



Monitoring hydrological shifts in the Hawizeh Marshes (2000–2025) using different remote sensing indices

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Abstract

Monitoring long-term hydrological dynamics in wetland ecosystems is a major challenge in remote sensing due to seasonal variability, spectral confusion, and data limitations. Accurate detection of surface water changes is especially critical in transboundary and ecologically sensitive wetlands such as the Hawizeh Marshes, located along the Iran–Iraq border. In this study, four widely used spectral indices—NDWI, mNDWI, AWEI(SH), and AWEI(NSH)—were first evaluated using Landsat 8 imagery from January 2025. Their performance was quantitatively assessed against the Dynamic World water probability product using metrics such as F1-score, IoU, and MCC. Among them, AWEI(NSH) achieved the highest accuracy, with an F1-score of 0.98, IoU of 0.96, and MCC of 0.75. This step allowed us to select the most robust index under current environmental conditions. Following the index evaluation, AWEI(NSH) was applied to monthly Landsat imagery in 2024 to capture intra-annual water dynamics. The analysis revealed that water extent peaked in January and reached its minimum in July. These two representative months were then used as reference points in a long-term trend analysis using multi-temporal Landsat 7 and 8 imageries from 2000 to 2024. Results from both linear regression and Support Vector Regression (SVR) showed a significant and consistent decline in surface water coverage after 2010. Binary water maps for 2020 and 2024 indicated a 74.67 % reduction in winter water extent and a 74.31 % reduction in summer, reflecting rapid wetland degradation. These findings underscore the operational value of spectral indices for near real-time monitoring and highlight the importance of continuous satellite observation and coordinated transboundary water governance to preserve the ecological sustainability of the Hawizeh Marshes.

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1. Introduction

Wetlands are vital yet fragile ecosystems that play key roles in biodiversity, climate regulation, and water management. The Hor al-Azim Wetland, shared by Iran and Iraq, has long supported local livelihoods, but over the past two decades it has suffered severe hydrological stress due to cli-

mate change, dam construction, and water diversion. These pressures have led to significant surface water loss, threatening ecosystem balance and increasing land degradation risks (Acar et al., 2022; Günen 2022; Şan et al., 2024). Surface water decline is a key indicator of land degradation, impacting regional hydrology and sustainability. Given these challenges, remote sensing-based monitoring is essential for tracking water fluctuations and long-term trends (Albanwan et al., 2024; Elmi et al., 2024; Madhavi et al., 2024; Jahanbakhsh et al., 2025; Jin et al., 2023; Zahiri et al., 2025). Optical satellite imagery, with its high spatial

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and spectral resolution, enables precise water mapping based on the distinct reflectance of water across spectral bands. Spectral water indices, simple but powerful mathematical tools, are widely used for this purpose. Compared to costly and time-intensive field surveys, satellite-based methods offer a fast, scalable solution for regional and long-term water monitoring (Li et al., 2022). Although optical sensors work best in clear-sky conditions, microwave sensors provide all-weather capabilities. Yet, their accuracy may decline due to interference from a rough surface or vegetation. Thus, optical data remains central to most water detection efforts. A variety of methods have been developed to improve water body extraction from optical remote sensing data, including water indices, machine learning, and deep learning techniques. Water indices offer a fast and computationally efficient means of distinguishing water from other land covers using spectral reflectance differences (Li et al., 2021; Rad et al., 2021; Anand et al., 2024; Chen et al., 2024; Günen and Atasever 2024). Machine learning approaches (Acharya et al., 2016; Acharya et al., 2019; Wang et al., 2022; Carroll et al., 2025) enhance classification by capturing complex patterns in multispectral data. More recently, deep learning models (Li et al., 2022c; Notarangelo et al., 2025; Peng et al., 2025; Santos et al., 2025; Song and Jung 2025) have shown promising results, particularly when applied to high-resolution imagery.

These advanced techniques enable more robust, automated, and scalable water monitoring systems, further enhancing the accuracy of surface water mapping and change detection. Machine learning and deep learning techniques primarily rely on classification algorithms for water body detection. While these methods can achieve higher accuracy in certain cases, they require effective feature extraction, such as analyzing the histogram distribution of remote sensing images (Yang et al., 2022). In contrast, water indices remain the most widely used approach due to their simplicity, computational efficiency, and ease of implementation in separating water from non-water areas. However, classification-based methods often demand high-quality training samples, reliable prior knowledge, and expert interpretation, making them more challenging to apply at a large scale. Despite their strong performance in specific cases, the algorithmic complexity and data dependency of machine learning and deep learning models limit their broader applicability. In contrast, water indices remain popular due to their simplicity and efficiency in large-scale water mapping. However, these indices are also sensitive to spectral noise, which can reduce classification accuracy, especially under challenging environmental conditions. Environmental factors such as topography, snow, ice, clouds, and shadows can cause spectral confusion, lowering the reliability of water classification (Günen 2024). Overcoming these issues requires advanced preprocessing and the integration of complementary datasets to improve the robustness of water index-based mapping. The Normalized Difference Water Index (NDWI) often overesti-

mates water in urban areas due to spectral confusion with built-up surfaces, which reflect more in the shortwave infrared (SWIR) than in the near-infrared (NIR) range. To overcome this, Xu (2006) proposed the Modified NDWI (MNDWI) by replacing NIR with SWIR, significantly improving water detection accuracy in urban settings (Xu 2006; Pan et al., 2020). Feyisa et al., (2014) introduced the Automated Water Extraction Index (AWEI) to improve classification accuracy in areas affected by shadows and dark surfaces. Similarly, Tasseled Cap-based methods have shown improvements in extracting water features in shadowed and vegetated environments (Chen et al., 2022). The robustness and accuracy of AWEI were systematically evaluated and compared with the Modified Normalized Difference Water Index (MNDWI) and Maximum Likelihood (ML) classifiers. Results demonstrated that AWEI significantly outperformed MNDWI and ML classifiers with a statistically significant P-value < 0.01 , confirming its superior effectiveness in water body extraction. Two variations of AWEI were developed to address specific classification challenges: AWEI for non-shadow areas (AWEI nsh), designed to effectively eliminate non-water pixels, including dark built-up surfaces in urban environments, and AWEI for shadowed areas (AWEI sh), which further improves classification accuracy by removing shadow pixels that AWEI nsh may not fully eliminate. These advancements have made AWEI a more reliable and precise water classification tool in complex urban and natural landscapes. The Water Ratio Index (WRI) and the New Water Index (NWI) both use combinations of four spectral bands to improve water detection. WRI requires the presence of the middle infrared (MIR) band (Shen and Li 2010), while NWI has shown better performance in mountainous regions compared to other indices (Haibo et al., 2011). The General Water Index (GWI) (Yang and Xu 1998) improves water extraction by enhancing the contrast between visible and infrared bands. Similarly, the Enhanced Water Index (EWI) developed by Yang and Du (2017) was designed for accurate delineation of water bodies in both urban and mountainous regions using Landsat TM data, offering reliable classification across diverse environments. Several additional water body extraction methods have been developed to enhance surface water identification across various landscapes. The Tasseled Cap Wetness (TCW) index, introduced by Crist (1985), utilizes a multi-band transformation to highlight moisture content in satellite imagery. Similarly, the Water Index (WI2006), developed by Danaheer and Collett (2006), and the Water Index (WI2015), proposed by Fisher et al., (2016), were designed to further improve water body delineation by optimizing spectral band combinations. These indices play a crucial role in hydrological research by improving the precision of water body classification in both natural and urban settings. Among the available extraction methods, basic band operations and thresholding techniques are the most employed, thanks to their simplicity and effectiveness. Applying a set threshold

to water index imagery produces binary maps that distinctly differentiate water from non-water areas. While thresholds are often manually determined through visual assessment, this study uses a fixed thresholding method to maintain consistency over time. In this framework, careful consideration is given to selecting the most appropriate index that demonstrates strong resilience against misclassification of non-water elements (such as shadows or dark urban features) making it a promising tool for long-term water monitoring in complex wetland regions.

As one of the most ecologically and geopolitically significant transboundary wetlands in the Middle East, the Hawizeh Marshes play a vital role in regional biodiversity, water regulation, and climate resilience. Several studies have utilized remote sensing techniques to monitor the changes in the Hawizeh Marshes, particularly in relation to water scarcity, climate change, and human impact. Nama et al., (2024) examined restoration efforts for the Iraqi marshes using indices such as NDVI, NDMI, and WI to assess vegetation cover and water extent. Their findings highlighted a significant water deficit, predicting a reduction in suitable areas for restoration due to decreasing water availability. Joorabian Shooshtari and Jahanishakib (2024) employed hybrid models and cellular automata to model land cover changes in the Hoor Al-Azim Wetland, demonstrating that water conservation could mitigate future wetland degradation. Aziz and Alwan (2021) performed land cover classification of the Al-Hawizeh Marsh using Maximum Likelihood Classification (MLC), Support Vector Machine (SVM), and Artificial Neural Networks (ANN), with MLC yielding the highest accuracy for wetland areas. Alawadi et al., (2023), and other studies applying NDWI and NDMI indices proved effective for monitoring water surface changes during floods, though they acknowledged challenges such as difficulties in measuring inflows and the complexities of wetland dynamics. Hussein et al., (2018) utilized GIS and remote sensing techniques to analyze land cover changes, noting a significant reduction in the water area and an increase in the sand, signaling ongoing degradation.

