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ENHANCING OPERATIONAL STRATEGIES IN WATER RESERVOIR MANAGEMENT THROUGH SATELLITE IMAGERY: ANALYSING TEMPORAL ANOMALIES IN WATER SURFACE VARIATIONS FOR CLIMATE ADAPTATION UNDER SEASONAL CHANGES

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ABSTRACT

Climate change variations have significant adverse impacts on water resources, particularly in regions where the water supply is primarily dependent on reservoir systems. For efficient management of water resources, it is essential to comprehend the dynamics of reservoir water levels and climate-driven anomalies. Quantitatively appraising the water budget is crucial for enhancing socio-economic water and energy demands. Analyzing fluctuations in water levels and cyclic patterns of drought seasons due to climate change can significantly aid in the pre-planning and managing reservoir systems. This study aims to enhance water reservoir management by using satellite imagery to identify drought periods through surface water area analysis. With the fusion of Landsat 8 and Sentinel-1 data, this research focuses on mapping water surface changes at the Victoria Lake reservoir, Sri Lanka, using the Normalized Difference Water Index (NDWI) from 2018 to 2023. Both satellite data were acquired and subsequently processed on the Google Earth Engine platform (GEE). The resulting maps were created using ArcMap desktop software. The correlation coefficient observed between Landsat 8 and Sentinel-1 NDWI area measurements is 0.771, indicating a strong relationship between the two datasets. This high correlation underscores the reliability of using both sources to comprehensively analyze water surface area. Factors such as sensor calibration, atmospheric conditions, and data processing techniques can affect recorded values and correlations. Results revealed a cyclic pattern in water levels, with a notable trough in March 2019, followed by a significant drop lasting until March 2022, and another rapid decline *observed within the subsequent year. Integrating satellite imagery in monitoring and decision-making processes offers a valuable tool for addressing the challenges of water and energy management under climate anomalies.*

Keywords: Landsat, Reservoirs, Sentinel-1, Temporal, Water Dynamics

1. Introduction

The evaluation of lake water surface area is important for studying the behavior of freshwater, regulating water resources, and studying the effects on the environment (Sogno et al., 2022). In this respect, remote sensing has assumed the role of a very effective tool to support hydrological research activities. A comprehensive water budget is vital for various applications, including hydropower generation, agricultural planning, and water supply management (Mohebzadeh & Fallah, 2019). As the demand for water and energy escalates rapidly, ecological protection measures have become increasingly crucial. Traditional reservoir decision-making practices must be adjusted to meet the requirements of social and sustainable development (Yang et al., 2022). It helps stakeholders make informed decisions about water allocation, ensuring that the reservoir's capacity is utilized efficiently without compromising its long-term viability. Monitoring and understanding the dynamics of surface water bodies over extended periods is of paramount importance for effective water resource management, disaster mitigation, and environmental conservation (Duong-Nguyen et al., 2020; Sogno et al., 2022). The integration of satellite imagery in water budget analysis significantly enhances the efficiency of these assessments, enabling proactive and sustainable water resource management (Y. Zhang et al., 2016).

Satellite imagery such as the optical imagery from Landsat 8 and Sentinel-1 Synthetic Aperture Radar (SAR) data offer a powerful means to analyze lake dynamics and monitor water surface area variations. By providing precise and consistent data over time, these remote sensing tools enable a detailed understanding of seasonal and temporal changes in water bodies. Such insights are essential for tackling water management challenges, particularly during periods of drought (Li et al., 2020). The integration of satellite data facilitates not only the mapping of current water levels but also the exploration of strategies to enhance electricity generation, optimize drinking water management, and predict future fluctuations in water levels, thereby supporting the sustainable management of critical water resources (Chen et al., 2021; Mohebzadeh & Fallah, 2019).

