

Detecting surface water changes from multi-temporal satellite imagery using the normalized difference water change index

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Article Info	ABSTRACT
Article type: Research Article	Objective: The main objective of this study is to propose a water change detection index, which directly extracts water body changes from two temporal images in a single step, instead of extracting surface waters from each temporal image separately and then comparing the results to detect the changes. Methods: The formulation of NDWCI incorporated the difference between the green and shortwave-infrared bands from two temporal Landsat scenes, aiming to create contrast between areas where water surfaces have changed versus those that remained stable over time. The primary goal behind constructing NDWCI was to fuse multi-temporal images of a given location into a single composite image, such that unchanged pixels were minimized or suppressed while water-related changes between the two acquisition dates were clearly emphasized. Results: The results demonstrate that although the accuracies of the NDWCI and NDWI differencing methods were close to each other, NDWCI consistently outperforms both NDWI and MNDWI differencing in terms of overall accuracy, Kappa coefficient, and commission and omission errors across the two test sites. At test site 1, NDWCI achieved the highest overall accuracy (98.33%) and Kappa (0.98), followed by NDWI (97.11%, 0.97) and MNDWI (94.85%, 0.91). A similar pattern is observed at test site 2, where NDWCI again records the best performance (96.32% accuracy, 0.93 Kappa), while MNDWI shows a marked drop in agreement (91.23% accuracy, 0.76 Kappa). Conclusions: The NDWCI index can be applied to detect changes across various water types. Nevertheless, a key challenge remains in identifying an appropriate threshold value to reliably differentiate changed from unchanged areas. In conclusion, the proposed method showed strong capability for monitoring water body changes at the selected test sites. Therefore, this approach holds potential for enhancing water body change detection in future research.
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1.Introduction

The study of how environmental changes affect both natural ecosystems and human communities spans numerous scientific disciplines. According to Green et al. (1994), change detection generally involves comparing the spatial characteristics of a location across different time points, while controlling for variations arising from extraneous factors, in order to isolate changes attributed to the variables of interest. Change detection can also be described as identifying alterations in an object or phenomenon by observing it at multiple times. As Lu et al. (2004) note, reliable and up-to-date observation of Earth's surface features enables a deeper understanding of the interplay between human activities and natural processes, ultimately supporting more effective resource utilization and management.

Surface water constitutes an essential strategic resource for human survival and societal progress, playing a vital role in supporting people, agricultural production, and ecological systems (Lu et al., 2011; Heshmatpoor and Sajadi, 2024). Accurate knowledge regarding the spatial configuration of exposed surface water is crucial across numerous research domains, including future water resource assessments, climate modeling, agricultural land suitability, river channel dynamics, wetland inventories, watershed analyses, surface water mapping and governance, flood disaster monitoring, and broader environmental surveillance (Tani and Omidvar, 2026; Zareie et al., 2026). Over recent decades, remote sensing satellites equipped with diverse spatial, spectral, and temporal capabilities have generated vast quantities of data, serving as a principal resource for identifying and delineating surface water bodies as well as tracking their temporal variations (McFeeters, 2013).

Extracting information about surface water and its dynamics from remote sensing imagery presents a significant challenge. Many researchers continue to rely on existing geographic information system (GIS) datasets or manual digitization to obtain necessary water-related information. However, over the past few decades, various image processing approaches, including single-band, multi-band, and classification methods have been developed to derive surface water data from satellite observations. More recently, satellite-derived spectral indices have emerged as the primary tool for mapping surface water and detecting its changes over time. In response to this need, several water-specific indices have been proposed, such as the normalized difference water index (NDWI: McFeeters, 1996), the modified normalized difference water index (MNDWI: Xu, 2006), the water ratio index (WRI: Shen and Li, 2010), and the automated water extraction index (AWEI: Feyisa et al., 2014).

The primary aim of this study is to detect water body changes from satellite imagery. A review of earlier studies on this topic reveals that water bodies are typically extracted individually from multi-temporal satellite images, followed by subsequent analysis and comparison to identify changes (Du et al., 2012). In contrast, the present study introduces an approach termed the normalized difference water change index (NDWCI), which enables direct detection of surface water changes between two different times. This method modifies the traditional NDWI differencing technique: rather than computing NDWI separately for each image and then comparing the results, the NDWCI formula directly extracts surface water changes from the two temporal images in a single step.

