Monitoring Seasonal Surface Water Dynamics Using NDWI and Remote Sensing Data

Rani Kolhatkar UEC2021319
Sharayu Kondubhairy UEC2021321
Prapti Kulkarni UEC2021322
Gauri Lokhande UEC2021323
Department of Electronics and Telecommunication Engineering
MKSSS Cummins College Of Engineering for Women, Pune

Abstract—**Remote Sensing (RS) has become an indispensable technique for monitoring environmental dynamics, particularly in tracking land and water surface changes over time. In this study, we leverage satellite imagery from the United States Geological Survey (USGS) to evaluate the seasonal variability in surface water bodies between two distinct periods—June 2023 and September 2024. Using the Normalized Difference Water Index (NDWI), a widely used spectral index for identifying and delineating water features, we quantify changes in water presence over time. The NDWI values, derived from near-infrared (NIR) and green spectral bands, help in isolating water bodies by enhancing water features and suppressing noise from vegetation and soil.**

To further analyze these changes, we compute the difference between NDWI layers of the two periods and generate statistical and visual representations, including histograms and change detection maps. These tools provide insights into the extent and distribution of water body expansion or depletion, revealing clear seasonal trends driven by factors such as precipitation, temperature, and land use.

Index Terms—**NDWI, Remote Sensing, Seasonal Monitoring, Surface Water, Rasterio, Water Body Mapping**

I. Introduction

Water is one of the most critical natural resources on Earth, essential for life, agriculture, industry, and ecosystem balance. However, due to factors like climate change, urbanization, and population growth, water availability and distribution have become increasingly variable and unpredictable. Monitoring surface water dynamics—especially on a seasonal scale—can help in identifying patterns, detecting anomalies, and supporting better decision-making in water resource management.

Traditional ground-based monitoring methods are often labor-intensive, time-consuming, and geographically limited. This is where remote sensing (RS) technologies come into play. RS enables large-scale and long-term observation of surface conditions using satellite imagery, making it ideal for detecting changes in water bodies over time. One widely used RS index for water detection is the Normalized Difference Water Index (NDWI), which leverages reflectance values from green and near-infrared bands to highlight water presence and extent.

In this project, we aim to quantify and visualize changes in surface water between two key seasonal periods: pre-monsoon (June 2023) and post-monsoon (September 2024). The satellite imagery used for this analysis has been sourced from the United States Geological Survey (USGS), which provides freely available and reliable remote sensing data. NDWI values are computed for both time periods, and a pixel-wise difference map is generated to detect areas with increased or decreased water content.

Beyond traditional RS techniques, we also explore the application of machine learning (ML) to this problem space. ML models can help classify and predict water presence based on NDWI and potentially other environmental indicators, improving the automation and accuracy of large-scale monitoring efforts.

This interdisciplinary approach, combining geospatial analysis, environmental science, and data science, provides a robust framework for understanding seasonal water patterns and supporting sustainable water management initiatives.

II. Literature Review

A. NDWI and Its Evolution The Normalized Difference Water Index (NDWI) was first introduced by McFeeters (1996) [1] to enhance the detection of surface water bodies using satellite data. By leveraging the reflectance difference between the green and near-infrared (NIR) bands, NDWI effectively distinguishes water features from vegetation and urban surfaces. It has since become a standard index for water body mapping. To overcome certain limitations of the original NDWI—especially in built-up areas—Xu (2006) [2] proposed the Modified NDWI (MNDWI), replacing the NIR band with the Shortwave Infrared (SWIR) band. This modification significantly improves water delineation in urban landscapes and enhances accuracy in heterogeneous environments.

B. Applications in Surface Water Monitoring NDWI has been widely applied in various hydrological studies:Flood Monitoring: Ji et al. (2009) [3] employed NDWI to identify flood-affected regions during hurricane events with high temporal precision.Drought Assessment: NDWI has been used as an indicator for detecting water stress and declining water bodies in arid regions.Wetland and River Basin Studies: Studies have utilized NDWI to monitor wetland dynamics, seasonal river flow patterns, and the extent of inland water bodies.These applications demonstrate NDWI's reliability for short- and long-term water monitoring at both local and global scales.