This study aims to enhance decision-making for the distribution of available water storage by analyzing the surface area of Victoria Reservoir in Sri Lanka, incorporating remote sensing observations to account for seasonal fluctuations in water levels throughout the year. Victoria Lake, also known as Victoria Reservoir, plays a significant role in Sri Lanka's water resource management and hydroelectric power generation. The reservoir was constructed as part of the Victoria Dam project, which commenced in 1978 and was completed in 1984. The Sri Lankan government executed this project with substantial funding and technical support from the British government (Nandalal et al., 2016). Located near the town of Teldeniya in the Kandy district, spanning a total area of approximately 22.7 square kilometers. The primary purpose of Lake Victoria is to generate hydroelectric power, providing a significant portion of the country's electricity needs. Additionally, it serves as a crucial source of water for irrigation, domestic consumption, and industrial activities. The reservoir's multipurpose use underscores its importance in the region's socio-economic development and environmental sustainability. Understanding and managing the water surface area and level fluctuations of such a vital resource is critical for optimizing its use and ensuring long-term sustainability. However, over the past decade, there have been growing concerns about fluctuations in the lake's water surface area and water levels, which have significant implications for the local communities and ecosystem (Sadeghi et al., 2018).

2. Literature Review

Climate change, seasonal changes, atmospheric extremes, and land use changes significantly influence surface water sources. Estimating the available water budget is crucial for optimizing the use of water resources for human needs, flood prediction modeling, wetland restoration, and disaster precautions (Shen et al., 2022; Yang et al., 2022). Several studies have focused on decision-based approaches for managing water reservoirs effectively, especially for hydroelectric production. The water level fluctuations in reservoirs are a key concern in this context, as they can have significant effects on ecosystem health, energy production, and water supply (Ljahin et al., 2021; Watts et al., 2011). Dam reoperation is one such strategy that involves modifying the way that current dam structures function to better adapt to the changing climate conditions (Watts et al., 2011). This method includes adjusting water release schedules based on real-time reservoir water levels, inflow forecasts, and anticipated energy demands, thereby optimizing water availability and meeting downstream needs. Decision support systems (DSS) that are integrated with weather forecasts, hydrological models, and real-time sensor data can be utilized to support the pre-planning stages of the operations (K. Zhang et al., 2014). While in-situ measurements provide accurate data, they can be prohibitively expensive for continuous monitoring and are often less economical. High-resolution satellite remote sensing offers a cost-effective alternative for comprehensive water estimation, particularly in areas that are difficult to access for in-situ measurements. However, accurate water estimation using remote sensing requires meticulous parameterization, calibration, and validation (Y. Zhang et al., 2016).

Remote sensing techniques offer the advantage of high spatial and temporal coverage, enabling continuous monitoring of surface water body dynamics. However, challenges such as cloud cover, atmospheric noise, and partial coverage over the study area can hinder the accuracy and reliability of the results (Shen et al., 2022). The growing body of literature on the application of remote sensing for inland water quality monitoring and surface water dynamics research underscores the significant contributions of these satellite imaging systems to our understanding of complex water systems, as well as the need for continued advancements in this field (Sogno et al., 2022).

2.1. Landsat 8 for Water Body Mapping

Recent studies have compared the performance of various remote sensing-based methods for identifying open water bodies using Landsat 8 imagery, highlighting the importance of assessing the accuracy and reliability of these techniques (Hashim et al., 2019)(Y. Zhang et al., 2016)(Chen et al., 2021). Landsat 8 satellite mission launched by NASA on February 11, 2013, is part of the Landsat program, designed to capture high-resolution images of the Earth's surface. Equipped with the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS). Data provides multiple spectral bands, including visible, near infrared, and thermal wavelengths (Sheffield et al., 2009). It features a spatial resolution of 30-meter bands and a 100-meter resolution for thermal bands, with a 16-day revisit cycle (Sahoo et al., 2011). This satellite mission operated by the United States Geological Survey, provides a longer historical record of satellite imagery, allowing for the analysis of long-term surface water dynamics (Irons et al., 2012). However, with its 30-meter resolution, finer details of lake bodies and surrounding areas may not be accurately captured, and the longer revisit time, along with cloud cover, can affect the consistency and reliability of the results (Hashim et al., 2019).

