MULTI-SENSOR CHANGE DETECTION OF SEASONAL WATER DYNAMICS USING SENTINEL-1 AND SENTINEL-2 IMAGERY

1. BRIEF INTRODUCTION

Changes in inland waterbodies play a critical role in freshwater resource management, with their monitoring offering valuable insights for flood forecasting, irrigation planning, and climate resilience. Reservoirs serve as key infrastructures for regulating, storing, and distributing freshwater across regions. Numerous studies have successfully leveraged satellite data to monitor these water sources; however, most have relied on single sensor approaches. Addressing this limitation, the present study integrates both microwave (Sentinel-1 SAR) and optical (Sentinel-2 MSI) datasets to assess seasonal water level variations across pre- and post-monsoon periods.

The analysis focuses on two hydrologically dynamic reservoirs in eastern India: Hirakud Reservoir, one of Asia's longest earthen dams with significant monsoon driven fluctuations, and Chilika Lake, India's largest coastal lagoon, known for its complex freshwater saltwater interactions and ecological sensitivity.

2. DATA USED

Two satellite datasets were utilized for the present change detection analysis across pre- and post-monsoon seasons. The first is microwave data from Sentinel-1 Ground Range Detected (GRD) products, acquired in VV and VH polarizations using the Interferometric Wide Swath (IW) mode. These scenes offer a spatial resolution of 10 m and are well-suited for water body delineation under all-weather conditions.

The second dataset comprises optical imagery from the Sentinel-2 Multi Spectral Instrument (MSI), specifically Level-2A products. These scenes provide 10 m resolution and are atmospherically and geometrically corrected, enabling accurate NDWI computation and visual interpretation of surface water dynamics.

3. METHODOLOGY

The overall workflow methodology comprises a sequence of systematic steps designed to ensure accurate and efficient analysis. Initially, the Region of Interest (ROI) is selected based on the study objectives, followed by the definition of an appropriate temporal window to capture relevant temporal variations. Subsequently, an automated data acquisition process is implemented to retrieve the required datasets. The acquired data then undergo preprocessing to correct for radiometric and geometric distortions, ensuring consistency and reliability. This is followed by data processing, where essential indices or features are derived as per the analytical requirements. Thereafter, both datasets are co-registered to achieve precise spatial alignment. Finally, change detection analysis is performed to identify and quantify temporal variations within the study area. The methodology is carried out in a Jupyter Notebook.

3.1 Automated Data Acquisition

The selected study area is delineated within a rectangular boundary defined by the minimum and maximum latitude and longitude coordinates, along with their corresponding centroids. The identified Regions of Interest (ROIs) are subsequently exported in GeoJSON format. The workflow is designed to accommodate flexible temporal windows, allowing users to modify the time frames as per analytical requirements. In the present study, the pre-monsoon period (April–May) and post-monsoon period (September - October) of the year 2024 were considered. The script establishes a connection with the Earthdata and ASF APIs using Well-Known Text (WKT) polygons for Sentinel-1 data acquisition, while Sentinel-2 data are accessed via the AWS STAC API with an integrated cloud filter. Detailed description of data is mentioned in Table 1.

Table 1: List of the datasets used in the present study.

Dataset	Platform / API	Data Level	Bands Used
Sentinel-1	ASF API (Alaska Satellite Facility) via Earthdata authentication	GRD (Ground Range Detected)	VV / VH (Polarizations)
Sentinel-2	AWS STAC API (Earth Search)	L2A (Surface Reflectance)	B02 (Blue), B03 (Green), B04 (Red), B08 (NIR), B11 (SWIR), SCL (Scene Classification Layer)

3.2 Pre-Processing, Processing and Co-registration of Data

Spectral-based enhancements were applied during preprocessing of Sentinel-2. Scenes with less than 30% cloud cover were prioritized to ensure high quality inputs with minimal atmospheric interference. The SCL was utilized to remove clouds and shadows while resampling techniques were applied to address resolution mismatches among the spectral bands. Radiometric normalization using percentile-based stretching (2^{nd}-98^{th} percentile) enhanced visual quality, and RGB composites were generated from Bands 4, 3, and 2.

For Sentinel-1, the workflow is generalized to accommodate any available polarization. However, VV polarization was predominantly employed in the present study. The preprocessing pipeline included extraction of compressed GRD files, spatial sub setting of the central portion of each scene covering the ROI, and radiometric calibration by converting backscatter values to decibel (dB) scale. To minimize speckle noise inherent to SAR imagery, a 5×5 Lee filter was applied, ensuring smoother backscatter patterns while preserving textural details. Georeferencing was subsequently performed using the ROI's bounding coordinates to ensure precise spatial alignment with the optical datasets.

