP), to model lake extent maps for the years 1992, 2002, 2012, and 2022. Utilizing the PCA tool within ArcGIS, the eight contributing factors underwent manipulation, resulting in an 8×8 matrix of factor eigenvectors and an 8×1 matrix representing the percentages of eigenvalues for the principal component (PC) layers, as described by (Keyantash and Dracup 2004).

To accommodate spatial-temporal variations in the primary influencing factors, Principal Component Analysis (PCA) was performed separately for each time period, as emphasized by (Kalantari et al., 2013). In order to minimize the influence of temporal fluctuations on factor weights, the obtained weights for contributing factors were normalized across all years. A geometric mean of the relative weights was then calculated for each contributing factor, as outlined in Table 7. Additionally, the normalized relative weights were utilized to amalgamate the eight reclassified factors for modeling lake extent maps in the years 1992, 2002, 2012, and 2022. Employing Saaty's (2003) reclassification approach, the lake extent maps were categorized into five levels (very low, low, moderate, high, and extremely high), and the area under each category was computed.

## Lake extent mapping using the GIS-ensemble modelling approach

To integrate the outcomes of AHP and PCA, a hybrid lake extent map for the years 1992, 2002, 2012, and 2022 were generated using the geometric mean. This synthesis was conducted within a GIS environment, employing the raster calculator tool. To evaluate the effectiveness of the GIS-ensemble model, various metrics including overall accuracy, Kappa statistics, producer accuracy, and user accuracy were calculated based on model simulated extents and the global positioning systems (GPS) points collected during fieldwork. Additionally, the lake extent map produced through the GIS-ensemble approach for each year investigated was reclassified into five classes (very low, low, moderate, high, and extremely high) using Saaty's (2003) methodology.

## Lake extent prediction using the Cellular Automata-Markov Chain Analysis

The study utilized the Markov chain model to illustrate changes over time (Mokarram and Pham 2022). Markov chain analysis was applied to the output of the ensemble approach to generate probability area matrix, transition suitability image, and Markov transition area files. This was done by using lake extent maps for 1992 as the earlier image and 2012 as later images and the number of years between the epochs was specified. The probability area matrix files and the suitability image obtained from the Markov chain analysis model were input into the Cellular Automata model for prediction of the nearing cells. To predict the lake extent map for 2022, the study input the generated transition suitability image and Markov transition area files, along with the 2012 lake extent map, into the Cellular Automata/Markov chain predicting tool. The number of Cellular Automata iterations was set to 10, and a standard 5×5 contiguity Cellular Automata (CA) filter was used to determine the weight factor of transition (Wanjala et al. 2020). Validation of the predicted lake extent map for 2022 involved a comparison with the simulated lake extent map for the same year. Kappa coefficients, were calculated for accuracy assessment to determine the reliability of the prediction model (Nath et al. 2020).

Additionally, using the lake extent map for 2022 as the base image, the study employed the generated transition suitability image and Markov transition area files to simulate the lake extent map for 2030. This simulation included 8 Cellular Automata iterations, corresponding to the number of years between 2022 and 2030, using CA-Markov chain analysis. The predicted lake extent map for 2030 was then classified into five classes, and the area of each category was computed.

# Results

## Lake extent modelling using AHP modelling approach

The reclassified AHP-based lake extent maps are shown in Fig. 3. The results depict that the lake extent had been fluctuating over the years which could be contributed by spatio-temporal variations of climatic, geomorphological and anthropogenic variables. Moreover, the results show that over the years considered, the percentage area of the lake extent in the region had been fluctuating. The very low class represented the waterbody and in 1992 the extent of the lake was large but in 2002 it shrunk drastically by 15% which may be attributed to climatic variables or anthropogenic variables, in 2012 the extent of the lake increased by 12.28% and in 2022 the extent also increases by 23% as shown in Fig. 3. Table 6 shows the transitions of classes area sizes of the lake from 1992 to 2022 whereby the very low class represented the waterbody, low represented the forest area, the moderate class represented the built-up areas the extremely high represented the cultivated fields and the high class represented bareland. Clearly the cultivated fields had a great impact upon the lake extent because they are the major anthropogenic activities that influence the lake.

Table 5
Statistics for the AHP area transitions of the classes for the years 1992, 2002, 2012 and 2022.

| Classes | 1992 | 2002 | 2012 | 2022 |
|---|---|---|---|---|
| Very Low | 3310.25 | 1790.25 | 1802.53 | 4102.67 |
| Low | 6019.54 | 7530.86 | 6012.12 | 3329.38 |
| Moderate | 6534.68 | 5422.71 | 2526.34 | 1587.94 |
| Extremely high | 16532.31 | 10307.61 | 18790.52 | 16600.65 |
| High | 2146.67 | 8210.68 | 4936.78 | 8912.62 |

# Lake extent simulation based on PCA modelling approach

The results for the weighted PCA-based lake extent maps are shown in Fig. 4. The results depict that the lake extent had been fluctuating over the years which could be contributed to the spatio-temporal variations of climatic, geomorphological and anthropogenic variables. Table 7 shows the PCA comparison matrix that has the weights obtained using the eigen vectors and eigen percentages.