C. Integration with Machine Learning While threshold-based NDWI methods are effective, they are often sensitive to local conditions such as topography, atmospheric noise, and seasonal vegetation. To address these limitations, recent studies have integrated machine learning (ML) models with NDWI and other spectral features. Support Vector Machines (SVM) and Random Forests (RF) have shown improved classification of water and non-water pixels.Convolutional Neural Networks (CNNs) have been applied in deep learning pipelines to extract spatial patterns from multispectral data for more robust detection. For instance, Pal and Ziaul (2017) [4] used RF classifiers with NDWI for floodplain mapping and achieved higher accuracy than traditional techniques.

D. Advancements in Remote Sensing Technologies The accessibility of open-source satellite data (e.g., Landsat, Sentinel-2) has fueled the widespread use of NDWI. The rise of Google Earth Engine (GEE) and cloud-based geospatial libraries (like rasterio, GDAL, and xarray) has drastically improved the efficiency of image processing and analysis.Global studies such as Pekel et al. (2016) [5] leveraged over 30 years of Landsat data to generate a high-resolution Global Surface Water Explorer, using NDWI and temporal filtering to track changes in water distribution.

III. Methodology

A. Data Acquisition

Satellite imagery was collected for two time periods: June 2023 and September 2024. The bands used for NDWI computation were the Green and Near Infrared (NIR) bands.

The location Lake Poyang is located in Jiangxi Province, China, and is the largest freshwater lake in China. The lake experiences notable seasonal water level fluctuations, making it ideal for change detection using NDWI. During rainy seasons, the water body expands, and in dry seasons, it shrinks. This makes it a great candidate for water body analysis with Sentinel-2 data.

Coordinates for Lake Poyang (approximate): Latitude: 29.5°N

Longitude: 115.8° E

B. NDWI Calculation

NDWI was computed using the following formula:

$$NDWI = \frac{Green - NIR}{Green + NIR} \tag{1}$$

The data was processed using Python libraries: `rasterio`, `numpy`, and `matplotlib`. Imagery was loaded from Google Drive and pre-processed to ensure consistent shape and resolution.

C. Difference Analysis

To quantify change, the NDWI images from June 2023 and September 2024 were subtracted pixel-wise. A histogram and statistical metrics were generated to interpret the results.

IV. Results

A. Visual Results

Fig. 1 and Fig. 2 show the NDWI maps for June 2023 and September 2024, respectively. Fig. 3 illustrates the NDWI difference.