2.2. Sentinel-1 SAR for Water Body Mapping

One of the widely used Earth observation satellite systems for water area mapping is the European Space Agency's Sentinel-1 satellite, which provides frequent and freely accessible SAR imagery. Several studies have successfully demonstrated the application of Sentinel-1 data for water body mapping and long-term change analysis (Duong-Nguyen et al., 2020; Pamungkas & Chiang, 2021; Shen et al., 2022). Sentinel-1, part of the European Space Agency's Copernicus Program, consists of two satellites: Sentinel-1A (operational) and Sentinel-1B (Non-operational from Dec 2021). These satellites are equipped with C-band (~5.7 cm wavelength) SAR instruments, offering single (HH or VV) and dual (HH + VH or VV + VH) polarization data, which are essential for analyzing water body dynamics (Kaplan & Avdan, 2018; Li et al., 2020). Unlike optical sensors, Sentinel-1's SAR data can penetrate cloud cover, and operate in all weather conditions and independent from daylight conditions, making it a valuable tool for consistent and accurate surface water monitoring (Nazir et al., 2023; Shen et al., 2022). By exploiting the differences in radar backscatter between water and land surfaces, Sentinel-1 data can be used to accurately map the extent and changes of water bodies over time (Duong-Nguyen et al., 2020). The high temporal resolution of the Sentinel-1 missions, with a revisit time of 6-12 days, enables the detection of short-term fluctuations in water levels and extents, which is crucial for understanding the impacts of climate variability, human activities, and other drivers of change (Sogno et al., 2022). Sentinel-1, with its 10-meter resolution, facilitates the generation of highly accurate water body maps. Since its integration into the Google Earth Engine (GEE) platform in 2015, Sentinel-1 data has been readily accessible for large-scale hydrological applications (Li et al., 2020).

3. Methodology

The methodology demonstrates an effective integration of multi-satellite data and advanced image processing techniques to monitor and analyze lake surface variations (Figure 1).

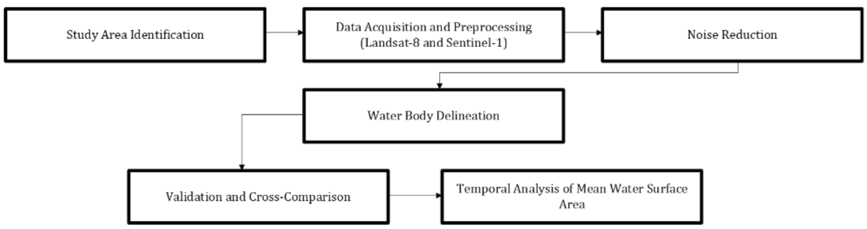

Figure 1: Conceptual Framework of Methodology.

3.1. Study Area

Figure 2 presents a visual representation of the study area, Victoria Lake, a critical water reservoir in Sri Lanka. The image delineates the geographical boundaries of the lake and its surroundings, providing a spatial context for the analysis conducted in this research. Understanding the physical characteristics and the specific location of Victoria Lake is essential for interpreting the subsequent findings related to water surface area variations and their implications for water resource management.

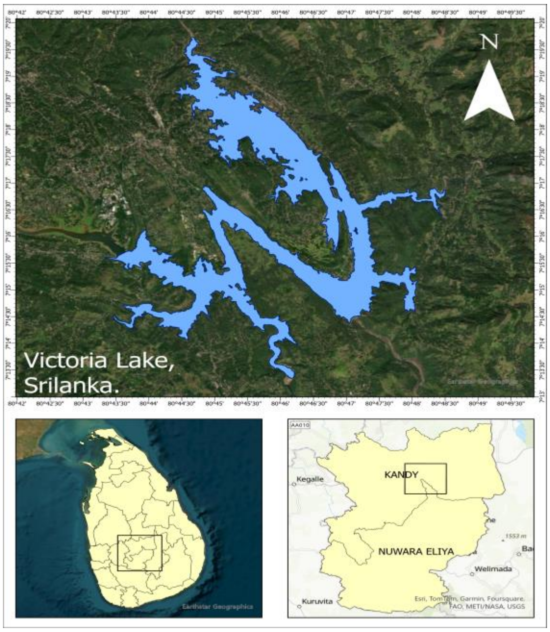

Figure 2: Study Area: Victoria Lake.