The Normalized Difference Water Index (NDWI) was employed as the primary metric for delineating surface water features using Sentinel-2 imagery, leveraging Bands 3 and 8 to effectively isolate water bodies and quantify seasonal variations. NDWI maps were generated for both pre-monsoon and post-monsoon periods of 2024, serving as the optical baseline for change detection. To ensure spatial alignment between optical and SAR datasets, Sentinel-1 backscatter imagery was co-registered to the NDWI reference grid using a geometry-driven reprojection approach via the *rasterio.warp.reproject()* function. This method extracted the coordinate reference system (CRS), affine transformation, and raster dimensions from the NDWI image and applied bilinear resampling to reproject the SAR data, preserving its radiometric fidelity. The resulting harmonized datasets enabled precise pixel-level comparison across modalities, facilitating robust spatio-temporal analysis of water extent dynamics. These processed outputs served as the foundation for subsequent change detection analysis, enabling the identification and quantification of spatio-temporal variations in water extent between the pre-monsoon and post-monsoon periods of 2024. All input products were reprojected to EPSG:4326 and coregistered using affine transformations derived from Sentinel-2 NDWI. The alignment between SAR and optical datasets was visually and statistically verified, with sub-pixel consistency across scenes. No significant geolocation drift was observed, ensuring reliable pixel-wise comparison.

3.3 Change Detection Analysis

The process integrated both Sentinel-1 and Sentinel-2 datasets, enabling a robust multi-sensor assessment of hydrological changes. The classified layers from previous processing steps used to generate pre-monsoon and post-monsoon water masks for each ROI. Subsequently, a pixel-by-pixel comparison was conducted between the two temporal water masks to detect areas of water gain, water loss, and persistence. The change detection analysis was conducted using both EO-EO and SAR-EO comparisons. The methodology employed pixel-wise logical operations to classify each pixel into one of four distinct categories

1. Persistent Water – pixels identified as water in both time periods,
2. Water Gain – pixels transitioning from non-water to water,
3. Water Loss – pixels transitioning from water to non-water, and
4. Persistent Land – pixels remaining non-water in both periods.

The resulting change detection maps were used to compute quantitative statistics, including the total number of pixels and the corresponding percentage of area under each class.

4. RESULTS AND DISCUSSIONS

The change detection analysis was conducted using two complementary approaches: EO-EO analysis and SAR-EO analysis. For the Hirakud Reservoir, the EO-EO method based on NDWI differencing between pre- and post-monsoon Sentinel-2 imagery revealed a net water gain of 2.88%, with 4.68% of the area transitioning from non-water to water and 1.81% experiencing water loss. In contrast, the SAR-EO analysis, which compared Sentinel-1 backscatter with Sentinel-2 NDWI, indicated a more conservative net gain of 1.26%, capturing 4.66% water gain and a higher 3.40% water loss. This discrepancy highlights SAR's enhanced sensitivity to surface roughness and moisture, which can detect subtle hydrological changes not always visible in optical data.

For Chilika Lake, the EO-EO analysis showed a dramatic net increase in water extent of 72.31%, with 72.69% of the area gaining water and only 0.38% showing loss. The SAR-EO comparison closely aligned, reporting a

73.74% net gain, with 74.10% water gain and 0.37% loss. The strong agreement between both methods in Chilika underscores the reliability of the optical signal in clear-sky conditions, while the SAR-EO fusion further validated the extent of seasonal inundation. The detailed analysis results are shown in Figure 1-4.

False Positives:

- NDWI occasionally misclassified vegetated wetlands as water.
- SAR backscatter over rough terrain or urban surfaces introduced noise in water detection.

False Negatives:

- Cloud-covered water bodies were missed in optical-only analysis.
- SAR may underrepresent shallow or low-reflectance water surfaces.

The chosen methodology for change detection combining NDWI-based EO-EO analysis with SAR-EO comparison offered several advantages, including high sensitivity to water presence under varying environmental conditions, seamless integration with automated cloud masking via the SCL, and the ability of SAR to detect water in cloud-obscured or optically ambiguous regions. However, the approach also presented limitations: NDWI can be affected by cloud cover and vegetation interference, SAR backscatter may misclassify rough terrain or moist soil as water, and bilinear resampling during co-registration can introduce minor radiometric smoothing. Despite these constraints, the results revealed distinct seasonal hydrological changes. Overall, the EO-EO method provided high-resolution water extent mapping under cloud-free conditions, while the SAR-EO approach offered robustness in detecting changes under variable atmospheric conditions. The integration of both modalities enabled a more comprehensive and resilient assessment of seasonal hydrological dynamics.

