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A tensor-based approach in restoration program monitoring for inland water bodies (case study: Urmia Lake)

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ABSTRACT

Effective management of water resources and preservation of aquatic ecosystems are pressing global challenges. With the ongoing impacts of climate change and the increasing demands on water resources, there is a growing need for targeted restoration of degraded inland waters and those experiencing declining levels. To achieve meaningful outcomes, it is essential to establish measures for evaluation the effectiveness of restoration efforts accurately. Such metrics enable clear insights into restoration progress and guide the adaptive management needed for sustainable water resource management. This study addresses critical gaps in current methodologies by introducing two novel, tensor-based approaches to assess inland water restoration programs. Using the Normalized Difference Water Index (NDWI) derived from satellite imagery, these methods significantly enhance spatio-temporal analysis and visualization of water level dynamics, providing more precise insights into restoration impacts over time. The methods are applied to evaluate the effectiveness of the project connecting the Zarineh River to the Simineh River, one of the restoration program of Urmia Lake. The analysis using two newly introduced operators reveals significant water level patterns in the southeastern part of Lake Urmia. First, a substantial increase in water coverage was observed on the left side of the study area in 10 of the 12 months following restoration, indicating the program's effectiveness. Conversely, a reduction in water presence on the right side was noted during 5 months, suggesting areas that need further intervention. These findings demonstrate the value of these methods for tracking water level variations and assessing restoration outcomes effectively.

1. Introduction

Restoring inland waters that are degraded or face reduced water levels is essential for multiple reasons. Ecologically, revitalized water bodies are crucial in maintaining balance and supporting biodiversity (Brown and Swan, 2010). The restored water sources economically ensure a reliable water supply for agriculture, industry, and human consumption (Scanlon et al., 2017). They also help mitigate the impacts of climate change by reducing the risk of floods and droughts (Schlosser et al., 2014). In the social aspect, the inland waters restoration is vital for providing safe drinking water, reducing health risks from waterborne diseases, and enhancing the quality of life by supporting recreational activities and cultural practices (Bowler et al., 2010). While restoration efforts are expanding globally, there remains a critical need to assess their effectiveness using reliable indicators and there are various indicators to quantify and measure restoration projects. Automated Water Extraction Index (AWEI) (Tourian et al., 2015), Tasseled Cap Wetness Index (TCW) and Augmented normalized difference water index (ANDWI) (Chen et al., 2024) are indicators that help in monitoring the temporal and spatial changes in lake areas, which is applicable tool for restoration projects management. However, conventional indicators often fall short in capturing the full complexity of restoration impacts, highlighting the need for more robust, multi-dimensional assessment approaches.

A wide range of approaches has been used to evaluate restoration program effectiveness, including ecological indicators, Post-Project Assessments (PPAs) (Downs & Kondolf, 2002), and integrated frameworks that combine hydrological, geomorphological, and socio-economic metrics (Woolsey et al., 2007; Roni et al., 2008; 2018). Specific to Lake Urmia, several studies have explored restoration outcomes through

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hydrological modeling and comparative lake assessments. Nikraftar et al. (2021) evaluated three nearby lakes with similar rainfall patterns to assess the effectiveness of Urmia's restoration programs. Esmailzadeh et al. (2023) examined the institutional roles and policy shortcomings in the Urmia Lake restoration process. In addition to field-based ecological and socio-environmental approaches, remote sensing has become a critical tool for restoration assessment, particularly in large or inaccessible areas. Satellite imagery provides consistent and repeatable observations over time, enabling the monitoring of surface water dynamics at regional and basin-wide scales. For example, Saemian et al. (2020) utilized a combination of remote sensing and ground-based data—including GRACE gravity observations and climate recovery indicators—to evaluate changes in Lake Urmia's water level, surface area, and volume. While remote sensing provides a powerful platform for large-scale analysis, most existing approaches rely on aggregated indicators or isolated time steps, offering limited temporal resolution and failing to capture the full spatio-temporal complexity of restoration processes. This is evident in studies that used spatio-temporal analysis to examine inland water bodies in different regions, such as China (Li et al., 2015), Egypt (Mohsen et al., 2018), and Romania (Şerban et al., 2022). These limitations underscore the need for methods that can jointly analyze spatial patterns and their temporal evolution—an analytical gap addressed in this study through the proposed tensor-based framework.

The NDWI is a widely used spectral index for detecting and delineating surface water bodies using satellite imagery. It offers a straightforward method for classifying pixels into water and non-water categories based on their spectral reflectance, making it a foundational tool for large-scale hydrological monitoring (Ali et al., 2019; Özelkan, 2020). Several studies have explored enhancements to this method to improve its accuracy. For instance, Qiao et al. (2012) proposed an adaptive NDWI-based extraction method to better distinguish water features in complex environments, while Rokni et al. (2015) and Khan (2022) demonstrated its utility in monitoring temporal fluctuations in inland lakes. NDWI and its modifications, such as the Modified NDWI (MNDWI) introduced by Xu (2006), have been applied across a wide range of satellite platforms. Yang et al. (2017) evaluated Sentinel-2A's performance for urban surface water extraction using NDWI at high spatial resolution. Özelkan (2020) analyzed the performance of three NDWI variants using Landsat-8 for Atikhisar Dam Lake in Turkey. Extensive research has been conducted by integrating this index with other analogous indices, yielding significant insights and advancements in the field. For instance, Ashok et al. (2021) combined NDWI with the Normalized Difference Vegetation Index (NDVI) to monitor seasonal changes in the Renuka wetland of India using satellite imagery. Naher et al. (2024) similarly employed both MNDWI and NDVI to assess the dry and wet season dynamics of Dau Tieng Lake in Vietnam. Additionally, numerous studies have been carried out to compare this index with other indices, aiming to evaluate its performance and effectiveness. Malahlela (2016) introduced the Simple Water Index (SWI) and compared its performance to MNDWI and the Automated Water Extraction Index (AWEI) using Landsat 8 data across South African ecosystems. Liu et al. (2023) conducted a large-scale evaluation of ten different indices including NDWI3, MNDWI, AWEI, MBWI, WRI, and others across two study regions in China, assessing their effectiveness for surface water extraction under varied conditions. However, even with these advancements, most NDWI-based methods reduce spatio-temporal analysis to simplified classifications or trend estimates, underscoring the need for a more structured framework capable of capturing dynamic, localized changes in restoration contexts.