Although these studies have greatly contributed to our understanding of the Hawizeh Marshes, some areas warrant further exploration. For instance, some studies face challenges with the temporal resolution of data, particularly in tracking long-term water dynamics. Others focus on specific short periods, which may not capture the full spatiotemporal complexity of hydrological shifts in these ecologically sensitive systems. Additionally, while indices like NDWI and MNDWI are widely used for water mapping, they often struggle with misclassification due to topographic effects, built-up areas, and shadow interference, especially in heterogeneous wetland environments. To address these gaps, this study incorporates several methodological innovations. It conducts a comprehensive comparison of four widely-used water indices (NDWI, mNDWI, AWEIsh, and AWEInsh) over a 25-year period (2000–2024) using multi-temporal Landsat-7 and Landsat-8 ima-

gery, an approach rarely adopted systematically in previous regional studies. The performance of each index is validated against the Dynamic World probability-based water product, providing a robust reference for assessing accuracy across space and time. Moreover, the study applies both linear regression and Support Vector Regression (SVR) to analyze and map seasonal and interannual hydrological trends, adding analytical depth beyond static classifications.

The primary objectives of this research are: (1) identifying the most suitable water index for accurate water body extraction in the study area. (2) Analyzing seasonal water trends by applying the selected index to monthly data, determining the peak water levels and the driest periods within a year. (3) Assessing long-term water changes in the Hawizeh Marshes from 2000 to 2024, evaluating wetland fluctuations over time. To achieve these objectives, satellite images of the Hawizeh Marshes were collected and preprocessed using Google Earth Engine (GEE). Ground truth data was obtained from the Dynamic World water band, providing a comprehensive reference dataset covering the entire study area (Brown et al., 2022). This dataset enables a wide-scale validation process, ensuring reliable accuracy assessments for the extracted water bodies.

2. Materials and study area

The Hoor Al-Azim Wetland is part of the Mesopotamian Wetlands, one of the largest wetland systems in West Asia, covering an area of over 9000 km². This extensive ecosystem consists of three major sections: Central Hor, Horalhammar (Hammar Marshes), and Horalhawizeh (Hawizeh Marshes). While Central Hor and Horalhammar are entirely within Iraq, approximately two-thirds of the Hawizeh Marshes lie within Iraq, and the remaining one-third is in Iran, where it is known as Hoor Al-Azim (Joorabian Shooshtari and Jahanishakib 2024). The Iranian portion of Hoor Al-Azim spans 771,161 ha, located in southwestern Khuzestan Province, northwest of Bostan city, and near Chazabe village, between approximately 46.1°E and 48.0°E longitude, and 30.5°N and 32.0°N latitude (Fig. 1). This wetland is a permanent freshwater ecosystem situated in Lower Mesopotamia, within the Iran-Iraq border region. The Mesopotamian wetlands are recognized among the 200 most critical biological areas globally (Makrouni et al., 2016). In addition to its ecological importance, Hoor Al-Azim holds significant historical, cultural, and environmental value. However, it has been subject to direct and indirect human-induced degradation at national and international levels. The primary anthropogenic threats include dam construction in Turkey, extensive groundwater extraction in Iraq, and the construction of the Karkheh Dam in Iran, all of which have substantially reduced the wetland's water levels. Furthermore, oil exploration, road and dyke construction, river diversions, and the long-term consequences of armed conflicts—in-

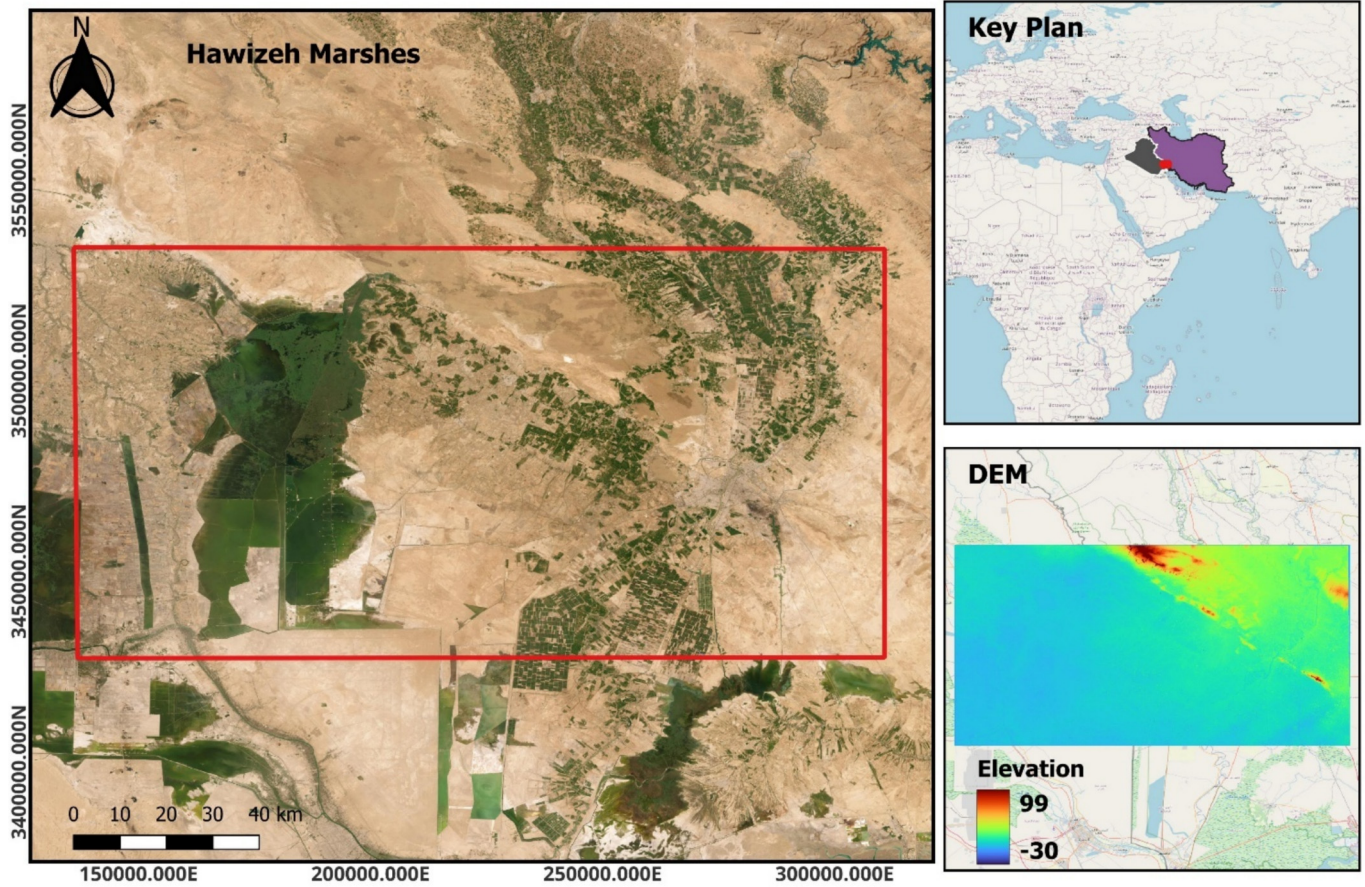


Fig. 1. Study area of the Hawizeh Marshes, showing the location and topography, along with a satellite image, key plan, and digital elevation model (DEM).

cluding the Iran-Iraq War and the Gulf Wars—have exacerbated the degradation of this vital ecosystem (Salmabai and Saeedi 2018). The reduction in the wetland's area has directly led to significant vegetation loss and diminished surface water coverage, intensifying the formation of dust storms and fine dust particles, which pose serious environmental and public health concerns (Mayahi et al., 2021).

2.1. Data acquisition and preprocessing

To assess the water dynamics of the Hawizeh Marshes over a 25-year period (2000–2025), this study utilized multi-temporal Landsat imagery and a set of water indices. High-resolution satellite images were obtained from the Landsat program, which offers extensive and consistent spatial coverage of the study area. Specifically, Landsat 7 imagery was used for the years 2000, 2005, and 2010, while Landsat 8 imagery was employed for 2015, 2020, 2024, and 2025 (Table 1). These datasets were selected due to their temporal consistency, free availability, and spectral quality, enabling robust long-term environmental analysis. All imagery was accessed and processed within the Google Earth Engine (GEE) platform to ensure computational efficiency and standardized preprocessing. Prior to index calculation,

Table 1

Band comparison among Landsat 7 ETM+, Landsat 8 OLI. Only selected bands used in this study were included here.