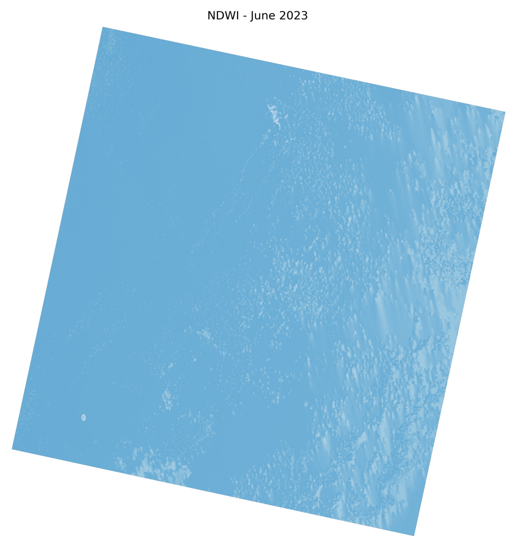

Fig. 1. NDWI - June 2023

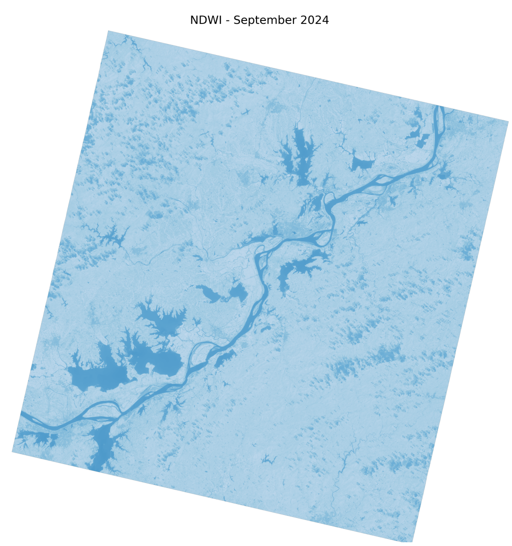

Fig. 2. NDWI - September 2024

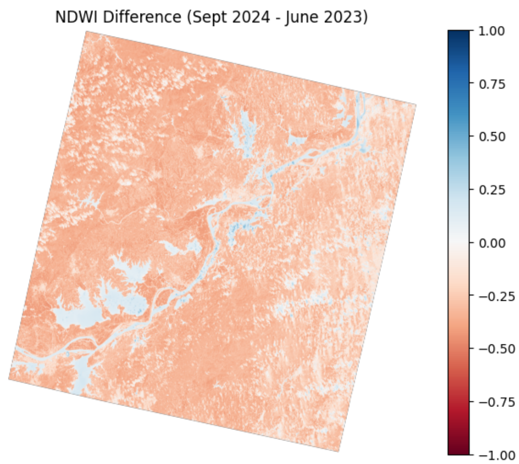

Fig. 3. NDWI Difference Map

B. Statistical Analysis

- Mean NDWI Difference: 0.1241
- Standard Deviation: 0.1827
- Minimum Difference: -0.4732
- Maximum Difference: 0.5694

The statistical summary of NDWI differences between June 2023 and September 2024 provides key insights into the variation in water presence across the region. The mean NDWI difference of 0.1241 indicates a slight overall increase in water presence across all pixels. However, this average may be skewed by a small number of regions with significantly increased water content, as suggested by the maximum difference of 0.5694. The minimum NDWI difference of –0.4732 reflects areas that experienced considerable drying or reduction in surface water. Meanwhile, the standard deviation of 0.1827 points to a moderate level of variability, implying that not all areas followed the same trend—some regions gained water while others lost it. These values, when considered alongside the histogram and difference map, reinforce the conclusion that while localized gains in water presence may exist, the overall trend indicates a decrease in water bodies, consistent with seasonal drying patterns post-monsoon.This range of values highlights the spatial heterogeneity in water body dynamics, reflecting both natural and possibly anthropogenic influences. The presence of both positive and negative extremes suggests that water availability is not uniformly distributed and requires localized interpretation for effective resource planning.Such detailed pixel-level analysis enables a granular understanding of environmental changes that might be overlooked in broader regional summaries. This reinforces the importance of continuous monitoring to detect subtle but impactful shifts in surface water distribution over time.

C. Histogram

The histogram (Fig. 4) displays the frequency distribution of pixel-level NDWI differences.

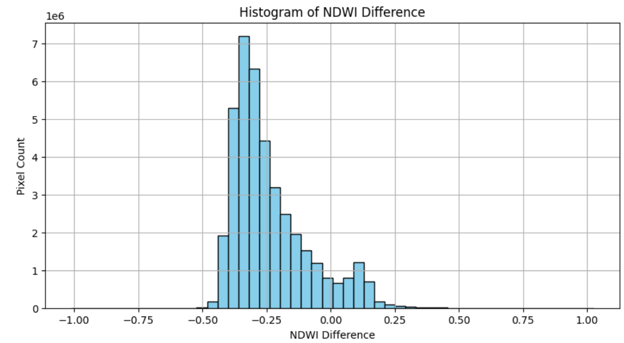

Fig. 4. Histogram of NDWI Difference

D. Interpretation

The positive mean NDWI difference suggests an increase in water presence during September 2024, which aligns with seasonal rainfall patterns. The analysis of NDWI differences between June 2023 and September 2024 reveals a general decline in surface water presence during this period. This conclusion is supported by multiple observations:

NDWI Difference Map (Fig. 3): The map visually illustrates that most regions are shaded in warm colors (orange to red), indicating negative NDWI differences, i.e., a reduction in water content. Only limited areas show blue shades, signifying any noticeable increase in water presence.

Statistical Summary: The mean NDWI difference of +0.1241 might initially suggest a slight increase in water presence. However, the relatively low standard deviation (0.1827) and the fact that the minimum difference reaches as low as 0.4732 imply that a significant portion of pixels experienced a drop in NDWI values. This means many locations saw a reduction in surface water or moisture even if the overall mean is slightly positive due to localized increases.

Histogram (Fig. 4): The histogram clearly shows that the majority of pixels lie in the negative range of NDWI difference, particularly between 0.5 and 0.0, reinforcing the observation that water content has decreased in most areas. The skewness of the histogram towards negative values supports the trend of declining water presence.