Despite the widespread use of satellite imagery and NDWI-based techniques for monitoring surface water in restoration programs, most existing approaches remain limited in their ability to fully analyze the spatio-temporal dynamics of inland water systems. This limitation is particularly critical when evaluating restoration efforts in dynamic inland water systems, where both spatial variability and temporal trends must be jointly assessed. Furthermore, few studies offer a structured framework that enables pixel-level analysis of change over time while retaining the multidimensional integrity of satellite data. To address these challenges, this study introduces two novel methods for evaluating and analyzing inland water restoration programs using tensor-based approaches, employing the NDWI derived from satellite imagery. These methods offer several key advantages: (1) they allow for the simultaneous detection of long-term trends and short-term fluctuations, helping to distinguish between climate-driven variability and restoration-induced impacts; (2) by standardizing data into consistent tensor representations, the approach enhances comparability across time periods, regions, and even different lakes, supporting transferable insights for broader restoration management; (3) the use of intuitive tensor operators translates complex data into accessible visual and numerical formats, improving interpretability for decision-makers; and (4) the method improves reliability by minimizing the influence of noise from cloud cover or anomalous pixels through multi-dimensional aggregation. Two novel operators are proposed within the tensor space: the Percentage Operator, which calculates the proportion of time each pixel is classified as water-covered, providing a clear and interpretable view of water presence over time at specific locations; and the Subtract Operator, which captures temporal shifts in water coverage by comparing pixel values across time steps, offering an alternative perspective on dynamic changes. Additionally, in the case of Lake Urmia one of the largest saltwater lakes in the world rehabilitation efforts have been the focus of several studies; however, few have examined the spatially and temporally specific effects of individual water transfer projects, such as the connection between the Zarrineh river to Simineh river, which played a key role in the lake's restoration strategy. By preserving the full spatio-temporal structure of satellite imagery, the tensor-based method enhances both the accuracy and interpretability of inland water monitoring, offering a novel and scalable framework for assessing restoration outcomes and informing practical water resource management.

2. Method

This section presents the methodology developed in this study, focusing on applying tensor-based approaches to monitor and analyze inland water restoration. The methodology consists of three main components; 1) an overview of the tensor concept; 2) the design of new tensor operators for water level analysis; 3) and the definition of scenario-based methods to interpret and visualize the results.

2.1. Tensor concept

A tensor is a multidimensional array that extends a matrix (a two-dimensional table) to multiple dimensions. Tensors are especially used in fields requiring complex data structures, such as spatio-temporal analysis, where data must be organized across different dimensions like location, time, and additional variables. For instance, the observed abundance of a species can vary across specific locations and times, forming a three-dimensional (third-order) tensor with dimensions representing species, geographical locations, and time points (Frelat et al., 2017). In tensor based spatio-temporal analysis, researchers investigate temporal changes in phenomena across different spatial positions, enabling efficient storage and handling of multidimensional data. This structured approach captures spatial and temporal attributes within a unified model and retains the data's original multidimensional structure (Kharaghani et al., 2023). By preserving the spatial and temporal characteristics of the phenomena being studied, tensors enable a deeper analysis without losing valuable context (Frelat et al., 2017).

Remote sensing images often contain multiple bands that span spectral and spatial dimensions, capturing details like texture and scale. When collected over time, these images are organized into a multi-temporal tensor that adds time as an additional dimension (Huang et al., 2019). Mathematically, tensors extend the familiar constructs of scalars, vectors, and matrices are zero, one and two order tensors, respectively. Fig. 1 illustrates the various mathematical structures.

Fig. 1(a) illustrates a scalar, a single numerical value representing a single data. As a zero-order tensor, it is the simplest data form, containing only a single piece of information. Fig. 1(b) shows a vector, an ordered array of values representing a first-order tensor. Fig. 1(c) depicts a matrix, a two-dimensional array representing a second-order tensor. In geospatial analysis, matrices are often used for raster data, where each cell corresponds to a geographic location and holds a value that represents a characteristic of that location. Matrices are essential for modeling continuous spatial data and enable operations like filtering and spatial transformations. Fig. 1(d) presents a 3D tensor, which extends the matrix structure into three dimensions, making it a third-order tensor. In geospatial analysis, third order tensors are used for data that vary across two spatial dimensions with an additional dimension such as time. A 3D tensor, for example, stores a time series of satellite images, where each layer represents the same area at different times. This structure is particularly valuable for analyzing temporal changes and multi-spectral satellite data, as it preserves spectral and spatial information, like texture and scale, without altering the original data.

The order of a tensor refers to its number of dimensions. First-order tensors, or vectors, are indicated by bold lowercase letters (e.g., $\mathbf{x}$), while second-order tensors, or matrices, are denoted by bold uppercase letters, such as $\mathbf{X}$. Tensors of higher order (third or beyond) are represented using bold Euler script letters; for instance, χ. The element at index i in vector $\mathbf{x}$ is represented as x_i, the element at indices *(i,j)* in matrix $\mathbf{X}$ as x_{ij}, and the element at indices *(i,j,k)* in the third-order tensor χ as x_{ijk}. Slices, or two-dimensional sections of a tensor, are produced by holding one index constant and letting the other two vary, creating matrices within the larger tensor. Fig. 2 illustrates the types of these slices.

Fig. 2 illustrates the concept of horizontal, lateral, and frontal slices within a third-order tensor χ, demonstrating how complex data is broken down for detailed analysis. These slices are critical for understanding data structure and behavior across different dimensions. In Fig. 2(a), horizontal slices are indicated by $\chi_{\ i::}$. Fig. 2(b) presents the lateral slices, represented by $\chi_{:\ j:}$. Fig. 2(c) displays the frontal slices, shown as $\chi_{:\ :k}$. This slicing method provides insights into temporal changes, showing how the data evolves over time at specific geographic locations (Kolda and Bader, 2009). In tensor analysis, fibers are analogous to the rows and columns of matrices but extend into higher dimensions. Each fiber represents a set of values corresponding to a fixed combination of indices in the tensor. Essentially, fibers facilitate the analysis of data across various dimensions or axes. This concept is further illustrated in Fig. 3, which delineates the different types of fibers.

Fig. 3 provides a visual representation of different types of fibers in a 3D tensor. In third-order tensors, fibers are categorized into three forms: column fibers, row fibers, and tube fibers. In Fig. 3(a), the column fiber is illustrated, represented by $\chi_{:\ jk}$. Fig. 3(b) shows the row fiber, indicated by $\chi_{\ i:k}$. Finally, and Fig. 3(c) presents the tube fiber, denoted as $\chi_{\ i\ j:}$. These fibers are fundamental components in tensor operations, as they show the different ways in which data is accessed, manipulated, and analyzed across three-dimensional arrays. Comprehending these fibers is important for tasks such as tensor decomposition, data fusion, and multi-way analysis. In the context of tensor analysis, fibers are akin to the rows and columns found in matrices but extend into higher dimensions. This characteristic makes fibers particularly useful for dissecting and grasping complex datasets by focusing on specific dimensions. By examining horizontal, lateral, and frontal slices, as shown in Fig. 3, researchers gain an extensive view of how data varies spatially and temporally (Kolda and Bader, 2009).

2.2. Tensor operators

Tensor operators are crucial for analyzing multidimensional datasets within tensor structures, especially for spatio-temporal applications like monitoring inland water bodies and assessing the effectiveness of restoration programs. In this study, new tensor operators are introduced to enhance the spatio-temporal analysis of water level changes using the Binary Normalized Difference Water Index (BNDWI), specifically the percentage operator and the subtract operator.

The percentage operator determines the percentage of time that a specific location remains covered by water. By summing the binary NDWI values for each pixel and converting these sums into percentages provides a quantitative measure of water presence over time, revealing patterns of consistent water cover or seasonal fluctuations.

The subtract operator, shows temporal variations by subtracting the BNDWI values for each pixel over time, providing information about surface changes. This method enables tracking of increases or decreases in water coverage, providing a dynamic view of inland water level changes over time.

