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Long-Term Surface Water Variability in Chilika Lake Using Archival Remote Sensing Data †

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Abstract: Asia's largest lake and the world's foremost tropical lagoon, Chilika, stands as a testament to ecological diversity. The lake is diverse in biodiversity and is a sanctuary for over 400 distinct brackish and freshwater species. However, the lake is confronted by ceaseless pressures from a confluence of natural forces and anthropogenic activities. These challenges threaten to unleash ecological transformations that could reshape this ecological marvel. This study examined the spatial–temporal variation in the lake for the years 1988 to 2017 using archival remote sensing data. The Normalized Difference Water Index (NDWI) derived from Landsat 5-TM and Landsat 8-OLI was used to understand the expansion and contraction happening in the extent of the lake. To determine the water spread area, from each NDWI image, the minimum (Min.) pixel values, maximum (Max.) pixel values, and mean pixel values were extracted, and a yearly composite for was created the aforementioned years.

Keywords: NDWI; Landsat; surface water

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1. Introduction

The amplification of human activities and the relentless progression of global climate change have precipitated substantial transformations in the Earth's surface water bodies. Surface water, being among the most indispensable strategic resource for human civilization and social advancement [1], stands as a linchpin resource susceptible to change. Alterations in surface water bodies carry profound ramifications, impacting ecosystems, agricultural production, and ecological well-being [2].

In this context, the utilization of remote sensing technology has emerged as a pivotal tool with versatile applications, encompassing land use/land cover change analysis [3], monitoring coastal ecosystems [4], tracking shifts in vegetation patterns, studying urban sprawl dynamics, and delving into hydrological processes. The significance of obtaining information regarding the spatial distribution of surface water is paramount across multiple scientific disciplines. This information underpins essential activities such as assessing current and future water sources, delineating flood-prone regions, examining river dynamics, conducting watershed analyses, and facilitating comprehensive environmental monitoring.

Remote sensing satellites, characterized by varying temporal, spectral, and spatial resolutions, have offered invaluable capabilities for surface water detection and ecosystem change monitoring over the past three decades [5]. Among these satellites, Landsat data emerge as a stalwart, with the longest archive of cost-free data spanning four decades, making these data an essential resource for the ongoing monitoring of these transformative processes. In recent years, unique image processing techniques were introduced for the extraction of surface water features from satellite imagery [6]; some of them are like single-band and multi-band techniques, enabling the classification of images and the generation of water indices. The Normalized Difference Water Index (NDWI) was developed for extracting water bodies from Landsat imagery [6]. The NDWI demonstrates slightly superior performance compared to other water index algorithms [7]. It employs green and near-infrared (NIR) bands, assigning positive values to water bodies and negative values to non-water areas [8].

Chilika Lake is Asia's largest brackish water lagoon, situated in the east coast of Odisha, India [9], and close to the lake's banks, eight large towns and 122 villages thrive, with approximately 70% of the population being dependent on fishing [10]. In [11], it is revealed that the oldest sediment in the lake dates back 13,500 years, as identified through pollen analysis. The shrinkage of the lake represents another significant ecological transformation, with the current annual shrinkage rate being approximately 14.7 km^2, and the water spread area shrinkage rate is about 1.5 km^2 annually [12]. This study aimed to understand the spatiotemporal variations in Chilika Lake over the period of 1988–2017 using archival remote sensing data. The analysis was performed on the Landsat-derived NDWI and extracted minimum, maximum, and mean pixel values from each NDWI image to estimate the area of water spread.

2. Material and Method

2.1. Study Area and Data Set

The lake is situated (85°20′ E, 19°44′ N) in the east coast state of Odisha, India (Figure 1). The dimensions of the lake exhibit a variation, with its length ranging from 70.81 km to 63.4 km and its width and depth fluctuating between 32.2 km and 20 km and 0.38 m and 4.2 m, respectively [13]. The lake experiences the influence of both the southwest and northeast monsoons during specific periods of the year. The southwest monsoon prevails from May to August, while the northeast monsoon occurs from November to December. The lagoon is geographically enclosed by the Bay of Bengal and maintains its connection to the sea through a few channels. The spectral bands selected for this study are given in Table 1. Figure 2 shows the workflow adopted to conduct this study.