Bands	Landsat 7 ETM+		Landsat 8 OLI	
	W ¹ (μm)	R ¹ (m)	W ¹ (μm)	R ¹ (m)
Blue	0.45–0.52	30	0.45–0.51	30
Green	0.52–0.60	30	0.53–0.59	30
Red	0.63–0.69	30	0.64–0.67	30
NIR	0.76–0.90	30	0.85–0.88	30
SWIR-1	1.55–1.75	30	1.57–1.65	30
SWIR-2	2.08–2.35	30	2.11–2.29	30

the raw digital numbers were converted to top-of-atmosphere (TOA) reflectance using band-specific radiometric scaling coefficients, ensuring accurate spectral measurements. To mitigate atmospheric and sensor-related noise, a cloud masking algorithm was applied using the QA_PIXEL band. Cloud pixels (Bit 3) and cloud shadows (Bit 4) were identified and excluded from analysis to prevent distortion in index values. The computed water indices, ranging from −1 to 1, were used to quantify surface water extent. A threshold of index < 0.0 was applied to mask non-water areas, as these typically exhibit lower

reflectance in relevant spectral bands. This thresholding step was applied uniformly across all indices for consistency. To reduce temporal noise and enhance reliability, a median composite approach was employed. For each observation year, all available images within that year were aggregated, and the per-pixel median water index was calculated. This method effectively reduced the impact of outliers, cloud artifacts, and other anomalies, yielding a stable and representative spatial depiction of water conditions across the study period.

2.2. Reference data: Dynamic world water band

Dynamic World is an advanced near-real-time (NRT) global land use and land cover (LULC) classification system that utilizes deep learning on 10 m Sentinel-2 imagery to provide continuous and high-resolution monitoring of land cover changes (Brown et al., 2022). Unlike traditional LULC datasets that are updated annually with significant processing delays, Dynamic World delivers rapid, globally consistent classification outputs, making it particularly valuable for monitoring dynamic ecosystems like wetlands. The system generates probability-based LULC classifications, offering enhanced flexibility compared to conventional categorical maps. In this study, we leverage the Dynamic World water band, which represents the probability of water presence and effectively isolates other land cover classes. The water probability ranges between 0 and 1, and we apply a threshold of ≥ 0.5 to delineate water bodies and make a binary map (Water-nonWATER) within

the Hawizeh Marshes. This classification approach ensures that only areas with a high likelihood of complete water coverage are considered, allowing for precise monitoring of hydrological changes. To evaluate the effectiveness of different spectral water indices, we compare their outputs against the Dynamic World water band.

3. Methodology

A clear and structured approach was followed in this study to gather and process the data in alignment with the research goals. Each step was carefully planned to suit the nature of the study. The flow chart in Fig. 2 summarizes the overall methodology.

3.1. Selection of suitable water indices

In remote sensing applications, choosing the right water index is critical for effectively identifying water bodies and monitoring changes over time. For this study, several well-established water indices were selected for their ability to accurately delineate water bodies and distinguish them from non-water areas in the Hawizeh Marshes. These indices, including the Normalized Difference Water Index (NDWI), the Modified Normalized Difference Water Index (MNDWI), the Automated Water Extraction Index for shadow regions (AWEIsh), and for non-shadow regions (AWEInsh) were chosen based on their proven efficacy in similar environments and their adaptability to the characteristics of the study area. To ensure robust index selection

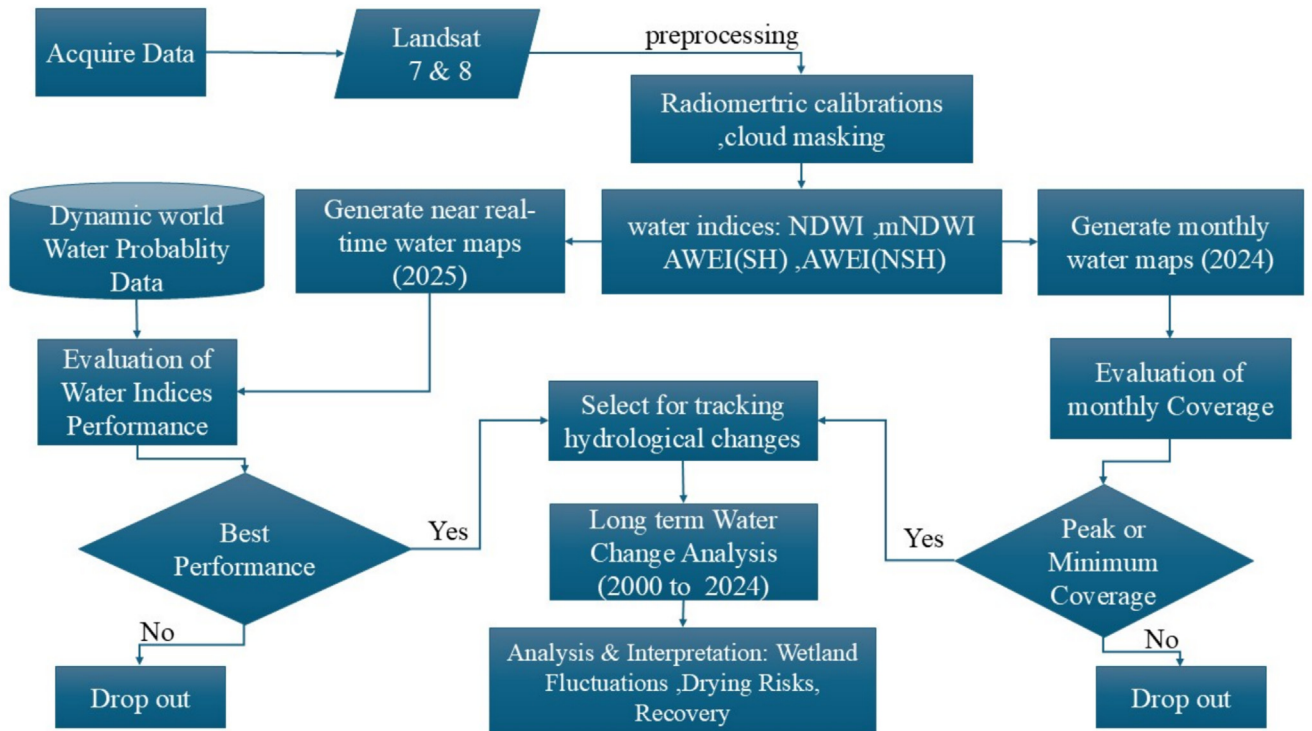


Fig. 2. The flowchart summarizes the key steps of data acquisition, preprocessing, and analysis.

for subsequent seasonal and long-term analyses, all four indices were first evaluated using Landsat 8 imagery from January 2025. Their outputs were quantitatively compared with the Dynamic World water probability product, which served as a reference dataset for assessing classification accuracy. This real-time comparison not only facilitated the identification of the most suitable index under current environmental conditions but also provided an up-to-date visual assessment of the wetland's hydrological status at the start of 2025. To extract water bodies from these indices, a uniform threshold value of 0.0 was applied across all indices and time periods. This threshold was selected based on prior literature and validated through visual inspection of representative images from different years (Li et al., 2021; Zhou et al., 2017). Although adaptive thresholding methods may improve local precision, the use of a consistent threshold ensures comparability across multi-temporal datasets and simplifies the trend analysis of long-term water changes.

3.1.1. Normalized difference water index (NDWI)

The NDWI, developed by McFeeters (1996) uses the Green and Near-Infrared (NIR) bands and is well-known for its straightforwardness and effectiveness in distinguishing water bodies. The formula is:

$$NDWI = (B_{\text{green}} - B_{\text{Nir}}) / (B_{\text{green}} + B_{\text{Nir}}) \quad (1)$$

where B_{green} is reflectance in the green band and B_{Nir} is reflectance in the Near-Infrared band. Although NDWI is useful for water body detection, it may produce mixed pixels, particularly in urban areas, due to the similar spectral characteristics between water and built-up surfaces (McFeeters 1996). This index improves the contrast between water and land, aiding in water body identification. However, NDWI can be sensitive to vegetation and soil moisture, potentially causing misclassification in regions with dense vegetation or moist soils (Laonamsai et al., 2023).