Table 6
Statistics for the PCA area transitions of the classes for the years 1992,2002,2012 and 2022.

| Classes | 1992 | 2002 | 2012 | 2022 |
|---|---|---|---|---|
| Very Low | 3262.23 | 1854.3 | 1793.10 | 3913.79 |
| Low | 6017.76 | 7479.09 | 5404.49 | 3328.38 |
| Moderate | 6475.54 | 5488.69 | 2533.54 | 1580.42 |
| Extremely High | 17355.24 | 10307.61 | 19770.16 | 16579.33 |
| High | 1091.16 | 8341.83 | 5264.32 | 9365.19 |

Table 7
Relative weights generated using eigenvectors and eigenvalues generated based on PCA

| PCA COVARIANCE MATRIX | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Aspect | Curvature | TWI | slope | NDVI | BSI | Rainfall | Percentage | Weights |
| Aspect | 0.99 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 59.67 | 59.17 |
| Curvature | 0.00 | 0.00 | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 13.56 | 11.71 |
| TWI | 0.00 | 0.07 | 0.33 | 0.06 | 0.68 | 0.19 | 0.00 | 11.71 | 8.52 |
| slope | 0.01 | 0.56 | 0.00 | 0.26 | 0.17 | 0.00 | 0.00 | 8.91 | 11.10 |
| NDVI | 0.00 | 0.03 | 0.00 | 0.01 | 0.15 | 0.81 | 0.00 | 3.95 | 2.89 |
| BSI | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 2.19 | 0.02 |
| Rainfall | 0.00 | 0.33 | 0.00 | 0.67 | 0.00 | 0.00 | 0.00 | 0.02 | 10.44 |
| total | 1.00 | 1.00 | 1.33 | 1.00 | 1.00 | 1.00 | 1.00 | | |

Moreover, the results show that over the years considered, the percentage area of the lake extent in the region had been deteriorating. The very low class represented the waterbody and in 1992 the extent of the lake was big but in 2002 it reduced by 18% which may have been attributed to by climatic variables or anthropogenic variables, in 2012 the extent of the lake increased by 13.58% and in 2022 the extent also increased by 26% as shown in Fig. 4. Table 6 shows the area transitions of the classes over the years.

# Simulating the lake extent using GIS-ensemble modelling approach

The results of the reclassified weighted PCA-based lake extent maps are presented in Fig. 5. The results exhibit that a large chunk of the Lake Olbolossat basin is occupied by cultivated fields and the waterbody extent fluctuates due to anthropogenic activities which may include deforestation that affected the rainfall and temperature patterns of an area thus attributing to a smaller lake extent in incidences of drought and increase in rainy seasons. Additionally, the results show that over the years considered, the percentage area of the lake extent in the region had been deteriorating. The very low class represented the waterbody and in 1992 the extent of the lake was big but in 2002 it reduced by 18% which may be attributed to by climatic variables or anthropogenic variables, in 2012 the extent of the lake increased by 13.58% and in 2022 the extent also increased by 26%. Table 8 shows the area transitions for the GIS−ensemble approach of the classes.

Table 8

Statistics for the GIS-ensemble approach area (km$^2$) transitions of the classes for the years 1992, 2002, 2012 and 2022.

| Classes | 1992 | 2002 | 2012 | 2022 |
|---|---|---|---|---|
| Very Low | 3262.23 | 1854.3 | 1793.10 | 3913.79 |
| Low | 6017.76 | 7479.09 | 5404.49 | 3328.38 |
| Moderate | 6475.54 | 5488.69 | 2533.54 | 1580.42 |
| Extremely High | 17355.24 | 10307.61 | 19770.16 | 16579.33 |
| High | 1091.16 | 8341.83 | 5264.32 | 9365.19 |

# Prediction of the lake extent

The results for the predicted lake extent map for the year 2030 are presented in Fig. 6. The validation results produced Kno, Klocation, KlocationStrata, Kstandard, and average index values of 0.80, 0.81, 1.0, 0.74, and 0.84, respectively. These statistical coefficients guaranteed the accuracy and reliability of the transition estimates (probability area matrix, transition suitability image, and the Markov transition area files) to generate future lake extent scenario map for the year 2030 (Fig. 6). The predicted lake extent map for the year 2030 exhibited that 20.01%, 9.52%, 4.6%, 11.6%, and 23.52% of the classes registered very low, low, moderate, high, and extremely high extent levels. This signified that the very low class will transition in the year 2030 which shows the waterbody and hence an increase in the lake extent. The blue colour shows the lake and from 1992 to 2022 significantly the area size significantly reduced and increased there after depicting that the lake faced threats of climatic conditions as well as the anthropogenic variables. On the other hand, the cultivated fields increased in area thus becoming threat to the lake levels. Table 9 shows the area transitions for the prediction of the lake extent for the year 2030.

**Table 9** Statistics for the predicted lake extent area (km$^2$) transitions of the classes for the years 1992, 2002, 2012 and 2022.

| LULC | simulated 2022 | predicted 2022 | predicted 2030 |
|---|---|---|---|
| Low (waterbody) | 3327.93 | 4304.67 | 3383.01 |
| Extremely High | 12150 | 14657.31 | 12259.08 |
| Very low | 3913.02 | 4304.67 | 6359.22 |
| Moderate | 9364.86 | 7062.66 | 7527.33 |
| High | 1579.68 | 1706.13 | 1817.73 |

# Discussion

The AHP-based lake extent maps showed that the largest area under cultivated fields had a major contribution to the lake extent as depicted in the land use land cover maps shown in Fig. 7. The spatio-temporal patterns could be attributed to climate change (Hampton et al., 2017) and anthropogenic activities (Scavia, et al., 2014). The extent of the lake kept fluctuating from one year to another which could be attributed to the dynamisms of the climatic and anthropogenic variables. Land use practices for the past 30 years show that after every ten years vegetation cover decreases due to increased population which only means that the vegetation cover has been cleared to create room for settlements on for fuel wood and also reducing the percolation of water and thus causing sedimentation that causes the lake to shrink (Wubie, 2022; Sugianto et al., 2022).