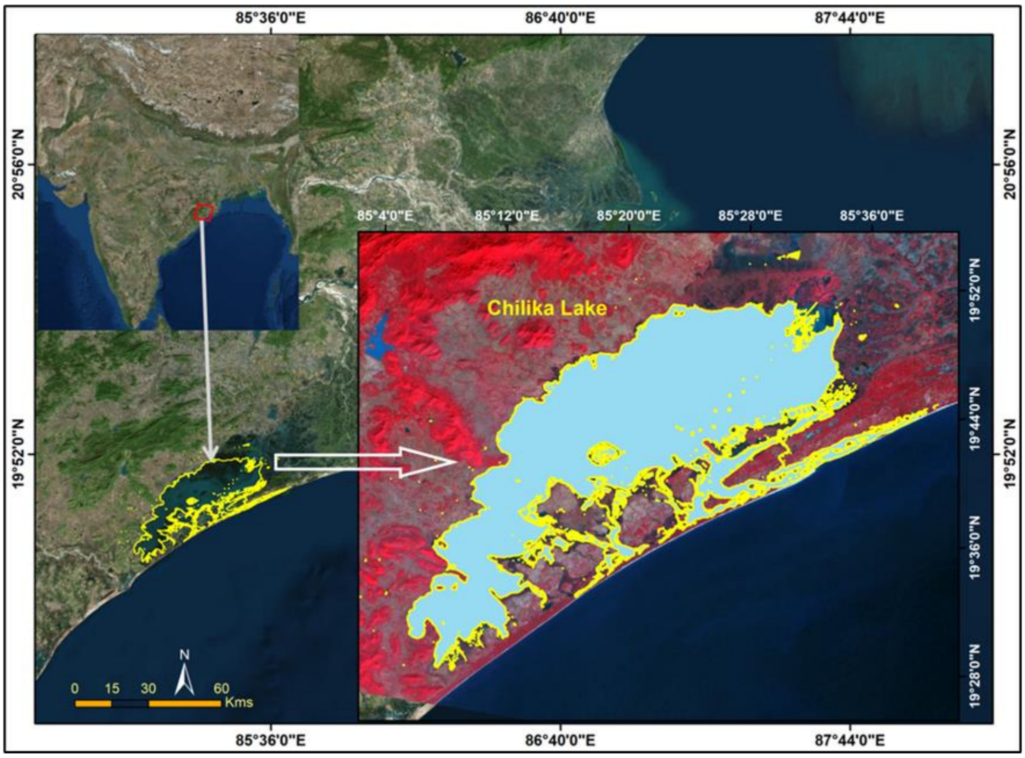

Figure 1. Map showing the location of the study area.

Table 1. Band details of Landsat TM and OLI data.

Landsat 8 (OLI/TIRS)			Landsat 4–5 (TM)			
Bands	**Wavelength (µm)**	**Res. (m)**	**Bands**	**Wavelength (µm)**	**Res. (m)**	**Path/Row**
1—Ultra blue	0.435–0.451	30	1—Blue	0.45–0.52	30	
2—Blue	0.452–0.512	30	2—Green	0.52–0.60	30	
3—Green	0.533–0.590	30	3—Red	0.63–0.69	30	
4—Red	0.636–0.673	30	4—NIR	0.76–0.90	30	140/46
5—NIR	0.851–0.879	30	5—SWIR1	1.55–1.75	30	
6—SWIR1	1.566–1.651	30	6—Thermal	10.40–12.50	120	
7—SWIR2	2.107–2.294	30	7—SWIR2	2.08–2.35	30	

(NIR = near infrared; SWIR = short-wave infrared).