By integrating these novel tensor operators and visualization techniques, the dynamics of inland water bodies are extensively monitored and analyzed. This comprehensive approach delivers valuable insights into water body dynamics, supporting informed decisions for inland water restoration and management programs. A binary NDWI index was created by applying a threshold to the NDWI values in Equation (1). Pixels with NDWI values above the threshold were classified as water (value = 1), while those below were classified as non-water (value = 0).

$$\mathrm{BNDWI} = \begin{cases} 1 if NDWI \geq a \\ 0 if NDWI < a \end{cases} \tag{1}$$

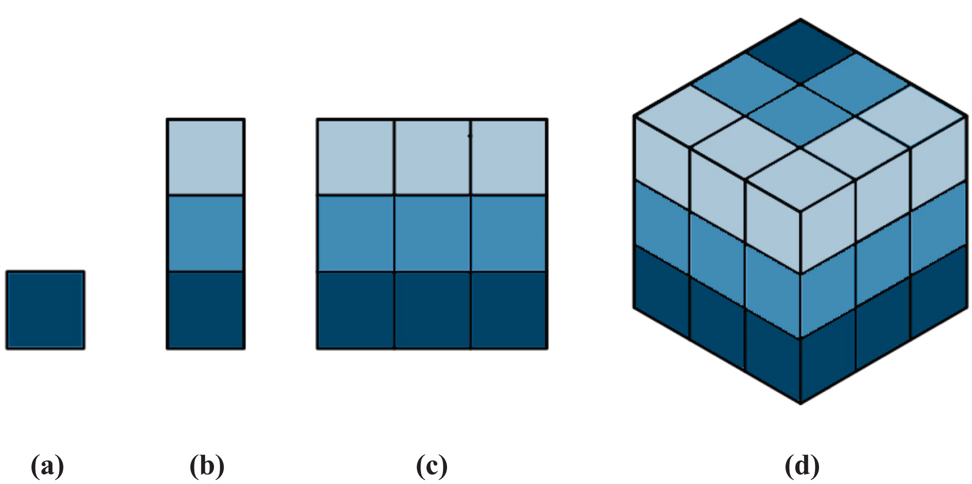

Fig. 1. Various mathematical structures (a) scalar, (b) vector, (c) matrix, and (d) 3D tensor.

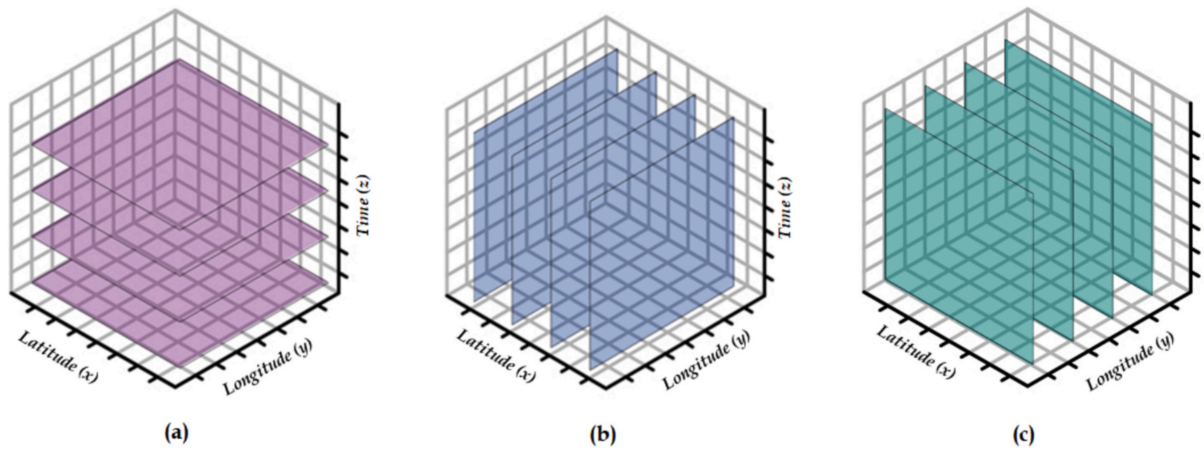

Fig. 2. Types of slices (a) Horizontal slices $\chi_{i::}$, (b) Lateral slices $\chi_{:j:}$ and (c) Frontal slices $\chi_{::k}$.

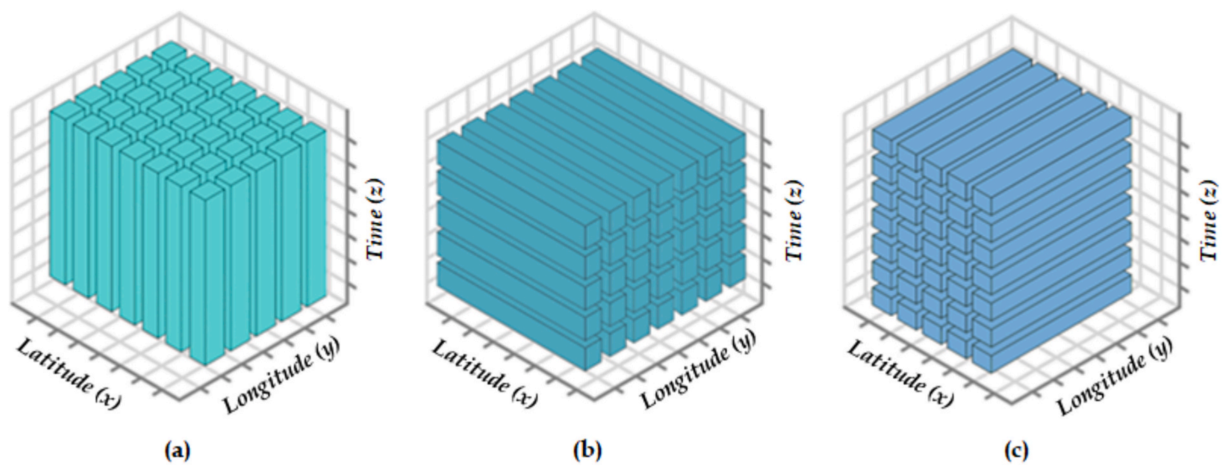

Fig. 3. Illustration of (a) Column $\chi_{:jk}$, (b) Row $\chi_{i:k}$, and (c) Tube Fibers $\chi_{ij:}$ in a 3D Tensor.

In Equation (1), the variable *a* serves as a threshold value used to distinguish between water and non-water areas within the satellite image based on the NDWI.

Equation (2) shows the process of summing binary NDWI values over time. Equation (3) shows the process of converting these sums into percentages:

For each pixel *(i.j)*

$$\mathbf{SBNDWI}_{ij} = \sum_{k=1}^{K} \mathbf{BNDWI}_{ijk} \quad (2)$$

where $\mathbf{BNDWI}_{ijk}$ is the binary NDWI value at voxel *(i.j.k)*, and K is the total number of time points.

$$\mathbf{PSBNDWI}_{ij} = \frac{\mathbf{SBNDWI}_{ij}}{K} \times 100 \quad (3)$$

where $\mathbf{PSBNDWI}_{ij}$ represents the percentage of time the pixel *(i.j)* is covered by water. Equation (4) shows the process of Subtracting BNDWI values over time that subtracting the BNDWI values for each pixel over time, providing information about surface changes

For each pixel *(i.j)*

$$\mathbf{DNDWI}_{ijk} = \mathbf{BNDWI2}_{ijk} - \mathbf{BNDWI1}_{ijk} \quad (4)$$

where $\mathbf{DNDWI}_{ij}$ represents the change in **BNDWI**1 value from **BNDWI**2.