2. Materials and Methods

In this research, an NDWCI approach was suggested for surface water change detection. For this purpose, two Landsat TM images of the years 2000 and 2010 for the area of Lake Urmia in Iran were acquired. Two test sites were selected and the suitability of the proposed approach for detecting surface water changes was evaluated in comparison with NDWI and MNDWI differencing methods.

2.1. Study area and dataset

A portion of Lake Urmia (locally named Urumiyeh) was selected as the study area to assess the proposed methods. Situated in northwestern Iran between latitudes $37^{\circ}03'N$ and $38^{\circ}17'N$ and longitudes $44^{\circ}59'E$ and $45^{\circ}59'E$, Lake Urmia is a shallow, saline water body with a maximum depth of 16 m and dimensions of approximately 140 km in length and 40–55 km in width (Delju et al., 2013). For implementing the change detection techniques, two Landsat Thematic Mapper (TM) scenes from August 2000 and July 2010 (both images are from the same season with similar environmental and weather conditions) were acquired through the U.S. Geological Survey (USGS) Global Visualization Viewer, as displayed in Figure 1. These Landsat images, which were level-1 terrain-corrected (L1T), came pre-georeferenced to the Universal Transverse Mercator (UTM) zone 38 North projection based on the WGS-84 (World Geodetic System 1984) datum. Any additional necessary corrections were performed as part of this study. Detailed specifications of the Landsat data used are provided in Table 1.

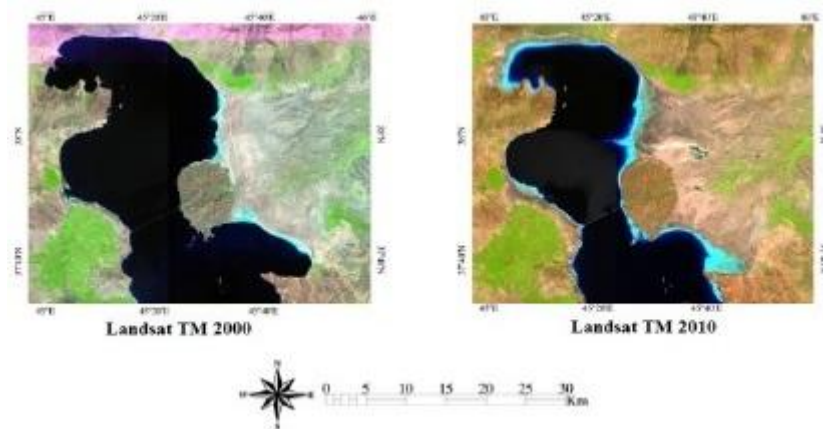


Figure 1- Landsat TM of the study area

Table 1- Specifications of the Landsat TM data

Satellite	Sensor	Path	Row	Year	Resolution (m)	Wavelength (μm)
Landsat-5	TM	169	34	2000 2010	30	Band 1: 0.45–0.52
						Band 2: 0.52–0.60
						Band 3: 0.63–0.69
						Band 4: 0.76–0.90
						Band 5: 1.55–1.77
						Band 7: 2.08–2.35

2.2. Image pre-processing

Prior to further analysis of the satellite imagery, several preprocessing steps were carried out, including radiometric calibration, atmospheric correction, co-registration, and resampling. Radiometric calibration and atmospheric correction followed the procedures described by Schroeder et al. (2006). Specifically, the acquired images were transformed to at-satellite radiance using the Landsat calibration tool available within ENVI 5.3 software. Following this conversion, each image was further converted to at-satellite reflectance. Necessary parameters, such as the date of data acquisition and sun elevation angle, were extracted from the Landsat header files. Since at-satellite reflectance does not account for atmospheric influences, the dark object subtraction method (Chavez, 1996) was applied to convert at-satellite reflectance into surface reflectance, thereby achieving full absolute atmospheric correction.

Reliable change detection requires precise co-registration of the input images. Accordingly, the images must be closely aligned with one another and accurately registered to a subpixel level. In this study, manual image-to-image co-registration was employed, achieving a root mean square error of less than 0.5 pixels. Subsequently, all datasets were resampled to a uniform size using the nearest-neighbor resampling technique and polynomial method.