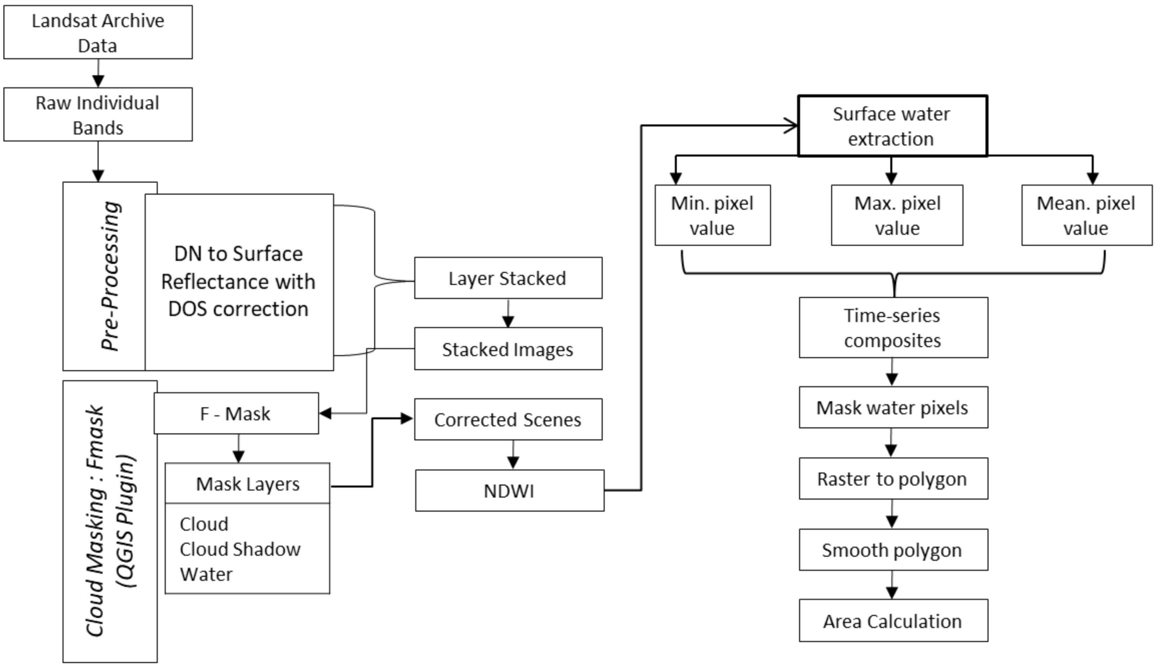

Figure 2. Workflow adopted for the analysis.

2.2. Pre-Processing

The pre-processing of archival data was performed in QGIS using an open-source tool called the Semi-Automatic Classification plug-in [14]. It enables pre-processing, post-processing, raster computations, and supervised and unsupervised classifications to be carried out on remote sensing data.

Individually processed data were stacked in layers for further processing. Landsat is an optical sensor, and the presence of clouds can have a significant impact on data quality. The cloud masking plugin (Fmask) [15] was applied to each stacked image. Fmask distinguishes between Potential Cloud Pixels (PCPs) and Clear Sky Pixels (CSPs) based on physical cloud features and removes all invalid data from the scenes. After pre-processing, the Landsat-derived Normalized Difference Water Index (NDWI) was generated to extract the surface water extent.

2.3. Surface Water Extraction Uisng NDWI

To detect the spread of the water, the surface water index for each temporal image was created for the period of 1988–2017. Using Equation (1), the NDWI was calculated. The band specifications of Landsat TM (green = band 2, NIR = band 4) and Landsat OLI (green = band 3, NIR = band 5) were used.

$$\text{NDWI} = (\text{Green} - \text{NIR})/(\text{Green} + \text{NIR}) \tag{1}$$

The minimum, maximum, and mean pixel values from each individual NDWI image were extracted for the period of 1988 to 2017, and annual composites were built for each year. To delineate water bodies accurately within the NDWI images, we utilized the raster calculator tool available in QGIS 3.281 software. The NDWI ranges from 1 to −1, with positive values corresponding to water areas and negative values corresponding to land. Using the raster calculator's algorithm (A > 0, 'A' represent raster image), water pixels with positive values are masked. This formula effectively masked out pixels with positive NDWI values, creating a new water mask image with binary values: Low (0) for land and High (1) for water bodies. The subsequent step involved converting the water mask raster image into a vector format. This conversion was performed using the 'Raster to Vector' tool in QGIS software, with a specified field name, 'DN'. To isolate only the water areas of interest, we applied an expression (DN = 1) within the attribute table of the vector image and selected the 'save only selected features' option when saving the vector layer.