These equations quantify the water presence over time and detect changes in water coverage, enhancing the analysis of inland water bodies.

3. Data and area

In this section, the data sources and the selected study area are introduced to demonstrate the effectiveness of the newly developed operators. A comprehensive dataset was utilized to precisely analyze water level fluctuations in Urmia Lake and assess the impact of restoration efforts. This dataset includes satellite-derived water indices NDWI, which, due to high spatial resolution and extensive geographic coverage, allow for pixel-by-pixel examination of spatio-temporal changes in water levels. Satellite images were sourced and processed through Google Earth Engine (GEE), a cloud-based platform designed for large-scale geospatial data analysis. GEE offers access to an extensive archive of satellite imagery and geospatial datasets and is supported by robust computational resources, enabling complex environmental research and detailed Earth systems analysis.

3.1. NDWI preparation

The NDWI has been specifically developed to identify and extract open water features in remote sensing imagery. This index not only enhances the visibility of water bodies but also simultaneously reduces the influence of soil and vegetation features. Using image processing software, open water areas a rapidly and accurately calculated in satellite images.

Water extents classified from satellite images served as validation sources in this study. Specifically, the distribution of surface water with high spatial and temporal resolution was detected using the MYD09GA product from the MODIS (MODerate-resolution Imaging Spectroradiometer) instrument. Satellite images, which is derived from the Aqua satellite, was downloaded from GEE platform for the period of September 2014 to September 2016. This product provided atmospherically corrected surface reflectance data with a spatial resolution of 500 m and a temporal resolution of 32 days.

The NDWI was calculated for each image using Equation (5):

$$\mathrm{NDWI} = \frac{\mathrm{G} - \mathrm{NIR}}{\mathrm{G} + \mathrm{NIR}} \tag{5}$$

where G is the reflectance in the green band, and NIR is the reflectance in the near-infrared band.

The NDWI values range as follows (Helali et al., 2022) (Table 1):

According to this classification, this study has binarized NDWI using a threshold of 0.2.

3.2. Case study

Analyzing an area that has experienced substantial water level fluctuations and targeted restoration programs enables a practical assessment of the operators' effectiveness and offers valuable insights into their capability to capture and quantify spatial changes accurately over time. Consequently, to demonstrate the efficacy of the newly introduced operators, Urmia Lake, the largest inland lake in Iran and one of the largest saltwater lakes in the world, was selected as the study area. Located between West Azerbaijan and East Azerbaijan provinces, Urmia Lake, spanned approximately 6,000 square kilometers in 1998, making it the 25th largest lake globally by surface area. Its basin supports a critical and diverse aquatic ecosystem, home to approximately eight hundred species of birds, mammals, and inland plants, including the unique Artemia sp. Due to these unique natural and ecological features, the lake and its adjacent wetlands have been recognized as a National Park, a Ramsar Site, and a UNESCO Biosphere Reserve. Urmia Lake has largely dried up over the last two decades, resulting in socio-environmental consequences. As depicted in Fig. 5, the water level of the lake and its surrounding areas has been below the critical level of 1,274.67 m above sea level (Abbaspour and Nazaridoust, 2007). This decline poses significant challenges for both the ecological health of the lake and the socio-economic stability of the surrounding region. In response to this, the Iranian government established the ten-year Urmia Lake Restoration Program (ULRP) (Shadkam, 2017). The ULRP has defined its main mission as the restoration of Urmia Lake, with the goal of increasing the lake's water level to reach ecological equilibrium by 2023. The target ecological water level of 1274.67 m above sea level was established based on the water quality conditions (240 g/L of NaCl) necessary to support the brine shrimp Artemia (Abbaspour and Nazaridoust, 2007). To restore the lake, the ULRP has determined three main phases within a ten-year program (Fig. 4).

Stabilization (2014–2016): Aimed at maintaining a minimum lake water level and mitigating adverse effects of the dried parts of the lake, such as dust storms. Restoration (2016–2022): Focused on meeting the entire lake water demand and gradually increasing the lake level. Final Restoration (2023): Aimed at stabilizing the water level at the ecological level. The hydrology of the Urmia Basin is characterized by 17 permanent rivers, 12 seasonal rivers, and 39 floodways. Simineh River and Zarineh River alone contributing 41.6 % of the total surface water inflow into the lake. One of the most significant restoration programs for Urmia Lake has been the connection of the Zarrineh River to the Simineh River. Due to the significance of this program, the present study evaluates the effectiveness of connecting the Zarrineh River to the Simineh River to demonstrate the utility of the newly introduced operators (Fig. 5).

For this purpose, the southeastern part of Urmia Lake has been examined, as analyzing this area provides deeper insights into the impact of the connection project on increasing the lake's water level and improving its environmental conditions. The project to connect the Zarineh and Simineh rivers is designed to enhance water inflow, stabilize water levels, and improve water quality in this critical region. By redirecting and optimizing the flow of these rivers, the initiative aims to restore the natural hydrological balance, support wetland ecosystems, and ensure sustainable water availability.

Table 1
NDWI values range.

Description	NDWI values range
water surface	0.2 to 1
flooding, humidity	0.0 to 0.2
moderate drought, non-aqueous surfaces	−0.3 to 0.0
drought, non-aqueous surfaces	−1 to − 0.3

4. Results

In this section, to demonstrate the application of the two methods presented in this study, the effectiveness of the project connecting Zarineh River to Simineh River for the restoration of Urmia Lake was evaluated. The southeastern part of Urmia Lake was analyzed using monthly satellite images from September 2014 to September 2016. The revitalization program's impact was assessed across two distinct time periods: September 2014 to September 2015, representing the year before its implementation, and September 2015 to September 2016, representing the year after. This comparative framework allowed for a focused analysis of the program's effectiveness. Monthly analyses facilitated a detailed examination of temporal variations, providing insights into the program's role in enhancing water levels in Urmia Lake. According to Equation (1), a binary system is used to indicate the presence or absence of water in each pixel, providing a detailed temporal analysis across the study area. BNDWI layers are organized into a spatio-temporal tensor, with each layer corresponding to one of the 24 months in the specified period. Pixels with a value of 1 indicate the presence of water, while pixels with a value of 0 indicate the absence of water. By providing a clear binary indication of water presence, it helps quickly identify areas of concern and evaluate the effectiveness of interventions.

4.1. Percentage operator

Using Equation (2) and Equation (3) along with monthly satellite data, PSBNDWI matrices were constructed to analyze changes. Fig. 6 illustrates these matrices, showing the percentage of water presence for each pixel over two periods.