Vegetation acts as surface runoff regulator which ensures that there is less runoff hence increasing infiltration and reducing soil erosion. These ensures that the runoff carries less silt load to the lake basin which increases the lake extent(Kamamia et al., 2022). But in contrast to this, the vegetation has been cleared and therefore there is a risk of the basin shrinking due to the silt carried to the rivers by surface runoff water (Plate 1). Even though the agricultural practices tend to reduce over the years, there is a fact that such practices have an effect on the lake.

Given that changes in land use and land cover practices, such as deforestation, contribute to decreased rainfall and increased sedimentation, there should be a focus on implementing and enforcing sustainable land use management practices. This may involve regulations to control deforestation, promote afforestation, and manage settlements to mitigate the impact on vegetation cover (Mzuza et al., 2019). This will directly assist in mitigating the anthropogenic activities which are a threat the ecosystem of lakes which was a major finding of this research (Dieng et al., 2023).

Similar results were obtained when modeling lake extent using the PCA-based approach where the lake kept dwindling and increasing from one year to another due to the climatic conditions and even the anthropogenic activities that are a major threat. Besides, the region around the lake has clay soils that are able to retain water and hence the ability to have a lake, the other regions to the west have loam soils and to the eastern sandy soils which are poor in water retention and hence easy sediment transportation into the lake (Zacharia et al., 2013). The region also is relatively flat and is bound by the Aberdare ranges which also makes sedimentation process of loads into the lake ecosystem as shown in plate 1.

Plate 1 gives a clear scenario of the effects of the anthropogenic activities such as farming that has invaded the shores of the lake and thus leading to reduction of the water levels. The results obtained in this study showed that the anthropogenic and climatic variables have largely influenced the lakes sustainability.

Similarly, the results from the GIS-ensemble model manifested that most parts of the lake basin are covered by the cultivated fields which are extremely high contributing factors to the depletion of the lake extent. Therefore, the comparisons of the three modelling approaches demonstrated the same spatial-temporal trends of lake dynamism on environs of the lake ecosystem with the years 2002 and 2022 exhibiting least and high levels of the lake extent, respectively (Fig. 4, Fig. 5 and Fig. 6). The results revealed that despite the AHP approach being subjective, its outcome agreed with the PCA-based output as well as for the GIS-ensemble based modelling approach. The results from the three approaches demonstrated that the largest section of the lake Olbolossat ecosystem is vulnerable to depletion which could be attributed to adverse climatic conditions, excess anthropogenic activities, relatively flat landscape configuration where the lake is situated while the vicinities comprise of ridges, escarpments and ranges (Karuku et al., 2019).

# Conclusions

The assessment of the lake extent of Lake Olbolossat was based on the following modelling approaches, that is, AHP-based, PCA-based, and ensemble-based. The research concludes that anthropogenic activities are the major contributor to lake expansion and depletion as well as the climatic variables while the geomorphological variables insignificantly affect the expansion and depletion of the lake. The average rainfall in the region can be attributed to various changes occurring in the basin. These changes encompass practices related to land use and land cover, such as deforestation, which ultimately result in reduced rainfall. Consequently, this issue can be resolved by efficient land use management.

Additionally, develop and implement integration of water resource management plans that consider the impact of both anthropogenic activities and climatic variations on the basin. This involves collaboration among stakeholders, including local communities, governmental bodies, and environmental organizations. With the policy makers and stakeholders, the issue of anthropogenic variables will be solved because the people will be educated on the matter and policies established hence minimizing the risks of shrinkage. However, few studies have been done on lake dynamism which was a limitation for this research, future researchers should take part in lake dynamism studies so that environmental management for the lakes is easier and hence a sustainable environment.

# Declarations


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### Authors’ contributions

**Janice Kemunto Nyambane:** Conceptualization, methodology, writing of the original draft and submission of the research article for publication. **Duncan Maina Kimwatu:** Conceptualization, methodology, writing of the original draft, supervision, reviewing and editing.


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### Availability of data and materials

The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

### Ethics approval

All authors have read, understood, and have complied as applicable with the statement on “Ethical responsibilities of Authors” as found in the Instructions for Authors.

### Competing interests

The authors declare no competing interests.