The resulting polygon boundaries exhibited sharp edges, which required smoothing for a more accurate representation. To achieve this, we employed the 'smooth polygon' tool available in ArcGIS 10.8.2 software. Given that our area of interest primarily centered on Chilika Lake, we undertook an additional step to exclude nearby water bodies by editing the polygon data. Subsequently, we calculated and analyzed the total surface water area for each annual composite image within the 1988–2017 timeframe.

3. Results and Discussion

3.1. Surface Water Change Detection Using NDWI Technique

Here, we studied the temporal variations in lake surface area from 1988 to 2017. The dataset encompassed three key variables: minimum lake surface area, maximum lake surface area, and mean lake surface area.

3.1.1. Minimum Lake Surface Area

There was a consistent trend in lake surface area expansion between 1988 and 1993, with yearly increases ranging from 30 km^2 to 504 km^2 (Table 2). This shows that causes such as increasing precipitation or other hydrological processes may have contributed to the lake's development during this time period. But, between 1998 and 2003 and 2003 to 2008, the results show a series of negative changes, indicating reductions in lake surface area. The largest decrease occurred between 2003 and 2008, with a decline of 383 km^2. After 2008, the results indicate a period of relative stability in lake surface area, with smaller changes as compared to the preceding years. Figure 3 shows the variations in the extent of lake by taking the minimum pixel value for the period of 1988–2017.

Table 2. Changes in lake surface area extracted from minimum pixel value method.

Year	Minimum km^2	Change in Lake Surface Area (km^2)						
1988	282	30						
1993	312		504					
1998	816			−55				
2003	761				−383			161
2008	378					11		
2013	389						51	
2017	440							