Fig. 6(a) illustrates the period from September 2014 to September 2015, before the start of the restoration program connecting the Zarineh River to the Simineh River. Fig. 6(b) represents the period from September 2015 to September 2016, after the start of the restoration program. This figure provides a spatial distribution of how frequently each pixel was covered by water across the study area during these two periods. By quantifying the water coverage for each pixel, this figure offers valuable insights into the stability and reliability of water resources in the region. For instance, a pixel showing 100 % indicates water presence throughout all studied months, whereas if SBNDWI values indicated water presence for 9 out of the 12 months, converting this to PBNDWI reveals that water was present 75 % of the time at this location. Areas with higher percentages are indicated by warm colors, while areas with lower percentages are represented by cool colors. The derived water presence percentages offer a clear visual and quantitative representation of changes in the lake's water coverage over the specified periods and is an important metric for comprehending the persistence and reliability of water bodies over time. By subtracting the water presence percentage from the first period (Fig. 6(a)) from the percentage in the second period (Fig. 6(b)) Fig. 7 is specifically designed to visualize

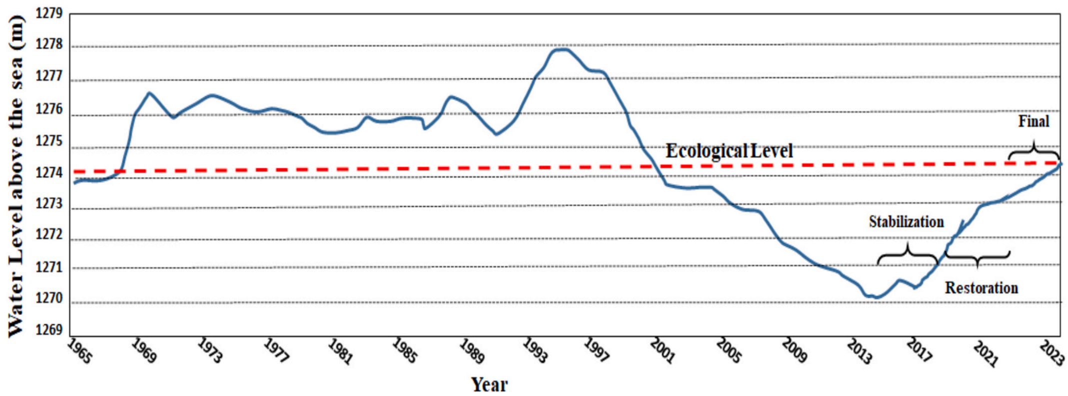

Fig. 4. Mean Annual Water Level Trends and Restoration Roadmap for Urmia Lake (Zarghami, 2011).

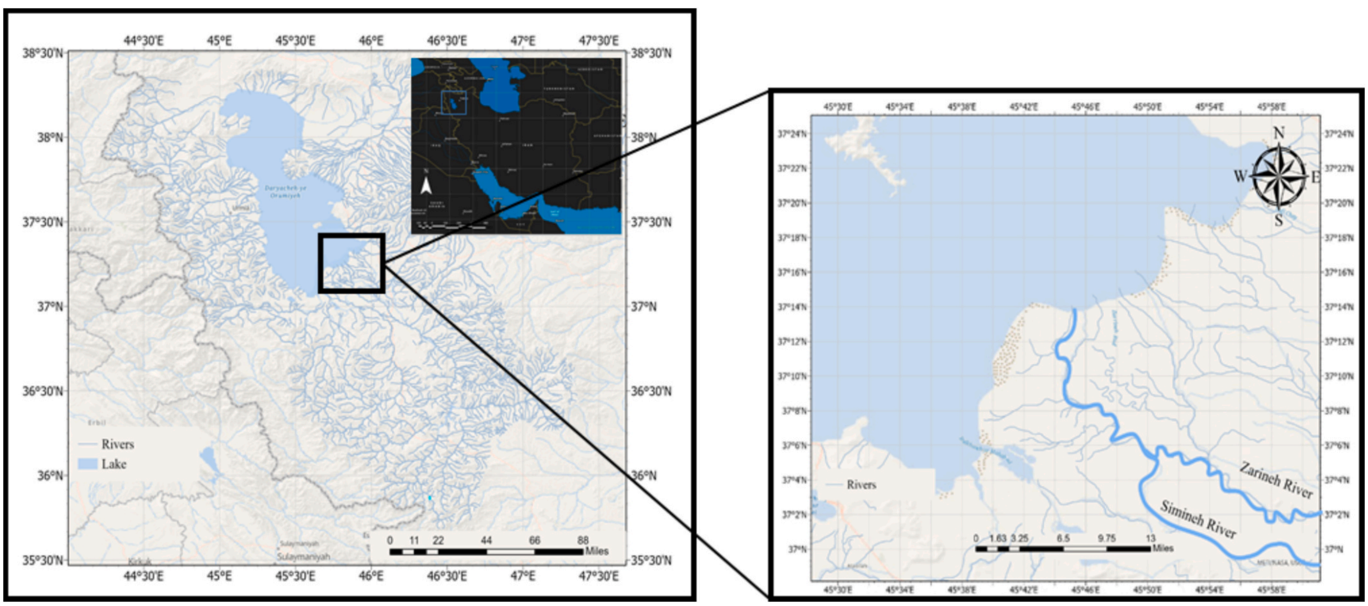

Fig. 5. Urmia lake basin and Southeastern part of Urmia Lake.

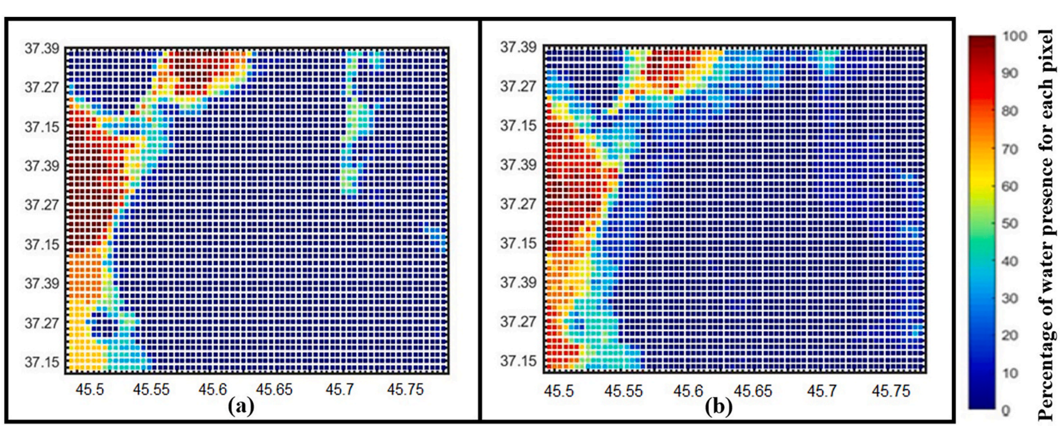

Fig. 6. PSBNDWI Matrices Using SBNDWI (a) Pre-restoration period)2014–2015(, (b) Post-restoration period)2015–2016(.

the change in water presence between the two time periods.