2.3. Developing the normalized difference water change index (NDWCI)

The formulation of NDWCI incorporated the difference between the green and shortwave-infrared bands from two temporal Landsat scenes, aiming to create contrast between areas where water surfaces have changed versus those that remained stable over time. The primary goal behind constructing NDWCI was to fuse multi-temporal images of a given location into a single composite image, such that unchanged pixels were minimized or suppressed while water-related changes between the two acquisition dates were clearly emphasized.

Special attention was directed toward improving the distinguishability between changed and unchanged surfaces. To achieve this, an iterative procedure was carried out, during which various spectral band combinations from the multi-temporal Landsat images were tested across different regions. The objective was to determine the optimal band set that would maximize the separation between changed and unchanged pixels within the resulting NDWCI image. Ultimately, this process led to the final formulation of NDWCI, presented as follows:

$$NDWCI = \left(\frac{SWIR_{t1} - G_{t2}}{SWIR_{t1} + G_{t2}} \right) - \left(\frac{SWIR_{t2} - G_{t1}}{SWIR_{t2} + G_{t1}} \right) \quad (1)$$

where G_{t1} is the green band of Landsat imagery in time 1; G_{t2} is the green band of Landsat imagery in time 2; $SWIR_{t1}$ is the shortwave-infrared band of Landsat imagery in time 1; and $SWIR_{t2}$ is the shortwave-infrared band of Landsat imagery in time 2. In the NDWCI formula, SWIR is band 7 of the Landsat TM image, with a spectral range of 2.08–2.35.

A thresholding technique based on trial and error and accuracy assessment was implemented to separate changed from unchanged pixels. The threshold value may vary depending on the study area and environmental conditions. The NDWCI was developed to achieve the following aims: (1) enhance water reflectance by employing shortwave-infrared wavelengths; (2)

suppress water reflectance using green wavelengths; (3) exploit the strong reflectance of soil in the SWIR portion of the spectrum; and (4) incorporate multi-temporal imagery to concurrently emphasize changes occurring between the two time points.

2.4. Evaluation and accuracy assessment analysis

Water-index differencing based on two well-known and widely used water indices, including NDWI (Eq. (2)) and MNDWI (Eq. (3)), was employed to compare and evaluate the accuracy of the proposed water change index.

$$\text{NDWI differencing} = \left(\frac{\text{Green} - \text{NIR}}{\text{Green} + \text{NIR}} \right) t_2 - \left(\frac{\text{Green} - \text{NIR}}{\text{Green} + \text{NIR}} \right) t_1 \quad (2)$$

$$\text{MNDWI differencing} = \left(\frac{\text{Green} - \text{MIR}}{\text{Green} + \text{MIR}} \right) t_2 - \left(\frac{\text{Green} - \text{MIR}}{\text{Green} + \text{MIR}} \right) t_1 \quad (3)$$

Accuracy assessment was conducted using overall accuracy and the kappa coefficient. Reference data were generated by manually digitizing multiple polygons over water and non-water pixels based on true-color composites of Landsat bands. Since the classification involved only two classes: water and non-water, visual discrimination between these surface types from satellite imagery was relatively straightforward. Given the limited spatial extent of the cropped test sites, efforts were made to distribute samples across the entire area of each site to maximize representation of true pixels during digitization. For each site, approximately five polygons were selected and distributed throughout the test area. Subsequently, the stratified random sampling technique available in ENVI 5.3 was employed to generate random samples from the prepared reference data. Finally, a confusion matrix was constructed to compute the accuracy assessment metrics.

3. Results and Discussion

Figure 2 presents the outcome of surface water change detection using the NDWCI, NDWI differencing, and MNDWI differencing methods at the selected test sites. Visual examination of the resulting change maps revealed that the MNDWI differencing approach produced lower accuracy in mapping water changes compared with the other two methods. The NDWCI and NDWI differencing techniques yielded relatively similar results for water change detection. However, to provide a more rigorous analysis and clearer interpretation, overall accuracy, kappa coefficient, and commission and omission errors were computed to statistically evaluate the precision of the generated maps. The results of overall accuracy and kappa coefficient are summarized in Table 2.