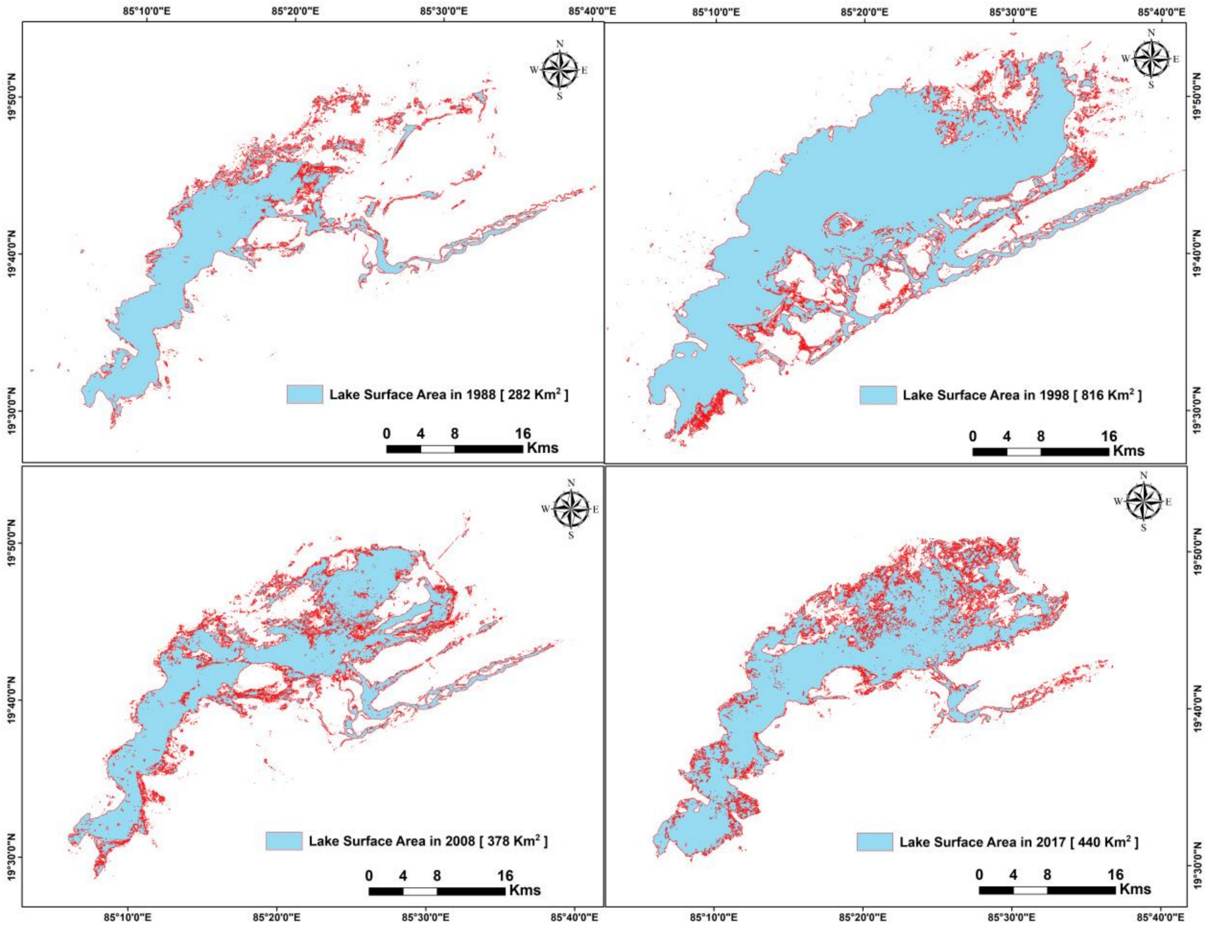

Figure 3. Chilika Lake surface area change maps using Min. method between 1988 and 2017.

3.1.2. Maximum Lake Surface Area

The results show a mix of positive and negative changes in lake surface area over the years (Table 3). In 1993, there was a slight increase of 3 km^2 in lake surface area, while in 2003, there was an increase of 60 km^2. The data also reveal years with negative changes, indicating a reduction in lake surface area. Notable periods of contraction occurred between 1993 and 1998, and again between 2008 and 2013 with a decrease of 67 km^2. The most substantial reduction occurred between 1993 and 1998, with a decrease of 145 km^2. After 2013, the results show relative stability in lake surface area, with positive changes. Figure 4 shows the variations in the extent of lake by taking the maximum pixel value for the period of 1988–2017.

Table 3. Changes in lake surface area extracted from maximum pixel value method.

Year	Maximum km^2	Change in Lake Surface Area (km^2)	
1988	959		
1993	962	3	
1998	817	−145	
2003	857	60	−82
2008	984	27	
2013	917	−67	
2017	957	40	