This subtraction provides a clear, pixel-by-pixel representation of how water coverage has changed over time, particularly in response to the restoration program. The colors represent the difference in the percentage of water presence for each pixel between the two time periods. Regions where the percentage of water presence has increased after the restoration program (shown by warm colors) are considered areas where the program has been effective. Conversely, areas where the water presence has decreased (shown by cool colors) still require targeted interventions to improve water availability. These areas represent

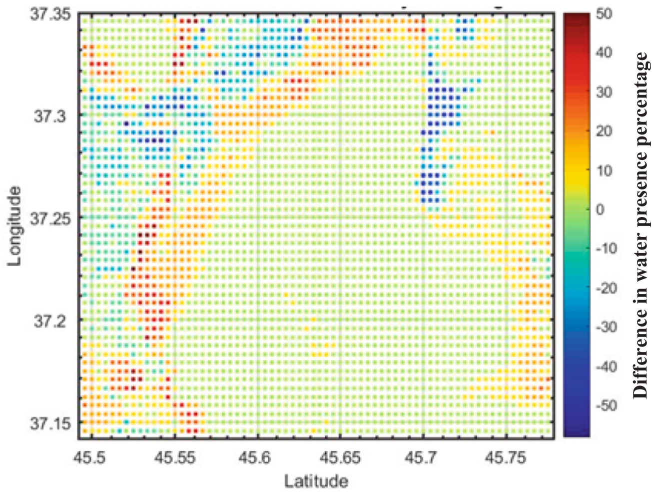

Fig. 7. Difference in Water Presence Percentages.

temporary water bodies that have dried up or regions where water management strategies need to be re-evaluated. The figure provides an extensive view of how water resources have changed across the region.

4.2. Subtract operator

Using Equation (4) and monthly satellite data from September 2014 onward for two years, DBNDWI matrices were constructed to analyze changes in the southeastern part of Urmia Lake. These matrices provide a detailed scientific analysis of the impact of the restoration program connecting the Zarineh River and Simineh River, which began in September 2015. The year preceding the start of the restoration program serves as the baseline for all subsequent comparisons. This baseline period, unaffected by the restoration efforts, shares similar conditions with the year in which the restoration program was implemented. Fig. 8 illustrates these matrices, depicting water level variations over time. The water level difference for each pixel was calculated by subtracting the BNDWI values from the corresponding month of the previous year. For example, the September 2015 matrix (8a) was created by subtracting the BNDWI values from September 2014. This method was applied to each subsequent month for instance, December 2015 was compared with December 2014, January 2016 with January 2015, and so forth. This approach accounts for seasonal variations and helps assess the specific impact of the restoration program.

The subtraction of BNDWI values results in three possible outcomes: -1, 0, and 1. Blue-colored pixels represent a value of -1, indicating areas where water was present before the restoration program but disappeared afterward. Conversely, red-colored pixels represent a value of 1, indicating locations where water appeared after the restoration program, even though no water was present in these areas before the program's implementation. The white pixels indicate a value of 0, signifying that the BNDWI values for these areas remained consistent during both time periods analyzed. Fig. 8(a) and 8(b) predominantly show the presence of blue pixels, indicating that, the study area experienced a greater presence of water in the months of September and October 2014 compared to the corresponding months in 2015, prior to the implementation of the restoration program. From Fig. 8(c) onward, red pixels appear, representing the emergence of water in new areas, due to the impact of the restoration project. Additionally, Fig. 8 shows that, in the right section of the study area, continuous water presence is indicated for October 2014 [Fig. 8(b)], November 2014 [Fig. 8(c)], December 2014 [Fig. 8(d)], January 2015 [Fig. 8(e)], February 2015 [Fig. 8(f)], and March 2015 [Fig. 8(g)]. This sustained water presence during the period prior to the initiation of the restoration program contrasts with the conditions observed from April 2015 onward, where the area became nearly dry. Notably, even following the implementation of the restoration program, the water did not return to these parts of the area. In Fig. 8(j), (k), and (l), a more distinct pattern of increased water presence in the area following the reclamation program is observed. The month-by-month comparison enabled by these matrices is important for identifying trends in water level changes over time, which are key to showing the effects of the ongoing restoration efforts in the Urmia Lake region. The detailed spatial representation of water level differences across multiple months helps in identifying specific areas that benefit most from the program and those that are still be struggling. These analyses are important for water resource management, as they show the areas of success and those needing further intervention. By comparing monthly water levels from September 2014 to September 2016, these figure provide an extensive view of the program's impact, aiding researchers and policymakers in making informed decisions to restore and manage the Urmia Sea's water resources effectively.

5. Discussion

The analysis of results derived from the matrices created by the two new operators introduced in this study reveals two distinct patterns, demonstrating both the utility and effectiveness of these methods in monitoring water level variations and assessing the impact of restoration programs.

5.1. Pattern 1: increased water presence post-restoration in certain areas

In the first pattern, both the Percentage and Subtract operators indicate a substantial increase in water cover on the left side of the study area over time (Fig. 9). This trend highlights the positive impact of restoration program focused on water replenishment and improved water accessibility. The increase is particularly notable, underscoring the effectiveness of the water transfer project from the Zarinh river to the Simineh River, and serves as a quantitative measure of the project's success.

To further validate that the observed changes in water presence were not solely the result of natural climatic variability, precipitation data from the CHIRPS dataset was analyzed for the southeastern part of Lake Urmia over the period from September 2014 to September 2016. The analysis was consistent with the NDWI-based timeframes used in this study. Specifically, the precipitation difference was calculated by subtracting the monthly precipitation values of the pre-restoration year (September 2014–September 2015) from those of the post-restoration year (September 2015–September 2016). Fig. 10 illustrates the resulting bar chart of monthly precipitation differences.

The precipitation analysis for the southeastern part of Lake Urmia (Fig. 10) revealed considerable month-to-month variability rather than a consistent upward trend. While March and April showed relatively high positive anomalies (+0.929 and +1.072 mm, respectively), most other months exhibited only modest increases or even declines in rainfall. The anomaly observed in April may explain the localized and short-lived increase in water presence detected in the eastern part of the study area. However, nearly half of the year's months experienced lower or negligible precipitation compared to the pre-restoration period, indicating no systematic climatic driver for the observed hydrological improvements. Moreover, the spatial distribution of increased water presence aligns closely with known restoration interventions. The most significant changes were concentrated in the western and central zones of the study area—particularly near the confluence of the Zarrineh river and Simineh river, which are major inflow sources directly targeted by the restoration program. If increased water presence were primarily driven by precipitation, a more uniform distribution of change across the entire lake, including the eastern basin, would be expected. The absence of such a pattern further supports the conclusion that the observed hydrological recovery is predominantly the result of targeted water management interventions rather than natural climatic