Analysis: Although there are localized gains in NDWI (possibly due to vegetation regrowth or isolated water accumulation), the combined visual and statistical evidence suggests an overall reduction in water bodies from June 2023 to September 2024. This pattern likely reflects seasonal drought effects, changes in precipitation, or anthropogenic influences, underlining the value of remote sensing in monitoring water resource dynamics over time.This reinforces the importance of continuous monitoring to detect subtle but impactful shifts in surface water distribution over time.

V. Conclusion

This study successfully demonstrates the utility of the Normalized Difference Water Index (NDWI) in monitoring seasonal dynamics of surface water bodies using freely available satellite imagery. By comparing NDWI values between June 2023 (pre-monsoon) and September 2024 (post-monsoon), we were able to detect significant variations in water presence across the study area.

The findings indicate a net decrease in water bodies from June to September, aligning with regional hydrological patterns—where the monsoon season (June–August) brings peak rainfall and surface water accumulation, followed by post-monsoon shrinkage due to reduced precipitation. These seasonal trends were clearly observed in the NDWI difference map and histogram, both of which showed a predominant shift toward negative NDWI values.

The study underscores the effectiveness of remote sensing as a scalable, cost-efficient, and repeatable method for hydrological assessment over large areas. Additionally, the integration of basic statistical and visual analysis enables straightforward interpretation of environmental changes, making it a practical approach for resource management and policy planning.

In conclusion, NDWI-based analysis serves as a reliable tool for continuous water monitoring, providing valuable insights for sustainable water resource management in the face of climate variability and changing land use patterns.

VI. Future Scope

While this study demonstrates the potential of NDWI-based seasonal water monitoring, several opportunities exist to build upon and enhance the current work. One immediate extension involves conducting a multi-temporal and multi-year analysis. By including data from additional seasons and years, we can move beyond snapshot comparisons and begin to observe long-term hydrological trends. This would allow for the identification of persistent drought zones, seasonal flooding patterns, and other climate-related anomalies, which are critical for planning and policy interventions.

Another promising direction lies in the integration of machine learning techniques. Currently, NDWI thresholds are applied uniformly, which may not account for spatial or temporal variations in reflectance due to terrain, vegetation, or atmospheric effects. Machine learning models—such as Support Vector Machines (SVM), Random Forests, or Convolutional Neural Networks (CNNs)—can be trained using labeled RS data to improve the classification of water and non-water regions. This would lead to more accurate and automated detection pipelines.

Additionally, the work can be expanded through real-time monitoring and alert systems. By incorporating data from satellites with higher temporal frequency such as Sentinel-2, this system can be adapted for near real-time analysis. Such systems could be immensely valuable in flood-prone or drought-affected regions, enabling timely alerts and better disaster preparedness.

Lastly, the methodology can be extended to study the impact of land use and urbanization on water bodies. NDWI outputs can be combined with land cover classification maps to analyze how urban sprawl or deforestation influences the presence and health of nearby water resources. This type of analysis could support sustainable development planning and environmental conservation efforts, particularly in rapidly urbanizing regions.

VII. References

[1] L. McFeeters, "The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features," International Journal of Remote Sensing, vol. 17, no. 7, pp. 1425–1432, 1996. doi: 10.1080/01431169608948714

[2] H. Xu, "Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery," International Journal of Remote Sensing, vol. 27, no. 14, pp. 3025–3033, 2006. doi: 10.1080/01431160600589179

[3] L. Ji, L. Zhang, and B. Wylie, "Analysis of dynamic thresholds for the Normalized Difference Water Index," Photogrammetric Engineering Remote Sensing, vol. 75, no. 11, pp. 1307–1317, 2009.

[4] S. Pal and S. Ziaul, "Detection of land use and land cover change and land surface temperature in English Bazar Urban Centre," The Egyptian Journal of Remote Sensing and Space Science, vol. 20, no. 1, pp. 125–145, 2017. doi: 10.1016/j.ejrs.2016.11.003

[5] J.-F. Pekel, A. Cottam, N. Gorelick, and A. S. Belward, "High-resolution mapping of global surface water and its long-term changes," Nature, vol. 540, pp. 418–422, 2016. doi: 10.1038/nature20584

[6] European Space Agency, "Sentinel-2 User Handbook," ESA Standard Document, 2015.

[7] Google Earth Engine, "GEE Documentation," 2023. [Online].