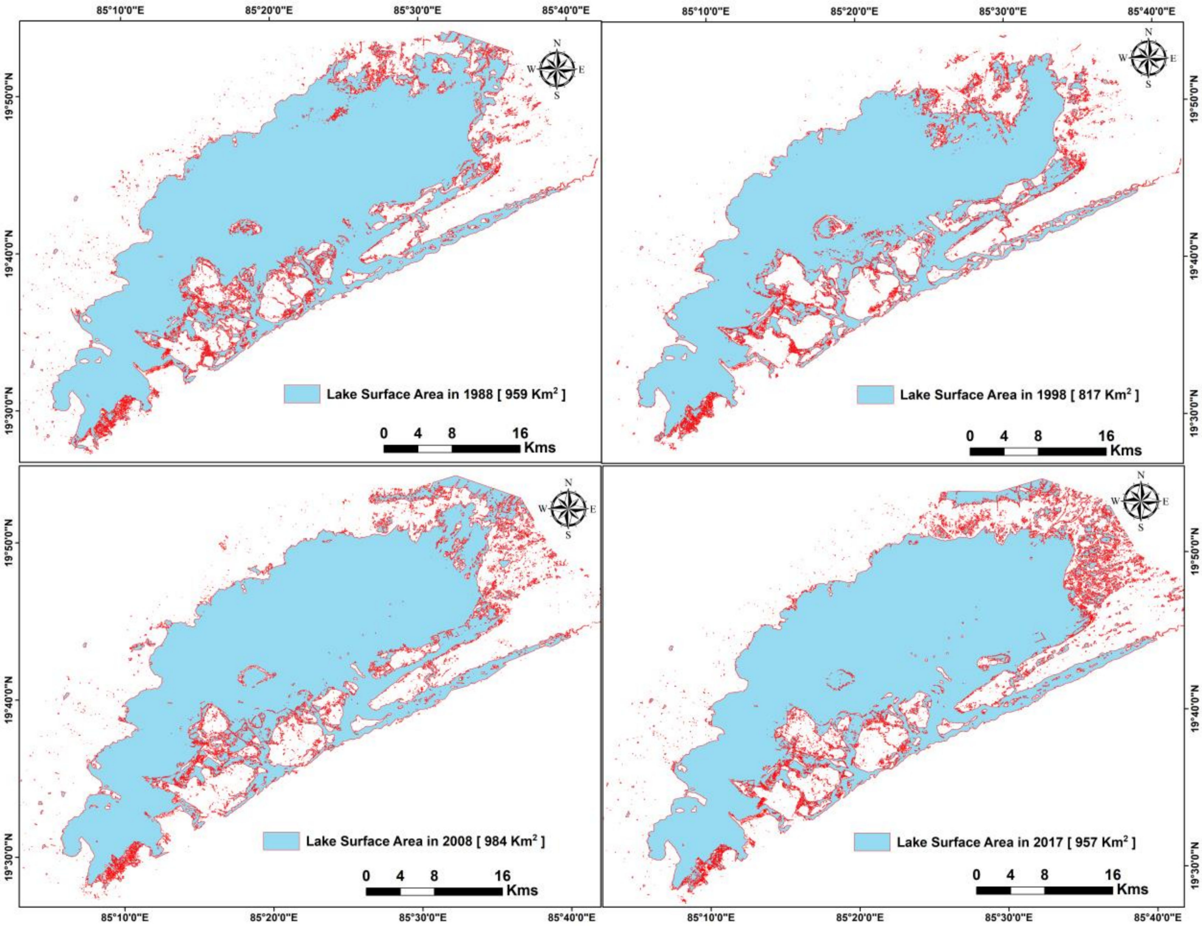

Figure 4. Chilika Lake surface area change maps using Max. method between 1988 and 2017.

3.1.3. Mean Lake Surface Area

Table 4 shows a notable increase of 15 km^2 in mean surface area from the year 1988 to 1993, followed by another increase of 137 km^2 in 1998. The results also reveal years with negative changes, indicating a reduction in mean lake surface area. Significant contractions occurred between 2003 and 2008, when there was a decrease of 122 km^2. After 2008, there was stability in the lake surface area, with an increase of 58 km^2 in subsequent years. Figure 5 shows the variations in the extent of lake by taking the mean pixel value for the period of 1988–2017.

Table 4. Changes in lake surface area extracted from mean pixel value method.

Year	Mean km^2	Change in Lake Surface Area (km^2)						
1988	665	15						
1993	680		137					
1998	817			14				
2003	831				−122			103
2008	709					58		
2013	767						1	
2017	768							