3.1.2. Modified normalized difference water index (MNDWI)

The **Modified Normalized Difference Water Index** (MNDWI), introduced by Xu (2006), is designed to enhance water body extraction by reducing the influence of built-up land and vegetation. Unlike the traditional NDWI, which utilizes the Near-Infrared (NIR) band, MNDWI replaces it with the Shortwave Infrared (SWIR) band. This modification significantly improves the distinction between water and urban surfaces, making it particularly effective for water extraction in densely built-up environments. The MNDWI is calculated using the following formula:

$$mNDWI = (B_{\text{Green}} - B_{\text{SWIR}}) / (B_{\text{Green}} + B_{\text{SWIR}}) \quad (2)$$

where B_{Green} is reflectance in the green band and B_{SWIR} is reflectance in the Shortwave Infrared band. By incorporating the SWIR band, MNDWI minimizes interference from

vegetation and soil moisture, thereby increasing the accuracy of water body delineation. However, despite its advantages, the index can still be affected by misclassification in regions with shadows or highly moist soils (Laonamsai et al., 2023).

3.1.3. Automated water extraction index (AWEI)

Building upon traditional water indices, the Automated Water Extraction Index (AWEI) was developed by Feyisa et al., (2014) to enhance water body extraction, particularly in challenging environments where shadows, vegetation, and built-up areas interfere with classification. Unlike NDWI and MNDWI, AWEI applies additional weighted coefficients to better suppress non-water surfaces, making it more effective in complex landscapes. AWEI comes in two variations: **AWEIsh (shadow)**: Designed for water extraction in shadowed areas. **AWEInsh (non-shadow)**: Optimized for areas without significant shadow interference. The formulas for these indices are as follows (Feyisa et al., 2014):

$$AWEIsh = B_{\text{Blue}} + 2.5 \times B_{\text{Green}} - 1.5 \times (B_{\text{Nir}} + B_{\text{SWIR-1}}) - 0.25 \times B_{\text{SWIR-2}} \quad (3)$$

$$AWEInsh = 4 \times (B_{\text{Green}} - B_{\text{SWIR-1}}) - (0.25 \times B_{\text{Nir}} + 2.75 \times B_{\text{SWIR-1}}) \quad (4)$$

where B_{Green} is reflectance in the green band and $B_{\text{SWIR-1}}$ is reflectance in the Shortwave Infrared band 1 and $B_{\text{SWIR-2}}$ is reflectance in the Shortwave Infrared band 2 and B_{Nir} is reflectance in the Near-Infrared band. AWEIsh is particularly useful in areas with significant shadow presence, while AWEInsh effectively eliminates non-water pixels in well-lit environments. Compared to NDWI and MNDWI, AWEI has demonstrated superior accuracy in water extraction, particularly in wetlands such as the Hawizeh Marshes, where shadows and built-up areas can interfere with water classification (Feyisa et al., 2013). However, the effectiveness of AWEI can still be influenced by the quality of input satellite data and the presence of mixed pixels (Jiang et al., 2014).

3.1.4. Water distribution mapping and thresholding

In this study, water distribution maps were generated for the year 2025 using various water indices (NDWI, MNDWI, AWEIsh, AWEInsh) to assess water presence and absence in the Hawizeh Marshes. To create these maps, the raw values from each index were processed using a thresholding technique. A threshold of 0 was applied to the index values to distinguish between water and non-water areas.

3.1.5. Binary map generation and comparison with reference data

After applying the thresholding process, binary maps were generated for each of the water indices used in the study. These maps represented water and non-water areas based on the threshold of 0, with class 1 for water and class

0 for non-water. To evaluate the accuracy and performance of these generated binary maps, they were compared with a reference binary map derived from the Dynamic World water band. Although the Dynamic World water band is derived from Sentinel-2 imagery with a spatial resolution of 10 m, it was employed in this study primarily as a reference dataset to enable a fair and consistent comparison among the 30-meter water indices derived from Landsat data. Since all indices were generated at 30-meter resolution, the evaluation remained balanced. To ensure compatibility, the Dynamic World water map was resampled to 30 m using nearest-neighbor interpolation before validation. While minor discrepancies due to resolution differences may occur, the objective was not absolute accuracy, but rather the relative assessment of index performance for selecting the most suitable one for subsequent change detection analysis. The Dynamic World water band provides a probability-based classification of water presence, with values ranging from 0 to 1, indicating the likelihood of water coverage across the study area. A threshold of 0.5 was used for the Dynamic World water band, where values greater than 0.5 were classified as water (class 1) and values below 0.5 were classified as non-water (class 0). The comparison between the binary maps generated from the different water indices and the reference binary map obtained from the Dynamic World data allowed for a performance evaluation. This evaluation focused on the accuracy of water detection and the ability of each index to accurately delineate water bodies in the study area. By comparing the results from multiple indices, this study aimed to identify the most reliable index for monitoring water dynamics in the Hawizeh Marshes. The binary classification maps and their comparison with the reference data provided insights into the effectiveness of each water index for detecting water bodies in the context of the Hawizeh Marshes, considering the challenges posed by vegetation, shadows, and other environmental factors.

3.1.6. Performance metrics

In environmental monitoring, the accurate delineation of water bodies is crucial for assessing ecosystem health and supporting effective management strategies. Identifying the right indices for the study area is essential before conducting long-term monitoring therefore, frequently used assessment parameters in water mapping studies were calculated (Rajeswari and Rathika 2024, Sun et al., 2024). For this reason, this study focuses on evaluating the performance of several water indices in identifying water features within the Hawizeh Marshes, an ecologically sensitive region located on the Iraq-Iran boundary. The region's complex environmental conditions and diverse water body features present challenges, making it necessary to use a comprehensive set of evaluation metrics to assess the effectiveness of these indices. To assess the accuracy of water body identification, we utilized a set of evaluation metrics derived from the confusion matrix, comparing predicted results with reference Data. These metrics included such

as True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). TP refers to the number of water pixels correctly identified as water, while TN represents the non-water pixels correctly identified as non-water. FP and FN reflect the misclassification of non-water pixels as water and water pixels as non-water, respectively. From these values, several performance measures were derived to evaluate the effectiveness of the indices. The True Positive Rate (TPR), also known as sensitivity or recall, measures the proportion of actual water pixels correctly identified. Specificity (SPC) measures the proportion of actual non-water pixels correctly identified as non-water. Positive Predictive Value (PPV) indicates the proportion of identified water pixels that are truly water, while Negative Predictive Value (NPV) reflects the proportion of identified non-water pixels that are truly non-water. The overall accuracy of the classification was evaluated using the Accuracy (ACC) metric, which represents the proportion of correctly classified pixels (both water and non-water) relative to the total number of pixels. The F1 Score, the harmonic mean of precision and recall, was employed to balance the trade-off between these two metrics. Additionally, we used Intersection over Union (IoU) and the Matthews Correlation Coefficient (MCC), providing a robust evaluation of the overlap between predicted and actual water areas and offers a balanced measure of binary classification performance. The use of these comprehensive evaluation metrics ensures a detailed understanding of the strengths and weaknesses of each water index. This is particularly important in selecting the most effective indices for accurately identifying water features in the Hawizeh Marshes. Such an informed approach is crucial for conducting long-term monitoring of water bodies, as it ensures the use of the most reliable methods for tracking changes in the region's aquatic ecosystems over time.

3.2. Monthly water index calculation and seasonal trend analysis

To assess the seasonal variations in water presence within the Hawizeh Marshes, the monthly water index values for the year 2024 were calculated. These calculations were for each month, allowing us to monitor the dynamic fluctuations in water bodies over the course of the year. This seasonal variation in water availability highlighted the critical differences in water conditions throughout the year.

3.3. Multi-year water change detection, trend analysis, and binary classification

To examine the long-term changes in water coverage within the Hawizeh Marshes from 2000 to 2024, we utilized Landsat 8 imagery for the years 2024, 2020, and 2015, and Landsat 7 imagery for the years 2010, 2005, and 2000. For each of these years, we calculated water indices to assess both the peak and low water levels, allowing for a detailed

analysis of seasonal fluctuations in water extent. To quantify the long-term trends in water changes, we applied two regression models: Support Vector Regression (SVR) and Linear Regression. These models helped generate a trend map that visualized how water coverage changed over time, revealing both gradual shifts and abrupt changes. To evaluate the changes in water area between 2000 and 2024, we created binary water maps for each year using a threshold value of 0.0. Areas above the threshold were classified as water, while those below were categorized as non-water. The binary maps were then analyzed to determine the total areas of water and non-water for each year, and the percentage change in water coverage was calculated. This combined approach allowed us to assess both seasonal variations and long-term trends in water dynamics within the Hawizeh Marshes.