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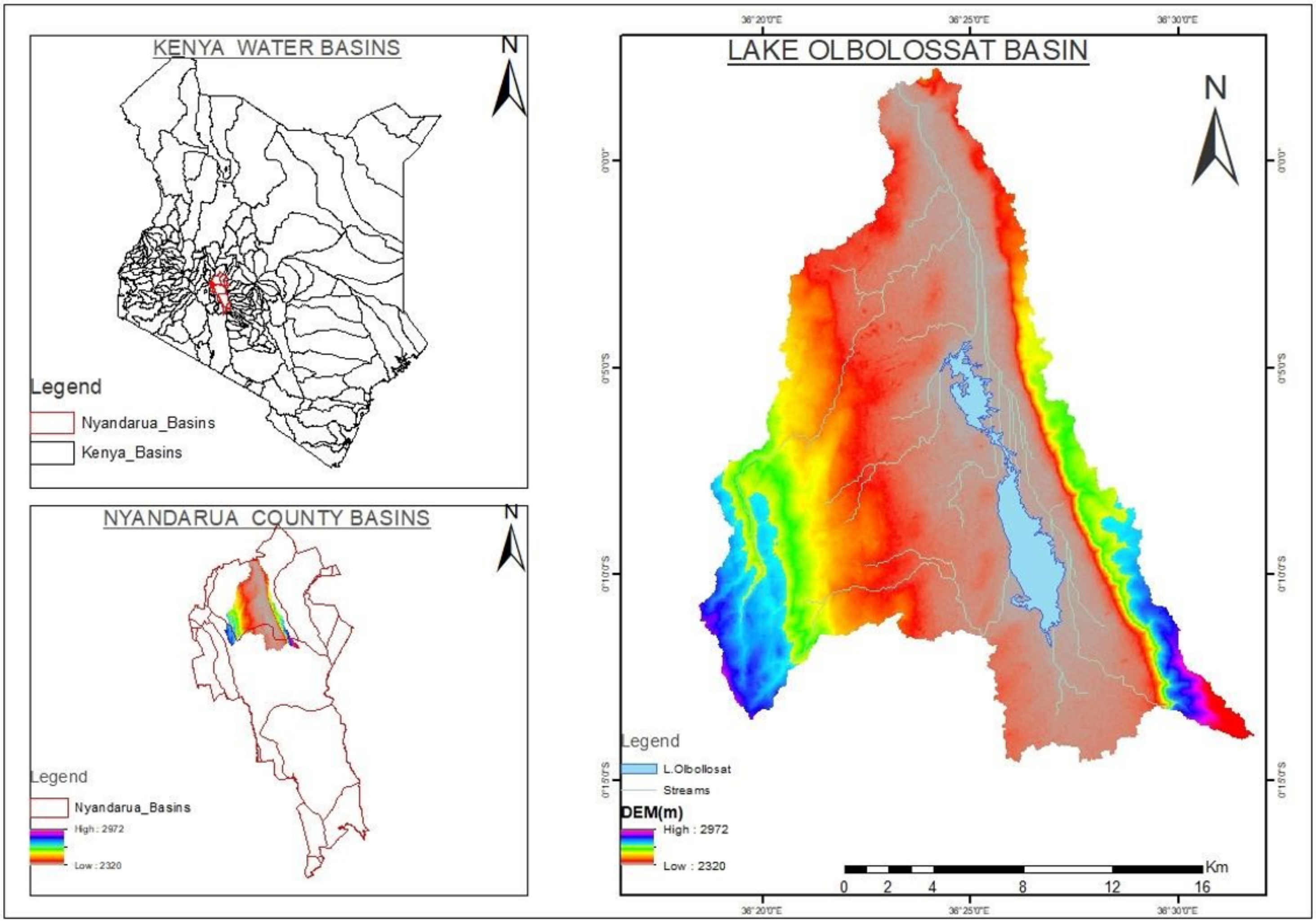
# Plate

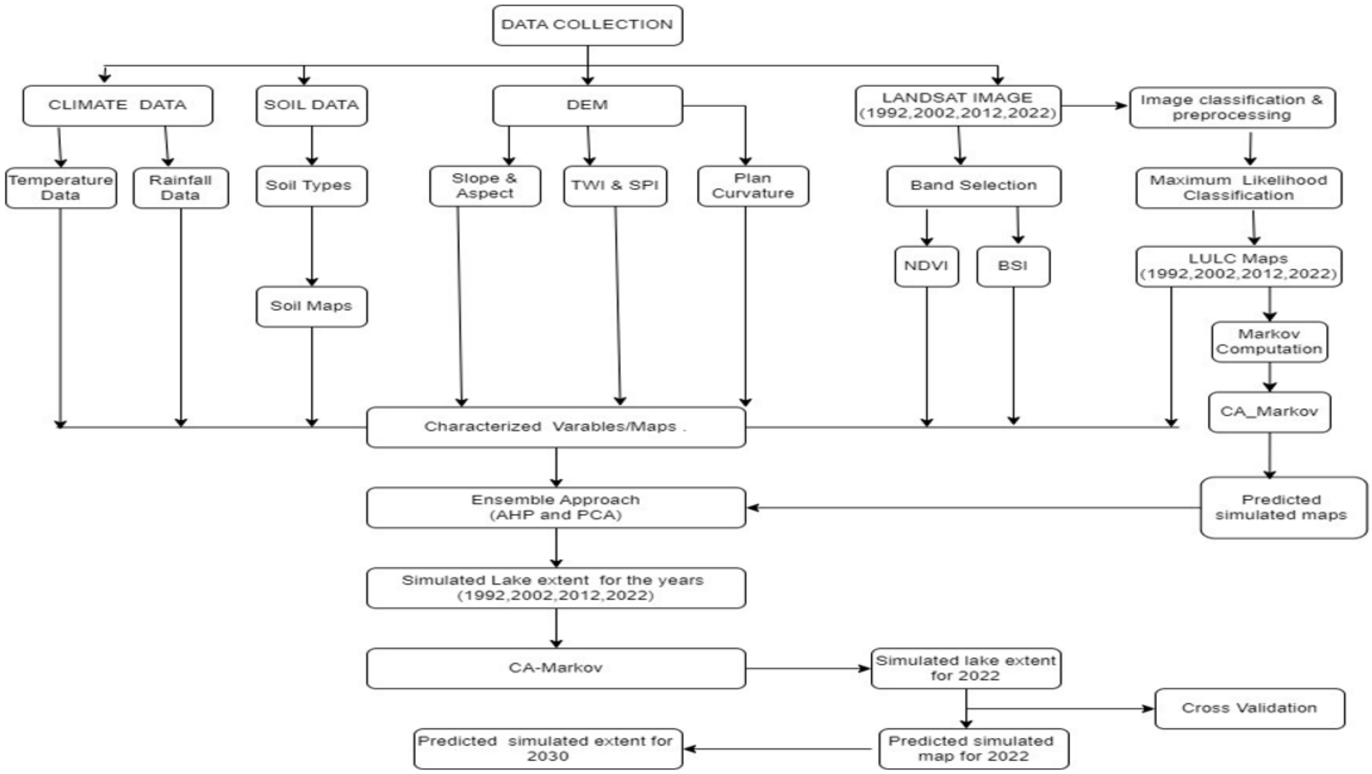
Plate 1 is available in the Supplementary Files section.