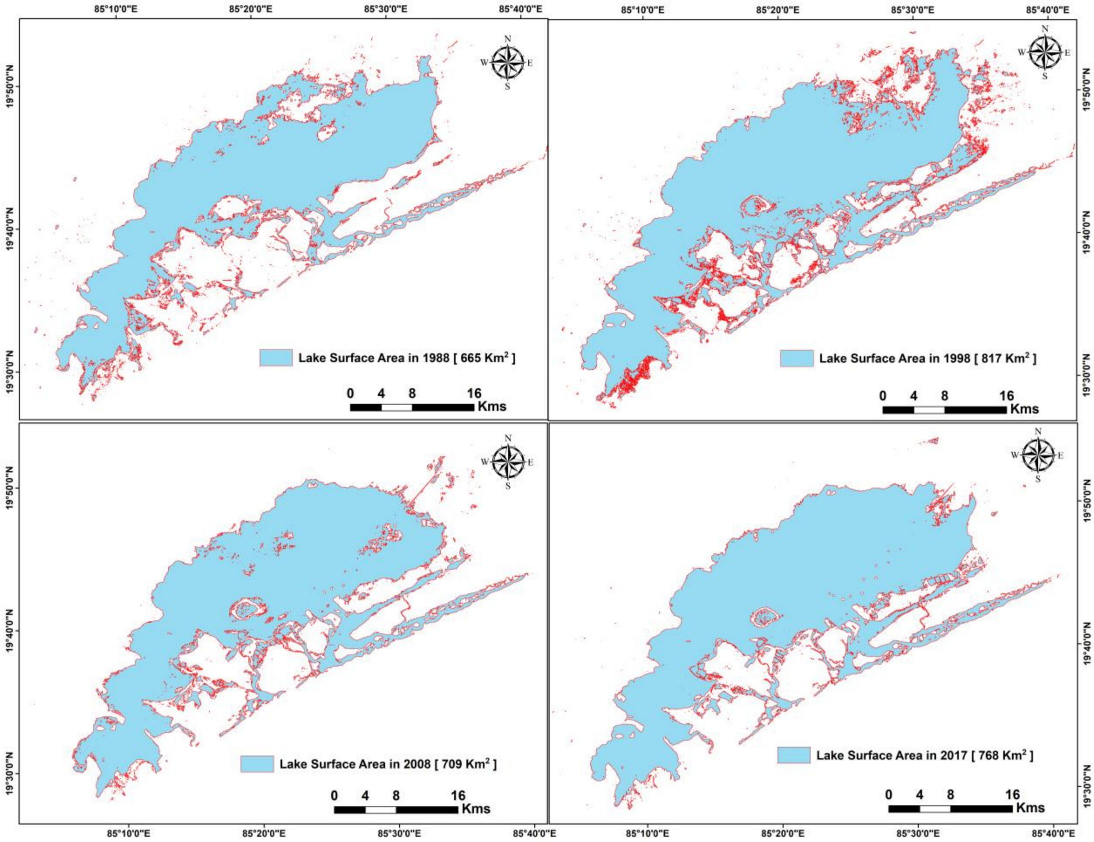

Figure 5. Chilika Lake surface area change maps using mean method between 1988 and 2017.

4. Discussion

The fluctuations in the lake surface area highlight the dynamic nature of the region's hydrological system. Factors such as groundwater inflow, outflow, and evaporation play a role in shaping the lake's size and can be influenced by climatic conditions. Understanding these statistics is crucial for assessing the ecological and environmental significance of the lake. Changes in the lake surface area can impact aquatic ecosystems, water quality, ease of access for fishing, and the availability of water resources for various uses, including agriculture and municipal supply. The surface area of a lake directly affects the amount of available fish habitat. A reduction in lake surface area due to factors like drought, excessive water extraction, or land reclamation can lead to a loss of critical fish habitats. This can result in lower fish populations and reduced catches for fishing communities.

Monitoring these trends over time is important for assessing the potential impacts of climate change on the region's hydrology. Shifts in precipitation patterns can have far-reaching consequences for water availability and ecosystem health. While this offers valuable insights, further research and comprehensive analysis are necessary to elucidate the complex relationships between these variables and their broader implications for the regional environment and water resource management.

5. Conclusions

This study aimed to identify the spatiotemporal changes occurring in Chilika Lake for the period of 1988–2017. The results show a mix of positive and negative trends in the lake surface area for the above-mentioned period. An intense contraction in the lake was observed between 2003 and 2008, when the lake lost about 383 km^2 of its surface area. However, the dataset presented in this study underscores the dynamic nature of the lake's surface area and annual precipitation in the region over a 30-year period. To monitor the changes in water bodies, Landsat satellite imagery provides appropriate temporal and spatial resolution data. The time-series analysis presented in this study will be continued with current Landsat data. For future work, will utilize the time-series data to examine how surface water dynamics and connectivity are affected by climate, water abstraction, and land use change spatially and temporally.

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