4. Results and discussion

4.1. Evaluation of water indices performance

In this study, we employed four water indices—NDWI, MNDWI, AWEIsh, and AWEInsh to assess water dynamics in the Hawizeh Marshes. These indices were evaluated using various performance metrics, including TPR, SPC, PPV, NPV, ACC, F1 Score, IoU, and MCC (Table 2). The results indicated that AWEInsh demonstrated the highest performance in accurately delineating water bodies, particularly in regions with complex land cover, where shadowed areas could interfere with the water detection process. The performance of NDWI, MNDWI, AWEIsh, and AWEInsh was compared against the reference data obtained from the Dynamic World water band (Fig. 3

Table 2

Performance comparison of water indices (NDWI, mNDWI, AWEIsh, AWEInsh) based on key metrics for water and non-water classes.

metrics	NON-WATER				WATER			
	NDWI	mNDWI	AWEIsh	AWEInsh	NDWI	mNDWI	AWEIsh	AWEInsh
TPR	0.9883	0.9979	0.9978	0.9964	0.6202	0.4882	0.5693	0.6193
SPC	0.6202	0.4882	0.5693	0.6193	0.9883	0.9979	0.9978	0.9964
PPV	0.9724	0.9428	0.9589	0.9675	0.7967	0.9658	0.9627	0.9376
NPV	0.7967	0.9658	0.9627	0.9376	0.9724	0.9428	0.9589	0.9675
ACC	0.9631	0.9440	0.9591	0.9659	0.9631	0.9440	0.9591	0.9659
F1 SCORE	0.9803	0.9696	0.9779	0.9817	0.6975	0.6486	0.7155	0.7459
IOU	0.9614	0.9410	0.9568	0.9641	0.5355	0.4799	0.5570	0.5948
MCC	0.6842	0.6646	0.7229	0.7465	0.6842	0.6646	0.7229	0.7465

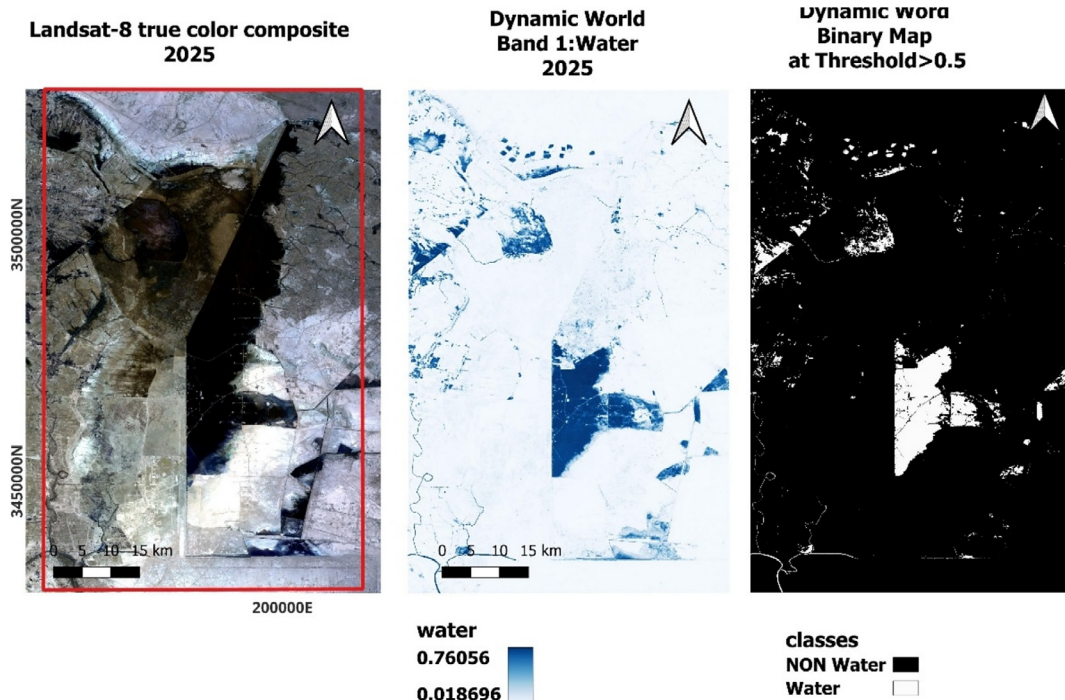


Fig. 3. Reference data showing the Landsat-8 true color composite for 2025 (left), the Dynamic World Band 1 (Water) map for 2025 (middle), and the corresponding binary map generated from Dynamic World with a threshold of 0.5 (right), illustrating water presence (white) and non-water (black) areas.

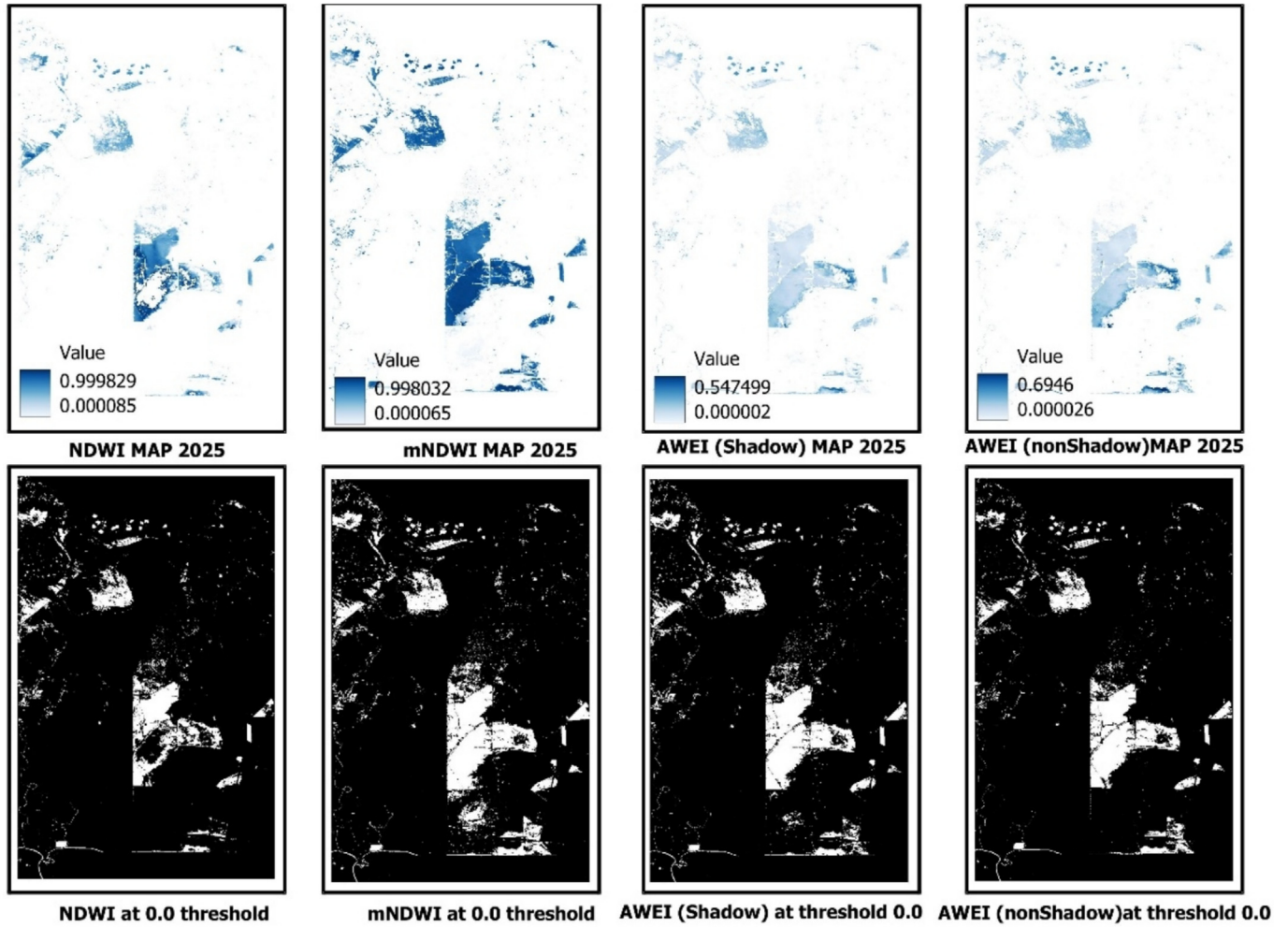


Fig. 4. Comparison of water indices maps for January 2025, showing NDWI, mNDWI, AWEI (Shadow), and AWEI (non-shadow) maps with their respective values (top row). The bottom row displays the same maps with a threshold of 0.0, where water areas are classified as white, and non-water areas as black, based on each index's thresholding technique.