Recommendations for work-flow or UI Environment:

- Extend the current SAR-based analysis beyond VV polarization by integrating VH and combined VV+VH channels. This would enhance sensitivity to vegetation, surface roughness, and mixed land-water interfaces, improving classification robustness in complex terrains.
- Instead of relying solely on NDWI, incorporate additional water-sensitive indices (e.g., MNDWI, AWEI) and explore supervised classification techniques using machine learning. This multi-index, data-driven approach can significantly improve water detection accuracy and reduce misclassification in heterogeneous landscapes.
- The current analysis is constrained by limited ROI size and temporal sampling. Scaling the workflow to include broader spatial extents and finer temporal granularity would yield more generalizable insights and support trend-based hydrological assessments.
- Validate the change detection outputs by comparing them with authoritative datasets such as the JRC Global Surface Water Occurrence (SWO) or national hydrological inventories. This cross-verification would help quantify model performance and identify areas for refinement.
- Enhance the fusion methodology by incorporating satellite altimetry data (e.g., from Sentinel-3 or ICESat-2) to estimate water level variations. This would enable volumetric assessments and support applications in flood modeling, reservoir monitoring, and water resource management.

Figure 1: Pre- and post-monsoon water mask comparison of Hirakud Reservoir.

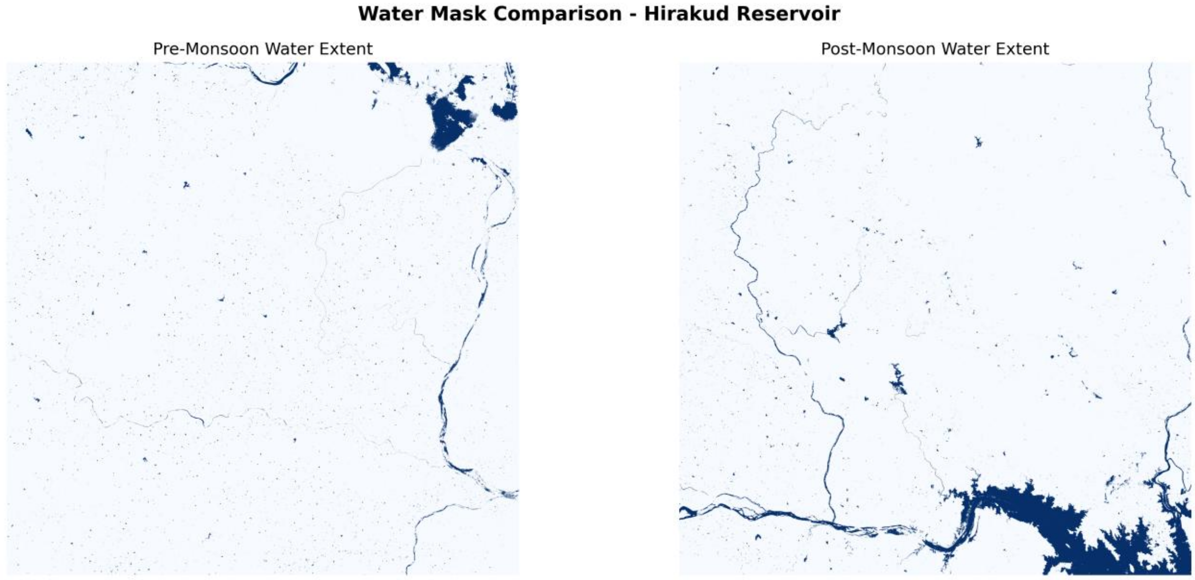

Figure 2: Change detection analysis of Hirakud Reservoir..