3.2. Data Acquisition and Preprocessing

The evaluation of the lake surface area variations commenced with the acquisition of Landsat 8 and Sentinel-1 – 1 satellite imagery. Data acquisition for this study was conducted using the Google Earth Engine (GEE) platform, which provides extensive access to satellite imagery. Utilizing GEE's robust capabilities, a total of 98 images were selected for analysis, including 26 Landsat 8 images acquired under low cloud cover conditions and with complete coverage of the study area, as well as 72 Sentinel-1 images collected between 2018 and the end of 2023. The temporal resolution is 16 days for Landsat 8 and 6 days for Sentinel-1. All Landsat 8 images were used in the study, while monthly mean values from Sentinel-1 were aligned with the corresponding months of Landsat data. By aggregating the images into monthly composites, we created a dataset that reflects the average conditions for each month. This approach mitigates the impact of short-term fluctuations, allowing for a clearer assessment of long-term trends and providing comprehensive temporal coverage essential for detecting and evaluating variations in lake surface area.

3.3. Noise Reduction

For Landsat 8 imagery, noise reduction was achieved through a series of steps such as filtering out images with significant cloud cover, removing images with zero bands, and excluding those with Normalized Difference Water Index (NDWI) areas below a specific threshold. By applying these techniques, analysis effectively minimized the impact of noise and artifacts, ensuring a more accurate and reliable assessment of surface area variations, in the Sentinel 1 data, to enhance the clarity and usability of the radar images, a speckle filter was applied to the monthly composites. This effectively reduces the noise inherent in radar data, thereby improving the accuracy of subsequent analyses.

3.4. Water Body Delineation

Filtered images were processed to compute the Normalized Difference Water Index (NDWI) using eq. 1 (McFEETERS, 1996), a recognized index for delineating water bodies in satellite imagery.

$$NDWI = (G - NIR)/(G + NIR) \quad (1)$$

The NDWI values were thresholded to identify and extract water bodies, ensuring accurate delineation across different image acquisitions, The NDWI is a vital tool in remote sensing for identifying and monitoring water bodies (Assaf et al., 2021; Duong-Nguyen et al., 2020; Li et al., 2020; Shen et al., 2022).

3.5. Spatial Visualization of The Reservoir Water Area Map

The analysis of NDWI areas from satellite observations enabled the visualization of peak and trough water areas over the period, facilitating a spatial understanding of surface variations. This mapping of water area extremes provides deeper insights into the spatial distribution of water body changes over time.

3.6. Analysis of Surface Area Variation

From the fusion of satellite observations, NDWI areas were extracted and analyzed to determine variations in surface areas of water bodies over time. By comparing NDWI areas across different months, changes in lake surface areas were quantified, offering insights into temporal dynamics. The observed changes in water surface areas are proportional to volume fluctuations, and this surface trend analysis can provide valuable insights into reservoir water storage anomalies relative to seasonal conditions.

4. Results and Discussion

4.1.1. Water Area Maps

Figure 3 illustrates the NDWI map of Victoria Reservoir in February 2018. This figure is crucial as it establishes a baseline for water surface area within the study period. By showcasing the extent of water bodies at this point, it serves as a reference against which subsequent variations are compared.

Figure 3: NDWI Map of Victoria Reservoir in February 2018.

4.1.2. Spatial Variations of the NDWI Area over the Period

Figure 4 demonstrates spatial variations in NDWI-derived areas from 2018 to 2023. This figure is important as it visually tracks the changes in water surface area over a year, highlighting the temporal dynamics of the reservoir. The data captured in this figure reflects seasonal patterns, environmental changes, and potential impacts of climate variations. These insights are critical for understanding the factors influencing water availability and for making informed decisions in reservoir management. This figure is essential for identifying long-term trends in water surface area fluctuations over multiple years. By comparing these variations over an extended period, the study can assess the impacts of climate change and human activities on the reservoir's water levels. The information depicted in this figure is crucial for developing strategies to mitigate adverse effects on water resources and for planning sustainable water management practices.