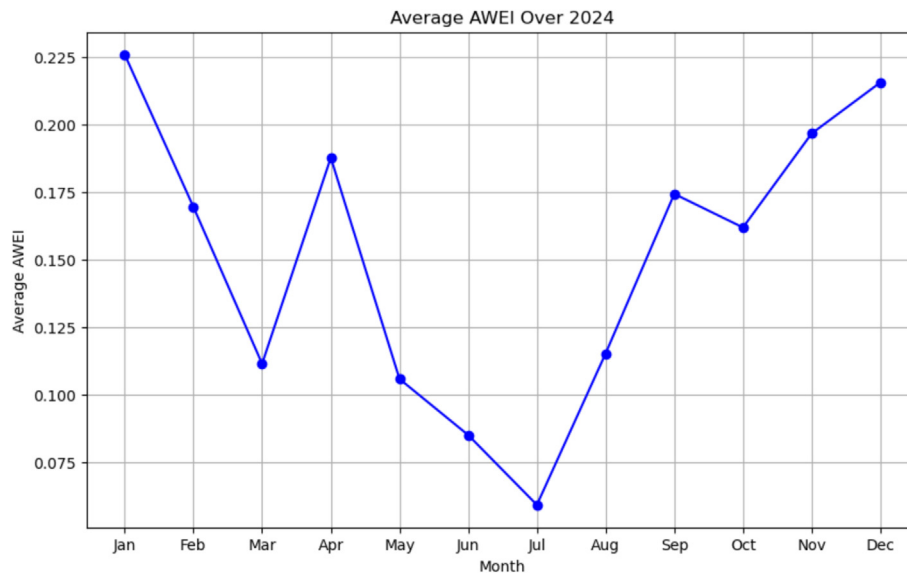


Fig. 5. Monthly variation of Average AWEInsh throughout 2024, illustrating seasonal trends in aquatic vegetation and water presence.

and 4). AWEInsh outperformed the other indices in terms of both accuracy and delineation precision, as it effectively mitigated issues caused by shadows and non-water surfaces. This result aligns with previous studies that have highlighted AWEI's effectiveness in mapping water bodies in complex environments (Feyisa et al., 2014, Fisher et al., 2016, Zhou et al., 2017, Acharya et al., 2018, Li et al., 2021, Li et al., 2022). Furthermore, MNDWI and NDWI performed well, but they were more susceptible to misclassifications in urban or heavily vegetated areas, where their sensitivity to vegetation or built-up areas affected the accuracy (Acharya et al., 2018).

4.2. Seasonal water level variations

A primary goal of this study was to examine the seasonal variations in water levels within the Hawizeh Marshes. Monthly AWEInsh values for 2024 were calculated, and both linear regression and Support Vector Regression (SVR) were applied to the median values for each month (Figs. 6 and 7). Regions exhibiting the greatest and least monthly variations

were mapped, with areas showing negative slopes and highlighted in red and yellow indicating more significant changes and potentially higher risk conditions. The analysis revealed considerable fluctuations in water extent, with the highest water presence occurring in January and the lowest in July (Fig. 5). These seasonal peaks and troughs offer valuable insight into the most suitable times for monitoring the marshes. The results indicate that the winter months, particularly January, correspond to the period of greatest water coverage, while the summer months, especially July, show the least water presence (Park J 2022). This pattern aligns with the seasonal hydrological behaviors observed in other wetland systems, where water levels fluctuate due to factors like rainfall, evaporation, and regional variations in water flow (Euliss and Mushet 1996). Recognizing these seasonal trends is crucial for effective water resource management, as it helps identify the optimal periods for monitoring and restoration efforts. Understanding the dynamics of water fluctuations allows for more informed management strategies, which can contribute to the preservation of the ecological balance in the marshlands.

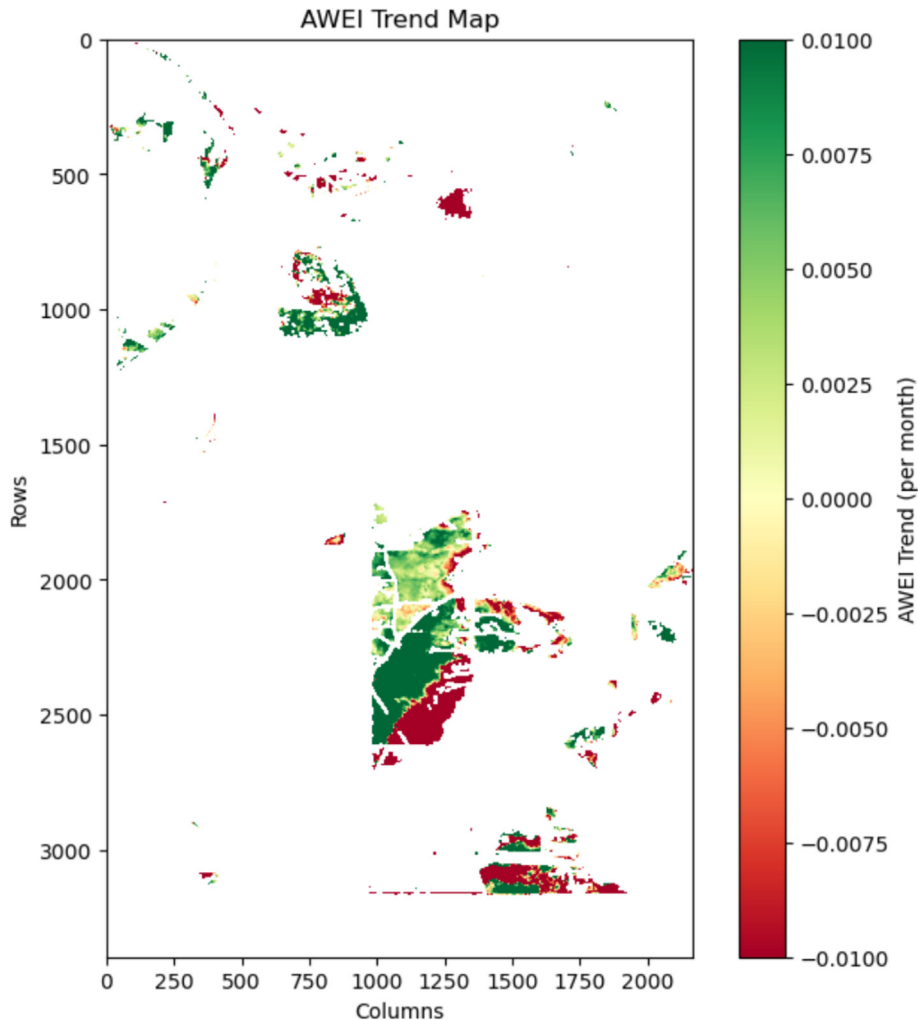


Fig. 6. AWEInsh trend map for 2024, showing spatial variations in aquatic ecosystem changes based on monthly trends using linear regression analysis.

4.3. Multi-year water change detection, trend analysis (2000–2024)

The temporal assessment of water dynamics in the Hawizeh Marshes from 2000 to 2024 reveals a sustained decline in surface water extent, with the most significant reductions occurring after 2010. The Automated Water Extraction Index for Non-Shadowed areas (AWEI(NSH)), selected for its superior performance compared to other spectral indices analyzed in previous sections, served as the primary indicator for monitoring water changes. Water coverage fluctuations were assessed during hydrologically contrasting periods—peak water levels in January and minimum levels in July—across selected years using multi-temporal Landsat 7 and Landsat 8 imagery. While a brief resurgence in water presence was noted in 2020, the overall spatial and temporal trends remain inconsistent and fragmented, indicating a growing threat of large-scale wetland degradation (Fig. 8). To further examine change patterns, seasonal change detection maps were developed for both summer and winter using Support Vector Regression (SVR) and

linear regression techniques (Figs. 9, 10, 12, and 13). Linear regression outputs revealed broader changes and a higher concentration of high-risk zones than those identified by SVR. Nevertheless, both approaches demonstrated considerable spatial agreement within each season. Areas marked by negative regression slopes (highlighted in red and yellow) were indicative of regions undergoing significant changes, suggesting increased vulnerability to long-term ecological degradation. Moreover, the mean seasonal values of the AWEI(NSH) index from 2000 to 2024 were analyzed to better characterize temporal trends (Figs. 11 and 14). Results showed that winter conditions were generally more favorable compared to summer, although both seasonal trends experienced a sharp decline around 2010, partial recovery in 2020, and a renewed decline in summer values through 2024. This downward trend raises concerns over the long-term stability of the marshland ecosystem. These findings are consistent with earlier studies attributing wetland degradation to a combination of climate change, hydrological alterations, and increasing water demands (Nama et al., 2024). Similar patterns have been docu-