# Figures



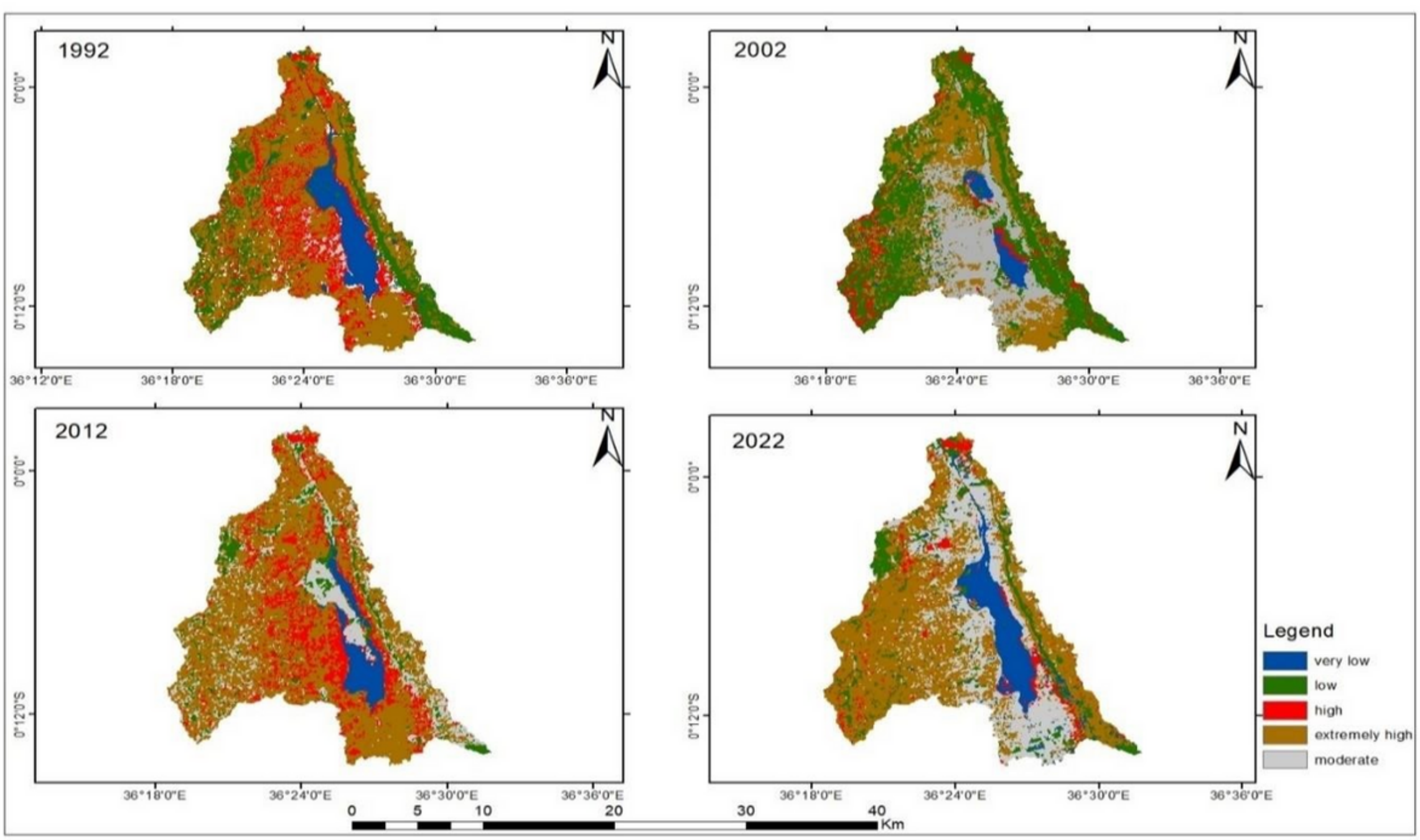

## Figure 1

Location map for Lake Olbolossat.