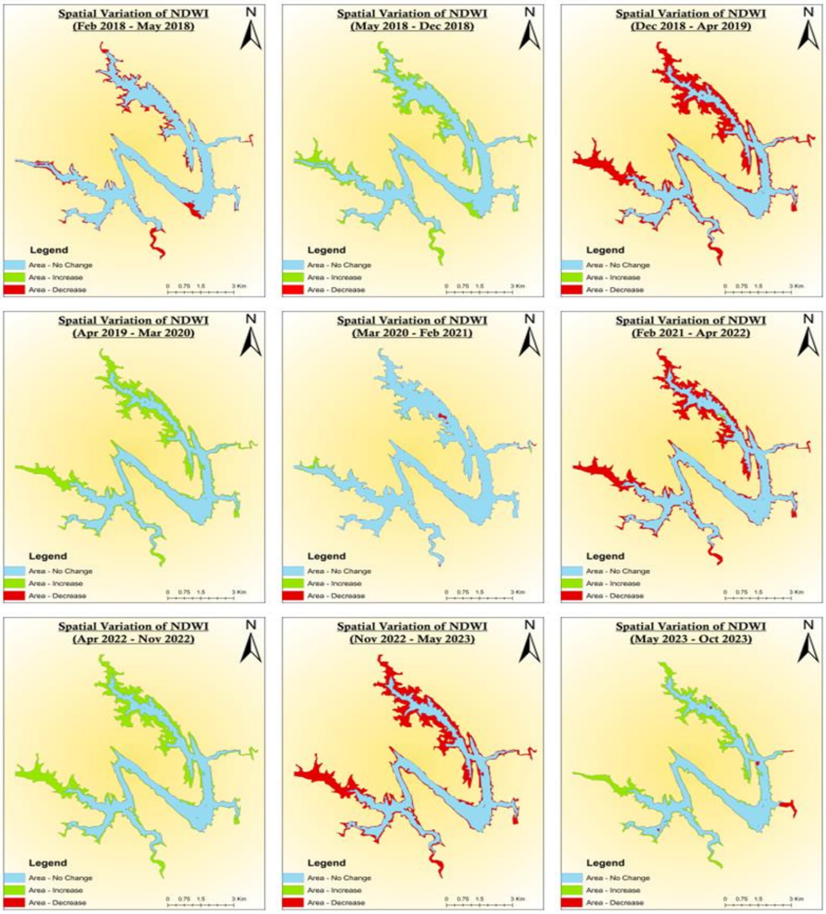

Figure 4: Variation of the Surface Water Extent from 2018 to 2023 using NDWI.

4.1.3. Landsat 8 and Sentinel-1 Water Surface Area

Figure 5 compares the NDWI areas derived from Landsat 8 and Sentinel-1 data over the study period. This figure is significant as it evaluates the consistency and reliability of the two satellite datasets in capturing water surface area. The correlation between these datasets, as depicted in the figure, supports the robustness of the study's methodology. By validating the data through cross-comparison, the figure enhances the credibility of the study's findings and provides a solid foundation for further analysis.

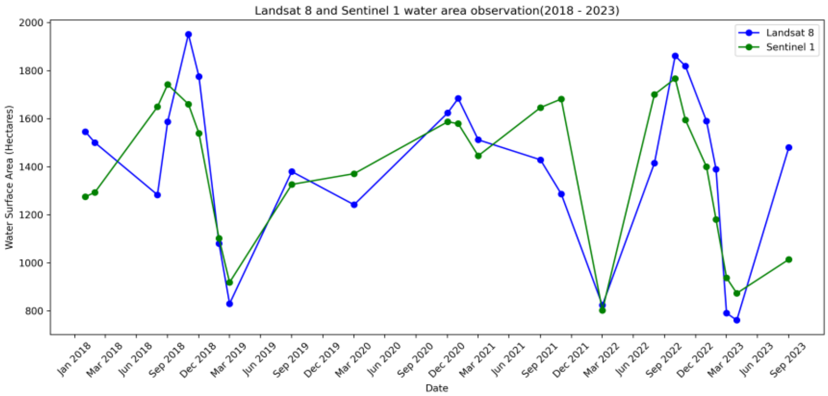

Figure 5: NDWI Area(ha) from Landsat 8 and Sentinel-1.