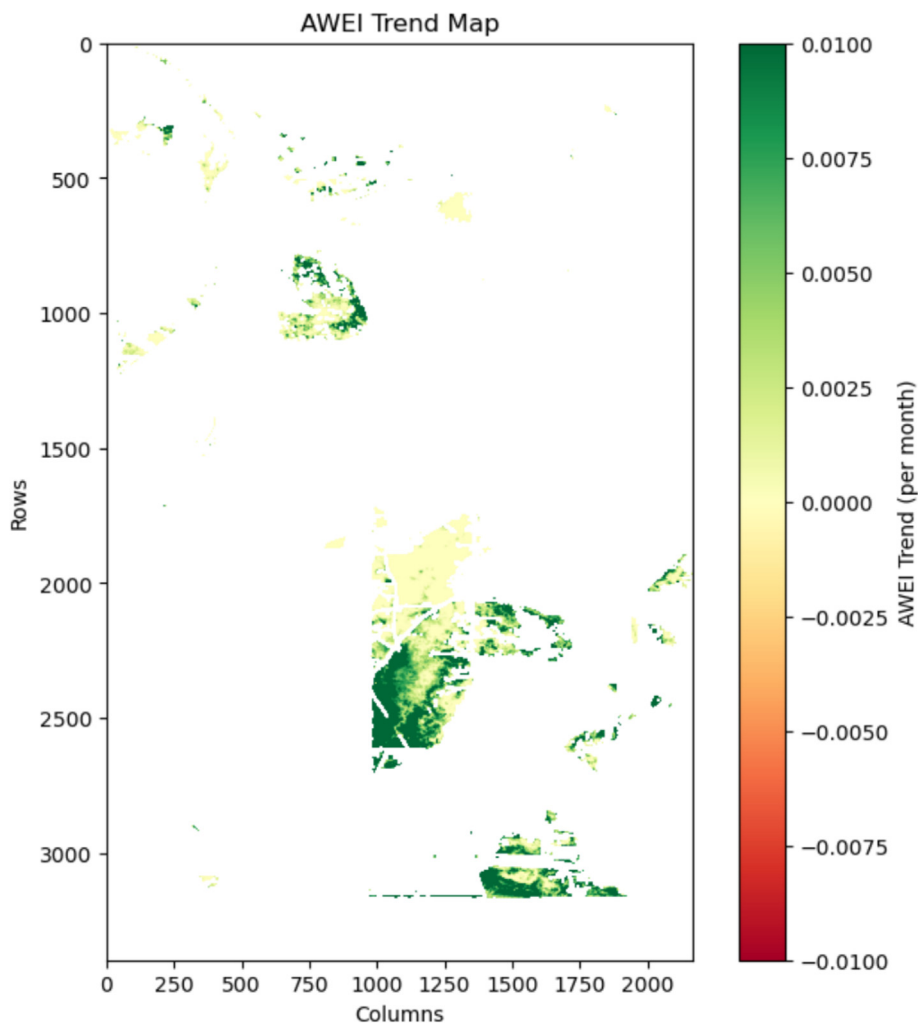


Fig. 7. AWEInsh trend map for each month of 2024, illustrating spatial variations in aquatic ecosystems derived using linear Support Vector Regression (SVR).

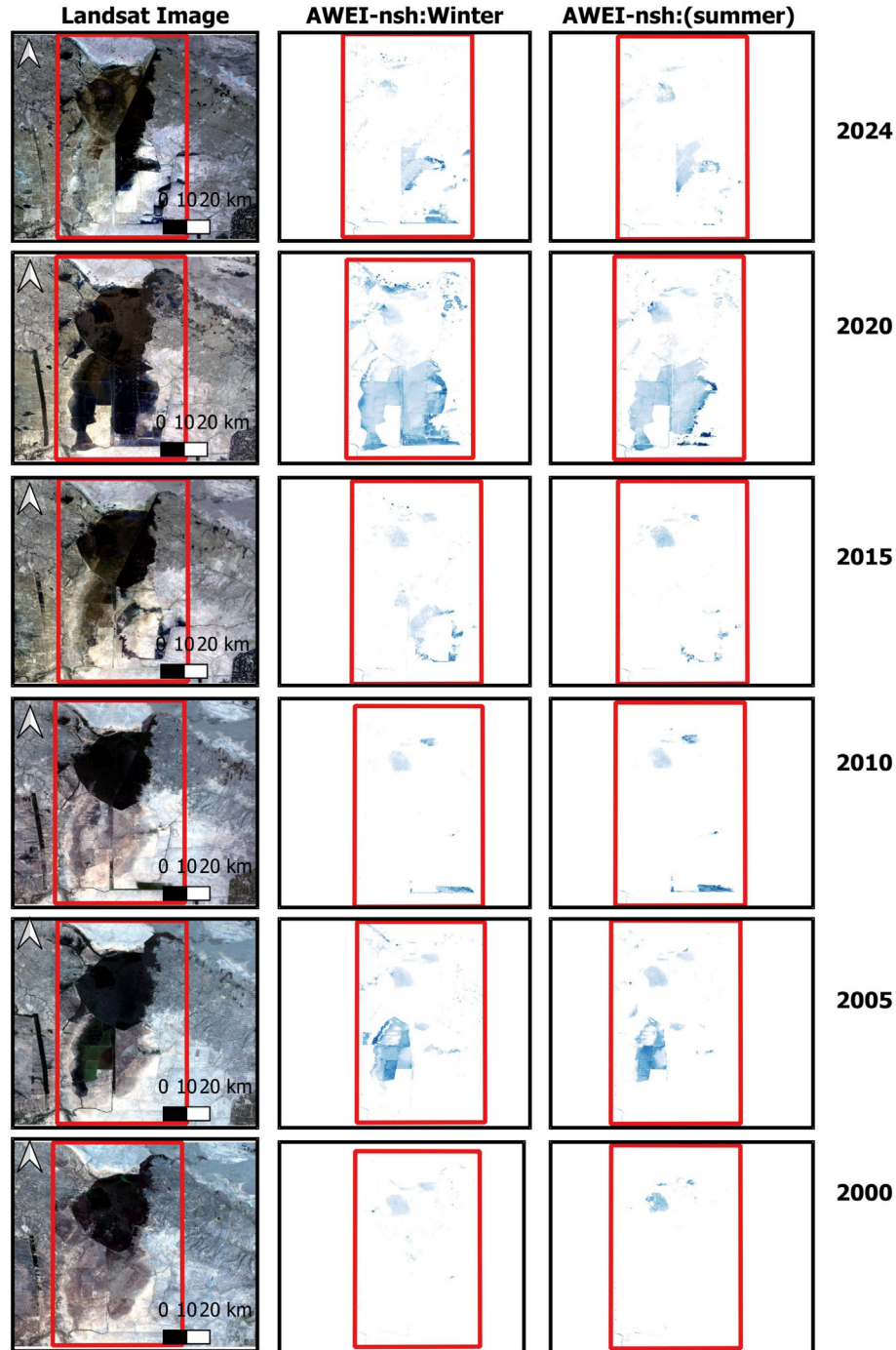


Fig. 8. AWEInsh changes between 2000 and 2024. Left column: Median Landsat image for the respective year; Middle column: Median AWEInsh for winter; Right column: Median AWEInsh for summer, highlighting seasonal and temporal variations in aquatic environments.

mented in the nearby Hoor Al-Azim wetland on the Iran-Iraq border, where a long-term decline in water bodies and expansion of salt-affected areas were observed from 1985 to 2015 (Joorabian Shoostari and Jahanishakib, 2024). Likewise, research on the Al-Hawizeh Marsh using NDVI and NDWI indices reported a 50 % reduction in vegetation cover and a 41 % decrease in water extent, alongside an increase in barren land (Hussein et al.,

2018). The current study's findings corroborate these observations, emphasizing the detrimental effects of hydrological modifications (such as dam construction and water diversions) on marshland ecosystems. In particular, infrastructure developments like the construction of the Karkheh Dam in Iran and widespread groundwater extraction in Iraq have been identified as major drivers of water scarcity in the region (Alawadi et al., 2023). These factors, com-