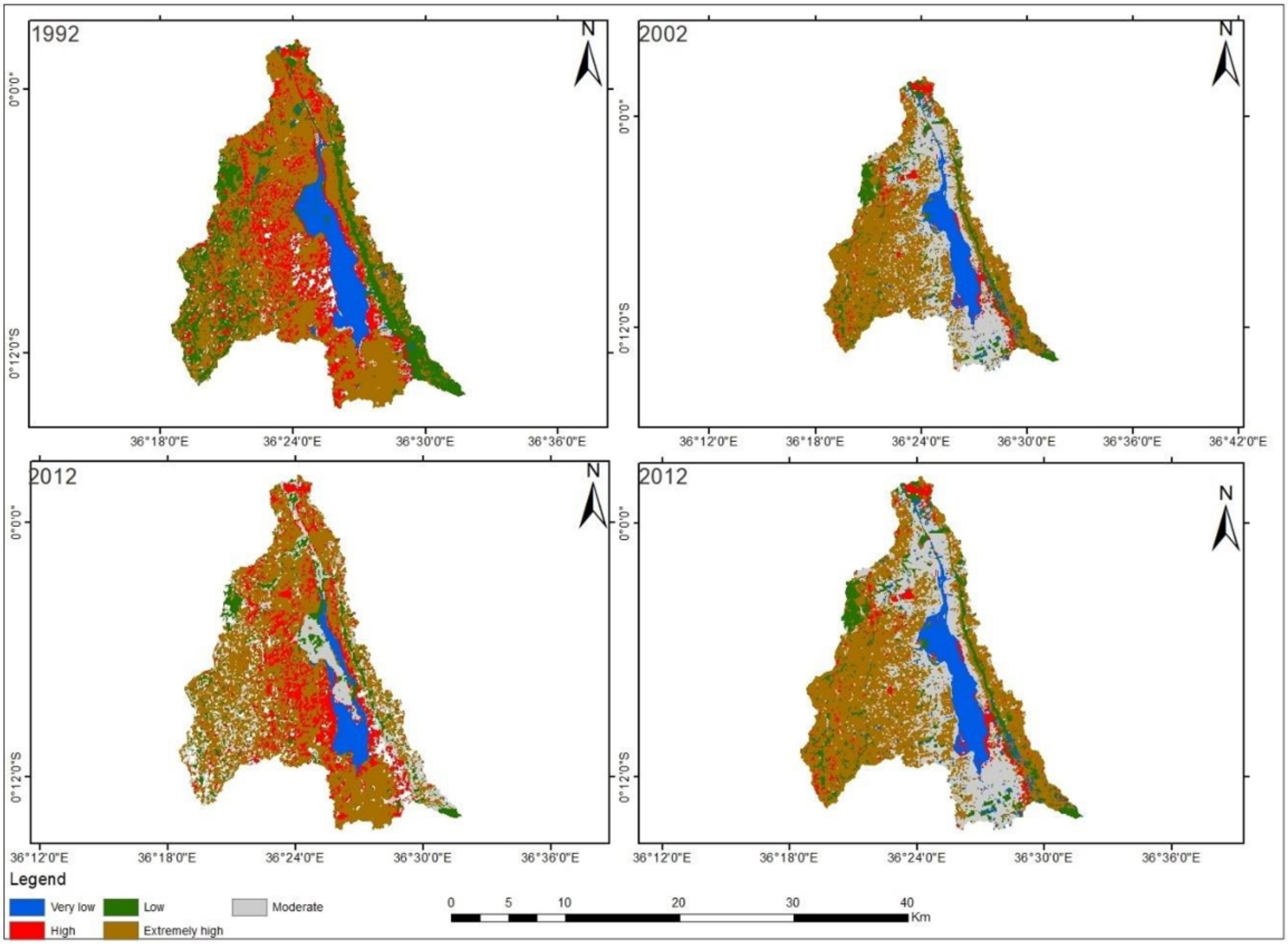

## Figure 2

The methodology framework



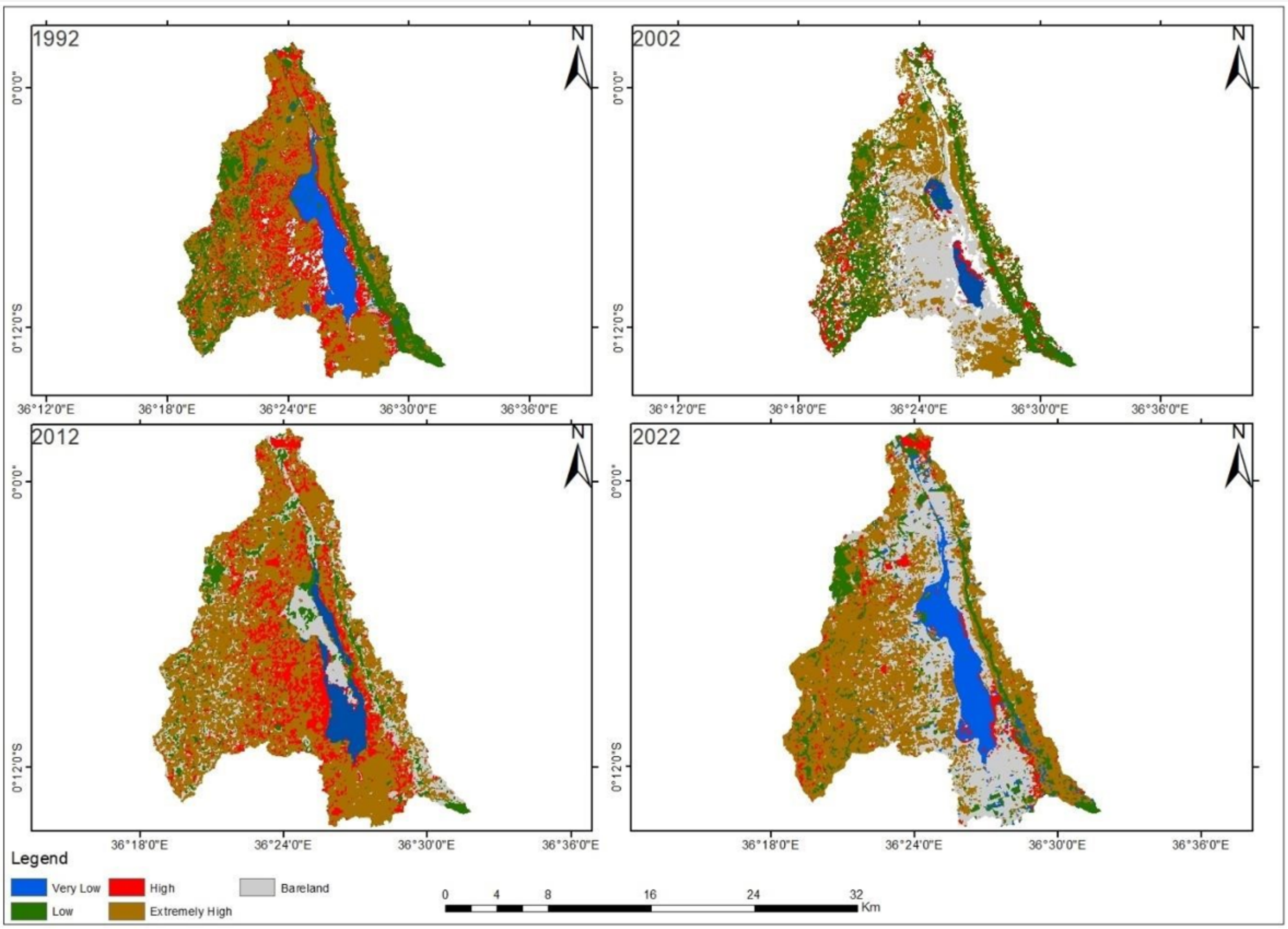
## Figure 3

Weighted AHP-lake extent maps for 1992, 2002, 2012 and 2022



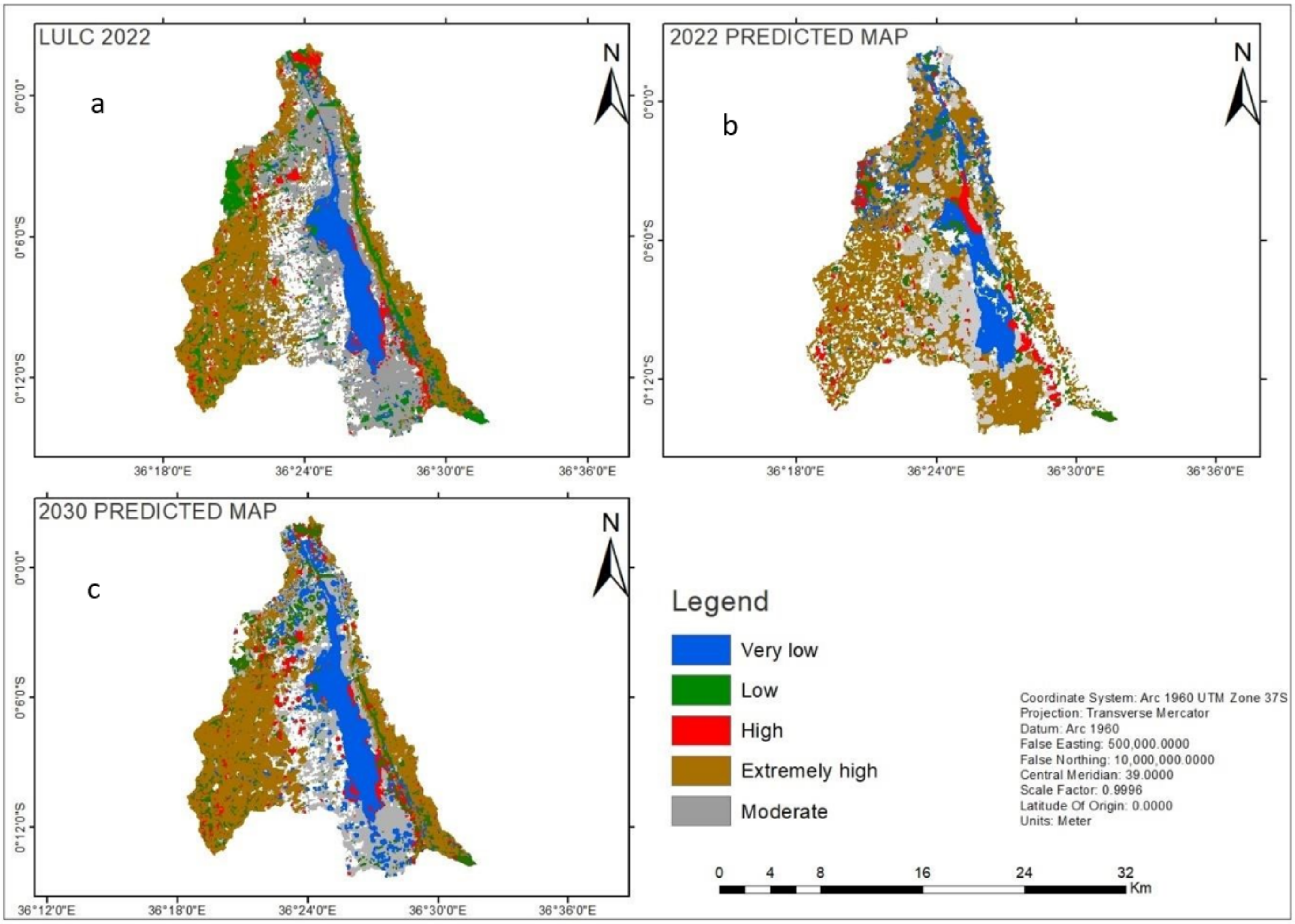