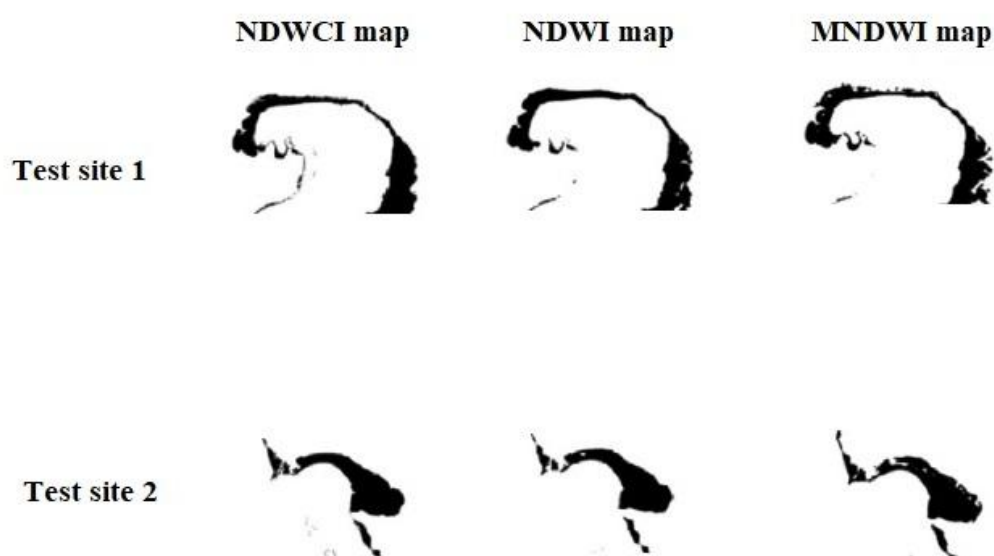


Figure 2- The generated NDWCI, NDWI, and MNDWI change maps at the test sites

Table 2- Accuracy assessment analysis

Test site	NDWCI		NDWI diff.		MNDWI diff.	
	Overall acc. (%)	Kappa coeff.	Overall acc. (%)	Kappa coeff.	Overall acc. (%)	Kappa coeff.
TS 1	98.33	0.98	97.11	0.97	94.85	0.91
TS 2	96.32	0.93	95.73	0.91	91.23	0.76

Similarly, the statistical results confirmed lower accuracy of MNDWI differencing in the detection of surface water changes. The results presented in Table 2 demonstrate that although the accuracies of the NDWCI and NDWI differencing methods were close to each other, NDWCI consistently outperforms both NDWI and MNDWI in terms of overall accuracy and Kappa coefficient across the two test sites (TS 1 and TS 2). At test site 1, NDWCI achieved the highest overall accuracy (98.33%) and Kappa (0.98), followed by NDWI (97.11%, 0.97) and MNDWI (94.85%, 0.91). A similar pattern is observed at test site 2, where NDWCI again records the best performance (96.32% accuracy, 0.93 Kappa), while MNDWI shows a marked drop in agreement (91.23% accuracy, 0.76 Kappa). The notable decline in MNDWI's Kappa coefficient at test site 2 (from 0.91 to 0.76) suggests that MNDWI may be more sensitive to site-specific conditions, such as variations in land cover, shadow, or built-up background compared with NDWCI. Moreover, the commission and omission errors were calculated for detailed analysis, as presented in Table 3.

Table 3- The calculated commission-omission errors

Test site	Class	NDWCI		NDWI diff.		MNDWI diff.	
		Comm. error (%)	Omi. error (%)	Comm. error (%)	Omi. error (%)	Comm. error (%)	Omi. error (%)
TS 1	change	0.00	4.77	2.24	0.00	17.37	5.74
	no-change	1.13	0.00	0.00	8.19	1.23	4.02
TS 2	change	0.33	15.79	5.64	0.66	3.15	7.31
	no-change	4.93	0.00	0.00	15.56	23.98	12.13

Based on the error metrics presented in Table 3, the analysis of commission and omission errors provides further insight into the performance of the three change detection methods. The NDWCI method demonstrates superior accuracy, particularly in minimizing errors for both the "change" and "no-change" classes across the test sites. At Test Site 1, NDWCI achieves a commission error of 0.00% and an omission error of 1.13% for the change class, indicating that it correctly identifies almost all actual changes without falsely detecting non-changes. In contrast, the NDWI differencing method shows a higher commission error of 4.77% for the change class, while MNDWI differencing exhibits a notable omission error of 17.37% for the same class, suggesting that it fails to detect a substantial portion of actual changes. At Test Site 2, NDWCI continues to outperform the other methods, with commission and omission errors of 0.33% and 4.93%, respectively, for the change class. Meanwhile, NDWI differencing shows a relatively high commission error of 15.79%, and MNDWI differencing exhibits both elevated commission (7.31%) and omission (23.98%) errors, further confirming its limited reliability in detecting water changes. Overall, these findings indicate that NDWCI provides more robust and reliable water detection than the traditional spectral indices, particularly in heterogeneous or challenging environments.