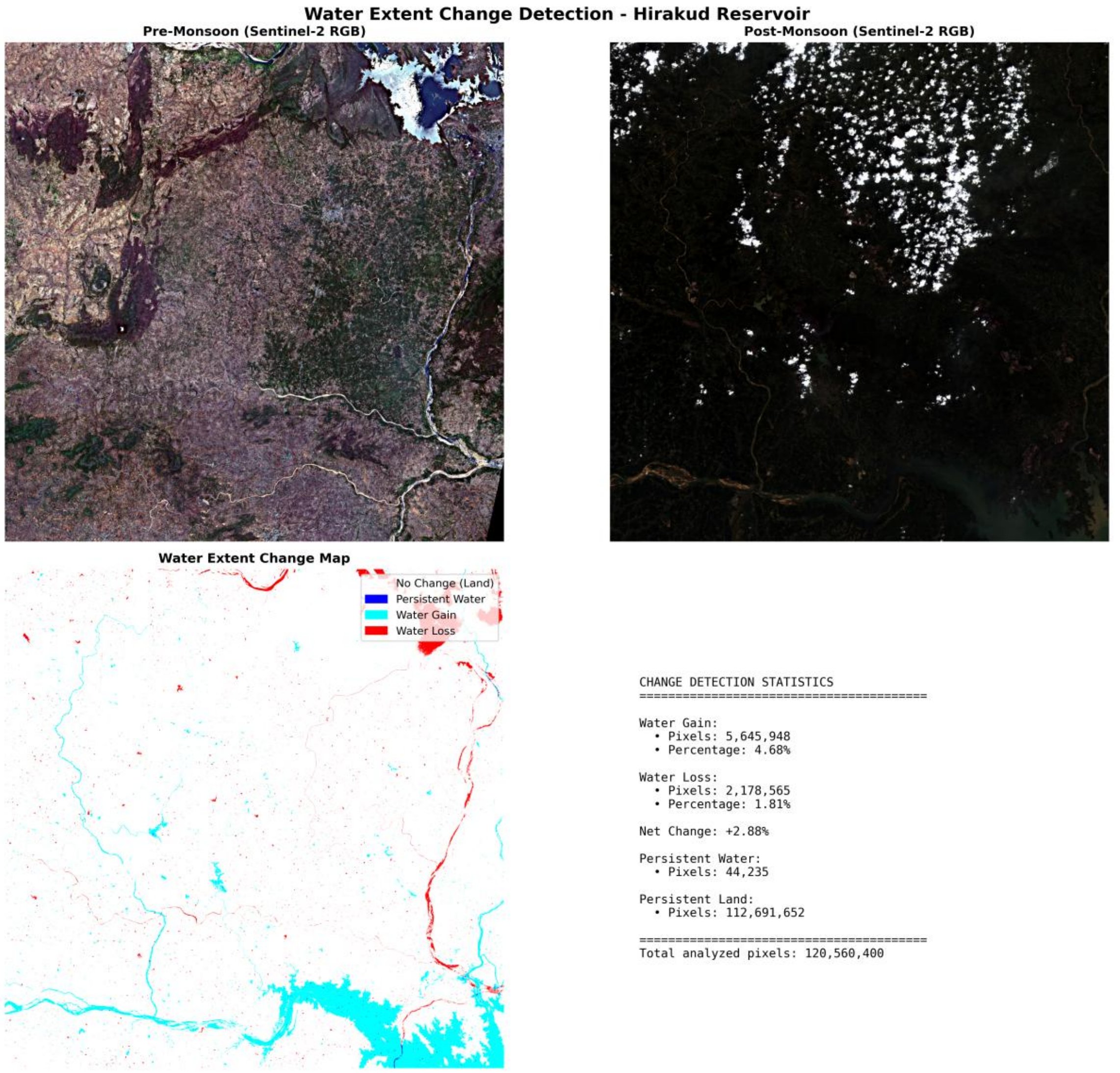

Figure 1: Pre- and post-monsoon water mask comparison of Chilika Lake.

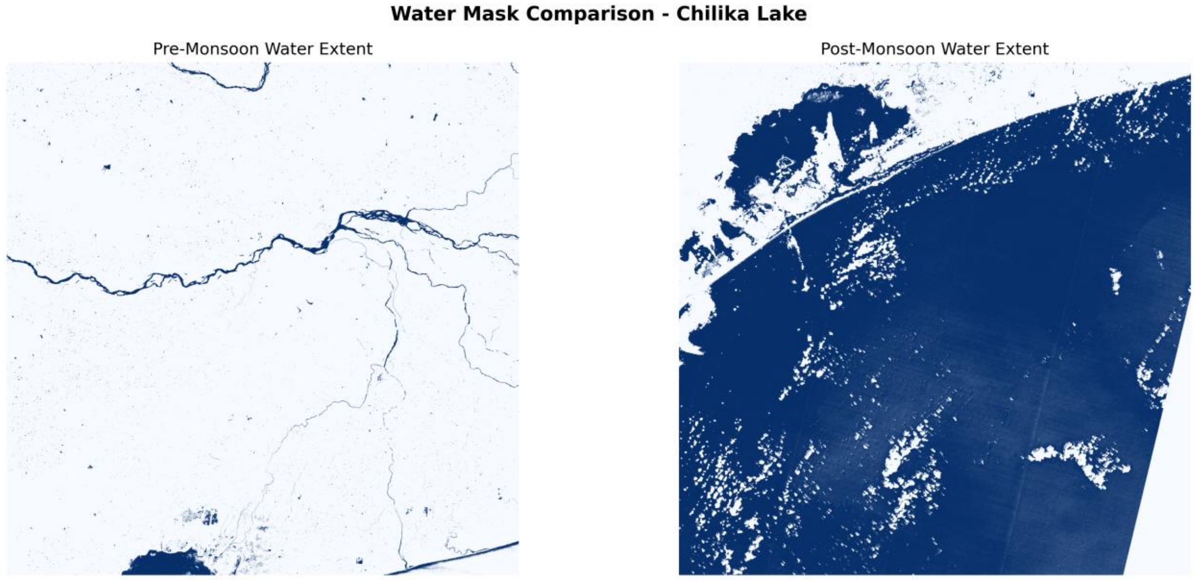

Figure 4: Change detection analysis over Chilika Lake.