## Figure 4

Weighted PCA-based lake extent maps for the year 1992, 2002, 2012 and 2022




## Figure 5

GIS-ensemble based lake extent maps for the years 1992, 2002, 2012 and 2022




## Figure 6

(a) Simulated Lake extent map for the year 2022 using the GIS-ensemble, (b) predicted lake extent map based on Cellular Automata-Markov chain analysis for the year 2022, (c) Predicted Lake extent map for the year 2030.

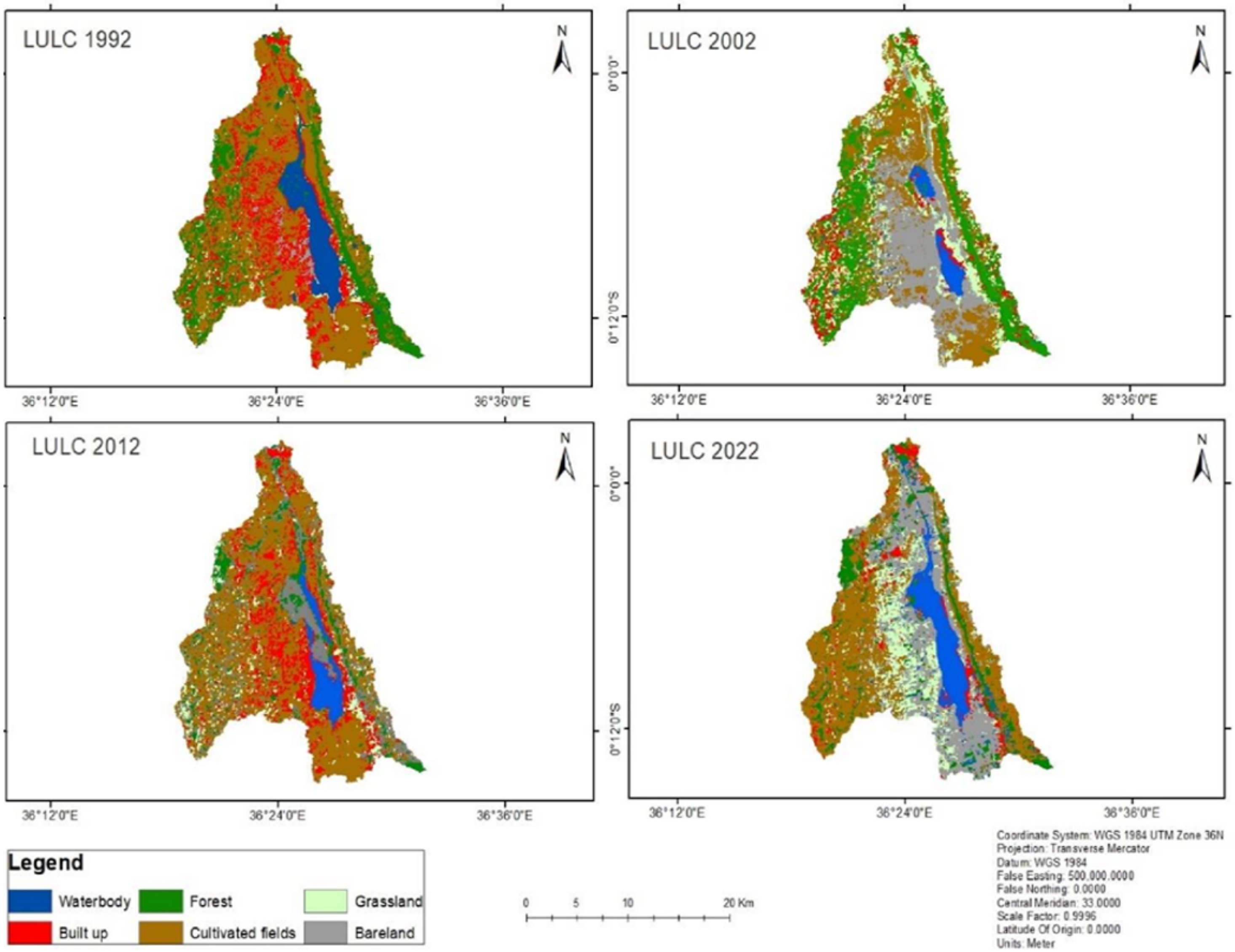



**Figure 7**

Land use land cover maps for the years 1992, 2002, 2012 and 2022.

# Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- plate1.png