When detecting changes between multi-temporal images, both increases and decreases in the target feature may occur simultaneously, making it impractical to apply a single fixed threshold for separating changed from unchanged pixels. Furthermore, the presence of various water types, ranging from shallow to deep, complicates the selection of a consistent and stable threshold. The appropriate threshold can also vary depending on local environmental conditions. Therefore, achieving higher accuracy requires the determination of a region-specific threshold. Additionally, factors such as the mixing of water pixels with diverse land cover types, as well as temporal and spatial variations in scene brightness and contrast can further influence the threshold value. Consequently, when applying NDWCI for change detection, the key consideration is the separability between changed and unchanged pixels rather than the specific threshold value itself.

Despite its demonstrated effectiveness, the NDWCI method is subject to certain limitations, particularly concerning threshold sensitivity and regional applicability. The selection of an optimal threshold to separate changed from unchanged pixels remains challenging, as simultaneous increases and decreases in water extent, coupled with the spectral heterogeneity of diverse water types and mixed land-water interfaces, preclude the use of a single fixed

threshold. Moreover, the appropriate threshold value is influenced by local environmental conditions, including variations in scene brightness, contrast, and atmospheric effects, necessitating region-specific calibration. This dependency on localized threshold determination may constrain the operational efficiency and transferability of the method across large-scale or multi-regional monitoring applications. Nevertheless, the proposed NDWCI method offers a distinct advantage in that it directly extracts surface water changes between two different time points, eliminating the need for independent water extraction from each image followed by post-comparison change detection, which not only reduces cumulative errors associated with multi-step processing workflows but also simplifies the overall change detection procedure.

In addition, the performance of the NDWCI method may be influenced by several factors, such as local environmental conditions, seasonal effects, and image quality. Local environmental conditions, such as land cover heterogeneity and topographic shading can introduce spectral confusion that complicates the accurate differentiation of changed and unchanged water surfaces. Seasonal effects further impact detection accuracy, as variations in precipitation, vegetation phenology, and evapotranspiration alter the reflectance properties of water and non-water features across different acquisition dates, potentially obscuring actual hydrological changes. Image quality issues, including atmospheric scattering, sensor calibration errors, and misregistration between multi-temporal scenes, may introduce noise that reduces the reliability of change detection results. Although preprocessing procedures were applied to minimize these effects, residual uncertainties may still persist, emphasizing the need for careful data selection and quality assessment when applying the NDWCI method.

4. Conclusion

In this study, a surface water change detection index, named NDWCI, was proposed to effectively detect water body changes between images acquired at two different times. The proposed index was evaluated in comparison with traditional NDWI and MNDWI differencing methods. Multitemporal Landsat TM images from 2000 and 2010 of Lake Urmia in Iran were utilized to implement the proposed change detection methods. Both visual and statistical analyses demonstrated the higher performance of NDWCI compared with the other methods in the detection of surface water changes. The NDWCI index can be applied to detect changes across various water types. Nevertheless, a key challenge remains in identifying an appropriate threshold value to reliably differentiate changed from unchanged areas. Based on the findings of this study, the following practical recommendations are offered for operational implementation of the NDWCI method. To ensure reliable change detection, users should employ multi-temporal imagery with minimal cloud cover and apply rigorous preprocessing, including radiometric calibration, atmospheric correction, and sub-pixel co-registration. Site-specific optimal thresholds should be determined empirically, given the sensitivity of threshold values to local environmental conditions, water types, and seasonal variability. Image pairs should ideally be acquired during comparable seasonal periods to minimize phenological and hydrological confounding effects. Furthermore, integrating NDWCI-derived change maps with ancillary datasets, including digital elevation models, land cover maps, and climatic records,

can enhance the interpretation of observed changes and support informed water resource management.

Author Contributions

This work was primarily conducted and written by Komeil Rokni. Davood Akbari contributed to the results analysis and manuscript writing.

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Conflict of Interest

The authors declare no conflict of interest.

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