4.1.4. Mean Water Surface Area from Landsat 8 and Sentinel 1 data fusion

Figure 6 illustrates the fluctuations in mean surface water area derived from the fusion of satellite imagery data. The results reveal significant peaks around mid-2018 and late 2022, where the surface water area exceeds approximately 1800 hectares. Conversely, a notable downward trend occurred around the early quarters of 2019, 2022, and mid-2023, with lows reaching roughly 900 hectares. A trough appeared in March 2019, followed by a significant drop that persisted until early 2022, spanning about three years. However, in the subsequent period, a dip was observed again within a short span of nearly one year. These variations suggest a possible seasonal or cyclical pattern, indicating that dynamic processes over time influence changes in the water surface area. It is distinguished that these fluctuations predominantly occurred at the beginning of each first quarter. This pattern suggests that environmental factors such as temperature, precipitation, or human activities may affect the availability and extent of the water body. Further study is needed to determine the specific causes of these variations and to assess their implications for water resource management and ecological stability in the region.

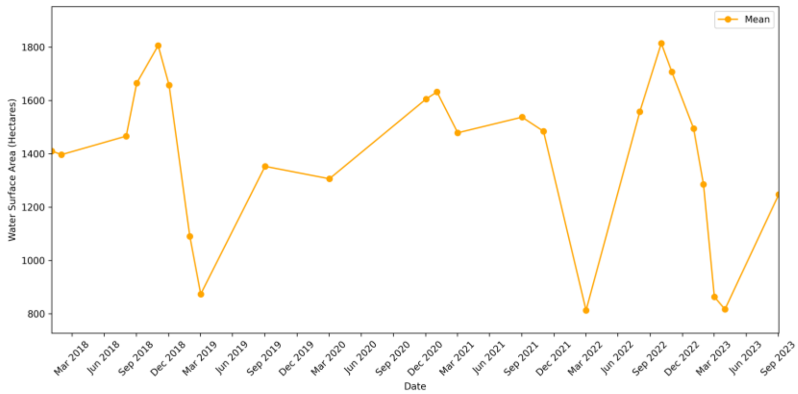

Figure 6: Mean Water Surface Area(ha) over the Period.

Additionally, satellite imagery processing involves cloud filtering and masking techniques especially for optical sensor-based Landsat 8, cloud patches over the lake are considered as non-water pixels, which may hinder the accuracy of water surface area estimation. The Landsat's 30-meter resolution also limits the differentiation between water and the other pixels. In contrast, the NDWI threshold values used during processing influence Sentinel-1 results, which are less affected by weather conditions. NDWI thresholds can impact accuracy by leading to either an overestimation or an underestimation of the actual water surface area. However, combining data from both Landsat 8 and Sentinel-1 can provide a comprehensive understanding of surface water area changes and assist the accuracy of water mapping.

5. Conclusion and Implications

In the context of decision-making regarding water usage practices for reservoirs, the study's findings on temporal anomalies in the water surface area, influenced by climate change, provide valuable insights for optimizing operational strategies. Understanding fluctuations in water levels can enhance water management to ensure a stable supply of water for power generation while quantifying the peak and trough periods can inform water release schedules based on water availability. Also, this pattern can assist in resource conservation and leads to effective planning to meet energy demands during either flood or drought periods. However, certain limitations and potential exceptions should be considered. Variability in sensor accuracy, atmospheric conditions, and seasonal variations may influence NDWI calculations, possibly affecting the consistency of surface area measurements across months. Additionally, fluctuations driven by external factors, such as unanticipated climate events or infrastructural changes, may challenge the generalizations inferred from typical patterns, requiring adaptive strategies. Furthermore, the integration of satellite data can be used for monitoring water quality parameters such as turbidity and chlorophyll levels, which is crucial for assessing the ecological status of the reservoir. Additionally, maintenance scheduling can also be optimized by aligning it with water levels to minimize operational disruptions. By integrating these findings into decision-making processes, power plants can enhance operational efficiency, adapt to environmental changes, and contribute to more sustainable water resource management.

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