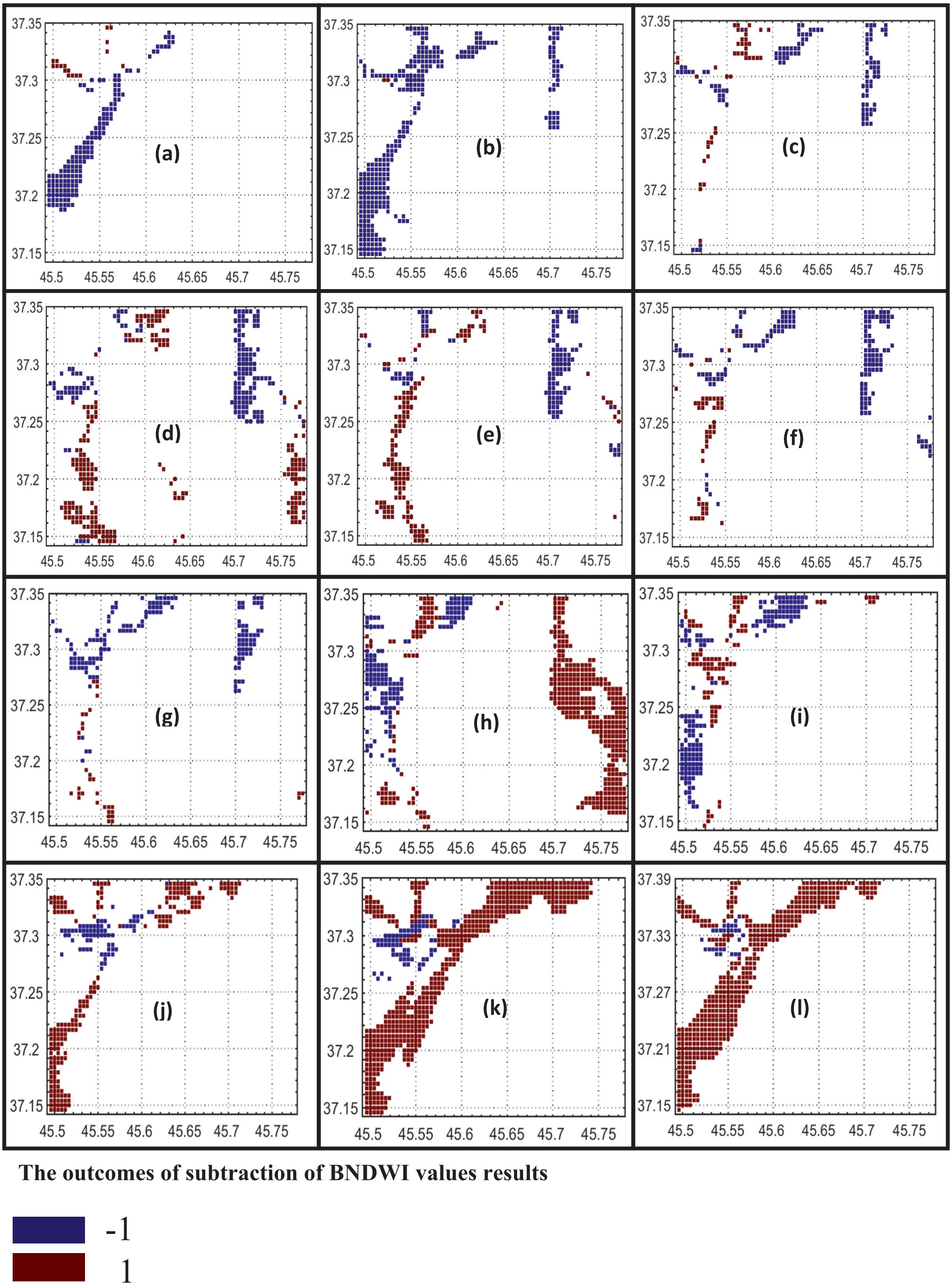

Fig. 8. Monthly DBNDWI Matrices Showing Water Level Differences by Subtracting Values from the Corresponding Month of the Previous Year, (a): September (2015–2014), (b): October (2015–2014), (c): November (2015–2014), (d): December (2015–2014), (e): January (2016–2015), (f): February (2016–2015), (g): March (2016–2015), (h): April (2016–2015, (i): May (2016–2015), (j): June (2016–2015), (k): July (2016–2015), (l): August (2016–2015).

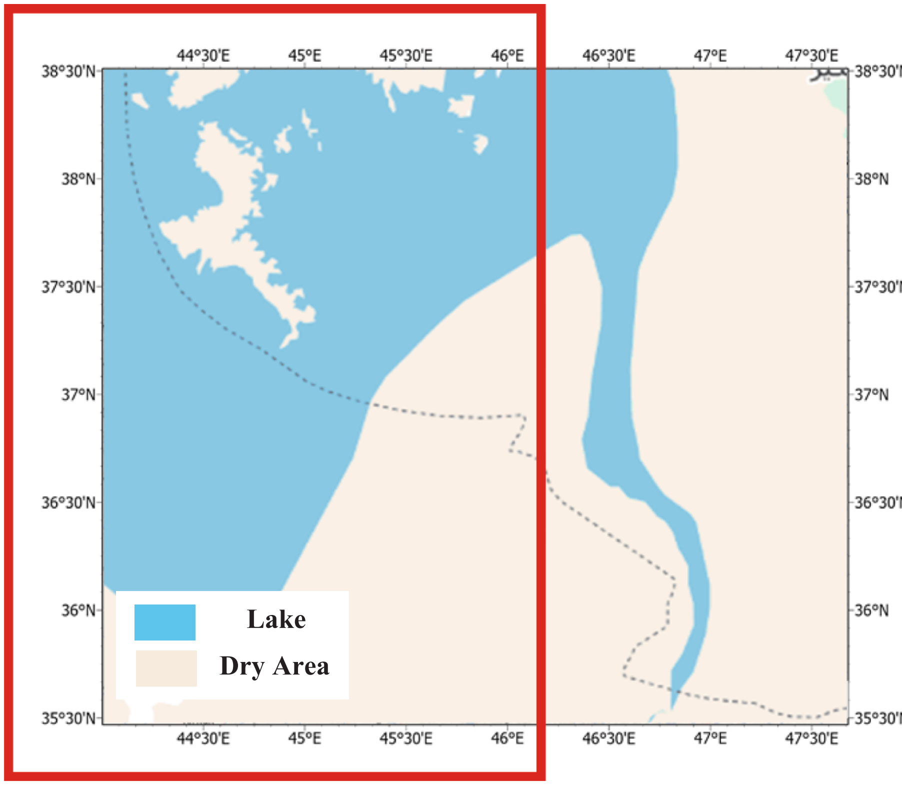

Fig. 9. Part of the study area where the presence of water has increased.

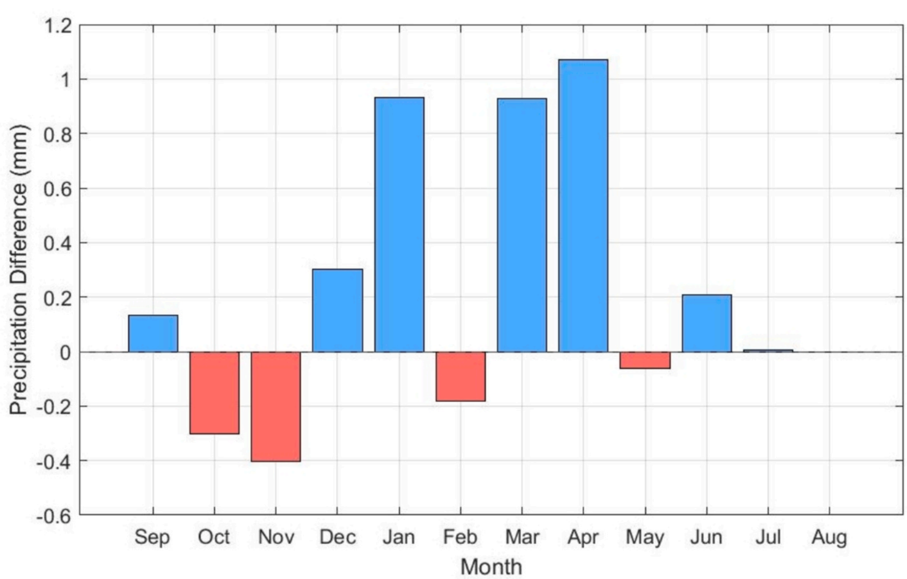

Fig. 10. Monthly Precipitation Difference in Southeastern Lake Urmia (2015–2016 vs. 2014–2015).

variability.

5.2. Pattern 2: decreased water presence in certain areas

In the second pattern, a decline in water presence was observed on the right side of the study area (Fig. 11). Both the Percentage Operator and the Subtraction Operator revealed a decrease in water coverage on this side over the study period.

To comprehend the underlying causes of this decrease, it is essential to consider several influencing factors:

Decreased Precipitation: Precipitation is one of the most direct influences on water levels. A decrease in rainfall during the study period could have significantly reduced water input into lakes, rivers, and other water bodies. However, the analysis conducted in this study using monthly precipitation data for the study area revealed no consistent increasing or decreasing trend during the examined period. Therefore, the results of this analysis indicate that the observed decrease in the eastern part of the study area cannot be solely attributed to decreased precipitation.

Increased Water Extraction: Increased water extraction for

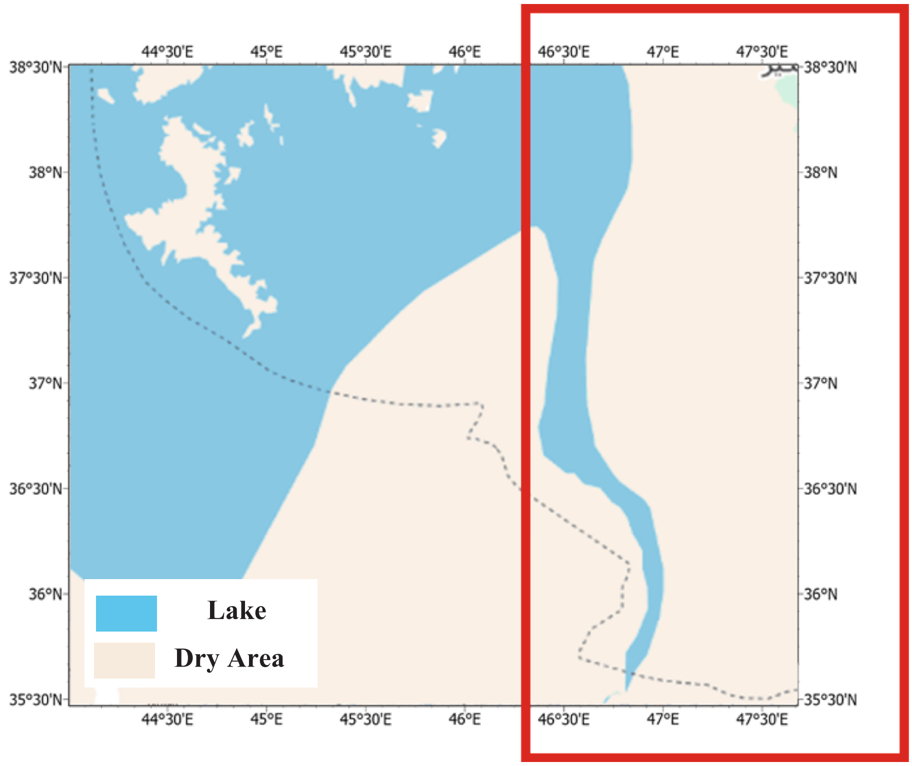

Fig. 11. Part of the study area where the presence of water has decreased.

agricultural, industrial, or urban use could also be an influencing factor. As demand for water resources grows, over-extraction can lead to a decline in surface water levels. For example, Abbaspour and Nazaridoust (2007), discussed how expanding agricultural activities in the Urmia Lake basin, particularly during drought periods, intensified water extraction from rivers and reservoirs, exacerbating water.

Land Use Changes: Changes in land use, such as deforestation, urbanization, or the expansion of agricultural land, alter the hydrological cycle in a region. These changes reduce the land's ability to retain water, leading to faster runoff and less infiltration into aquifers, ultimately lowering surface water levels. A study by Morandi et al., (2014) shows how increased urban development in the region led to greater surface runoff and reduced natural water retention, contributing to the observed decrease in water presence.

The findings of this study are further supported by those of Saemian et al. (2020), who analyzed the progress of Lake Urmia's restoration using both ground-based and satellite observations. Their analysis revealed positive trends in key hydrological parameters between 2015 and 2019—a period that partially overlaps with the timeframe of the present study. Specifically, they reported annual increases of 14.5 cm in water level, 204 km2 in surface area, and 0.42 km3 in lake volume, attributing these improvements to restoration interventions implemented in the basin. Although this study focuses specifically on the 2014–2016 period and employs a tensor-based approach, the identified spatial and temporal patterns of increased water presence align with the early phase of the broader restoration trajectory observed by Saemian et al. Notably, significant increases in water coverage were detected in the central and western zones of the lake, particularly near the confluence of the Zarrineh river and Simineh river—areas similarly recognized by Saemian et al. as primary zones of water accumulation. This correspondence reinforces the reliability of the proposed method and supports the interpretation that the detected hydrological improvements were largely driven by targeted restoration actions rather than by random climatic variability.

6. Conclusion

This research highlights the efficiency of innovative tensor operators, advanced indices, and remote sensing tools in comprehensively monitoring and analyzing water level fluctuations, as well as evaluating restoration program outcomes. By applying NDWI, the study offers a robust framework for detecting spatial and temporal changes in water bodies. The Urmia Lake case study showcases how these tools generate detailed insights into the dynamic responses of inland water systems to environmental pressures and targeted restoration initiatives. Analysis of NDWI-based matrices reveals trends and variations in water coverage, providing clear evidence of the restoration program's observable impact. These findings emphasize the importance of remote sensing and geospatial analysis in environmental assessment and resource management. Moreover, the methods and tools employed in this study have significant potential for application in other regions facing water scarcity, supporting the development of data-driven management strategies for sustainable water resource preservation. Future research could enhance monitoring capabilities and improve restoration outcome assessments by incorporating additional indices and higher-resolution datasets.

CRediT authorship contribution statement

Melika Sarkhosh: Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation. **Ali Abbasi:** Writing – review & editing, Validation, Supervision, Project administration, Investigation, Conceptualization. **Hossein Etemadfard:** Writing – review & editing, Validation, Supervision, Project administration, Methodology, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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