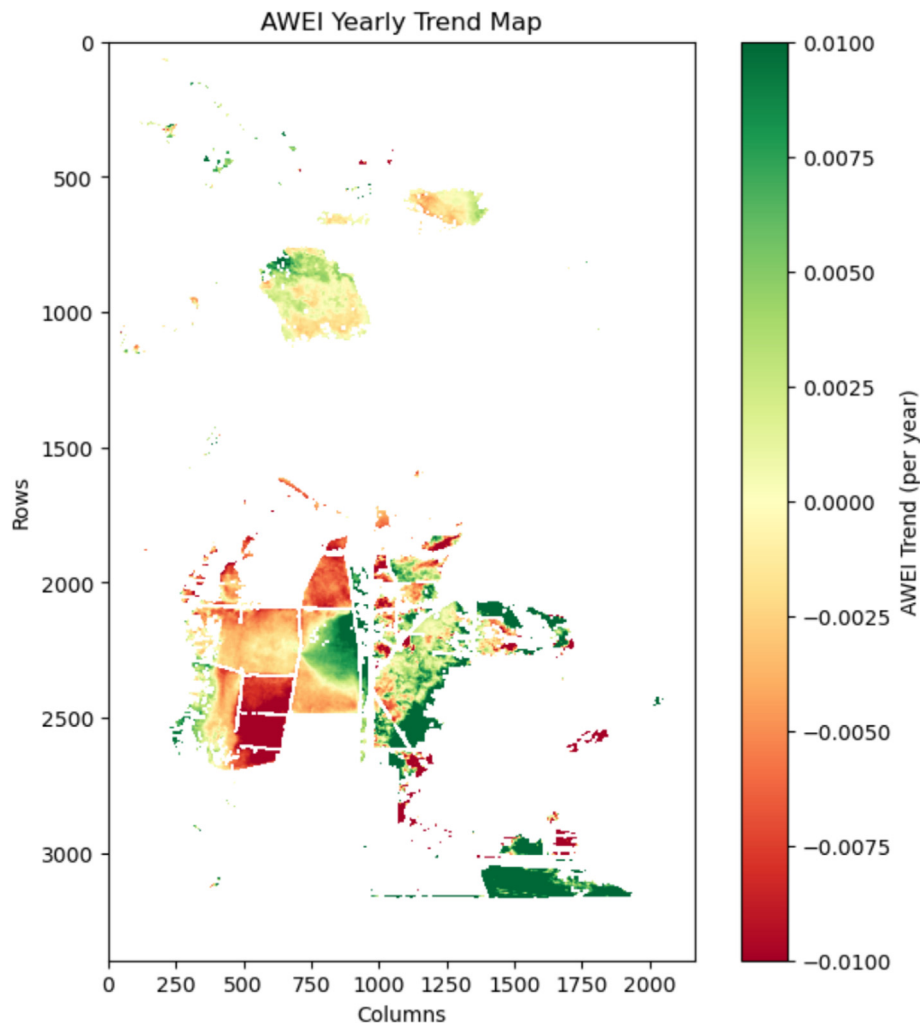


Fig. 9. AWEInsh yearly trend map (2000–2024) **for winter** illustrating spatial patterns of aquatic ecosystem changes derived using linear regression analysis.

pounded by climate variability, continue to pose significant threats to the ecological sustainability of the Hawizeh Marshes.

4.4. Quantitative analysis of water change

The binary classification of water maps for the years 2020 to 2024, using a threshold value of 0.0, enabled the delineation of water and non-water areas and allowed for a quantitative assessment of wetland shrinkage (Table 3). This threshold-based approach effectively distinguished between water-covered and dry areas, further confirming the ongoing reduction in the extent of the Hawizeh Marshes. The results revealed a significant decline in water-covered areas during both winter and summer seasons of the study period. Specifically, the winter water extent decreased from 2028.37 km² in 2020 to 513.60 km² in 2024, representing a 74.67 % reduction. Likewise, the summer water area dropped from 1411.00 km² to 362.46 km², marking a 74.31 % decline. Correspondingly, the extent of non-water areas increased substantially, with

a 32.88 % rise in winter and a 20.07 % increase in summer. These figures indicate a profound hydrological transformation in the marshland, raising serious concerns about its long-term ecological viability. Notably, the period between 2020 and 2024 experienced the most severe losses, which appear to correspond with intensified anthropogenic activities and recurring droughts. These findings are consistent with previous studies that highlighted the combined impacts of climate change and water management interventions (such as damming and diversion) on wetland degradation (Hussain et al., 2018). Furthermore, the observed seasonal discrepancies—particularly the greater water loss during summer—underscore the intensified effects of higher evapotranspiration and reduced inflows during dry periods, which exacerbate the vulnerability of the wetland ecosystem.

4.5. Implications and future considerations

Given the alarming trend of water loss in the region, there is a pressing need for comprehensive wetland man-

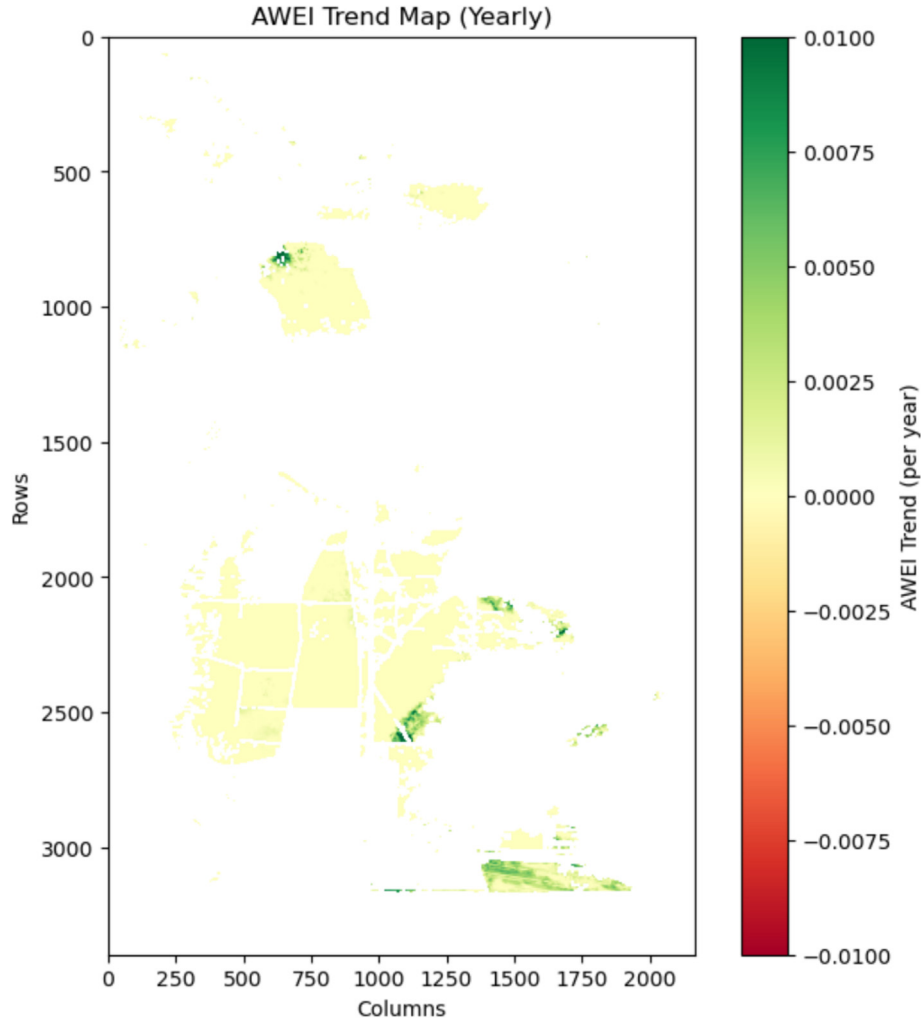


Fig. 10. AWEInsh yearly trend map (2000–2024) for winter illustrating spatial patterns of aquatic ecosystem changes derived using linear Support Vector Regression (SVR).

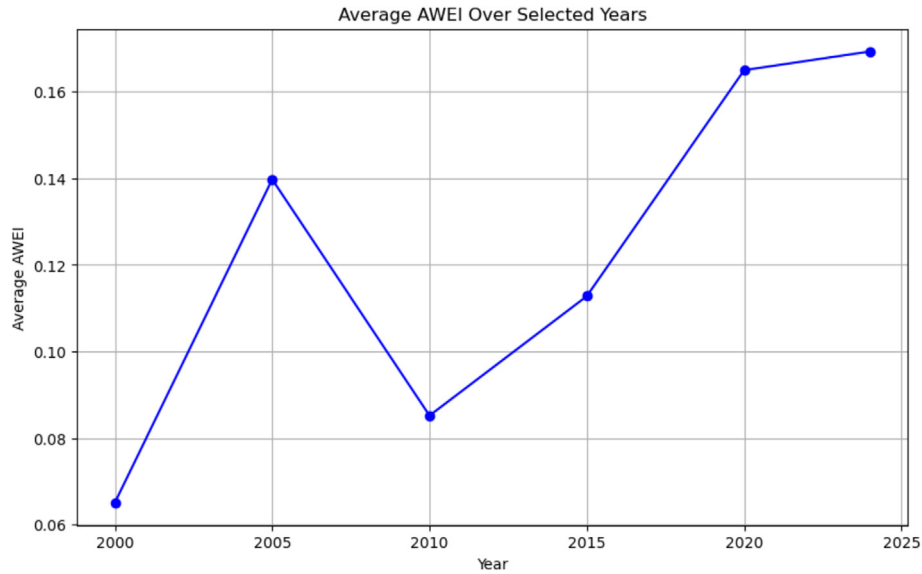


Fig. 11. Average AWEInsh during winter for selected years (2000–2024), showing temporal variation in aquatic ecosystem conditions.

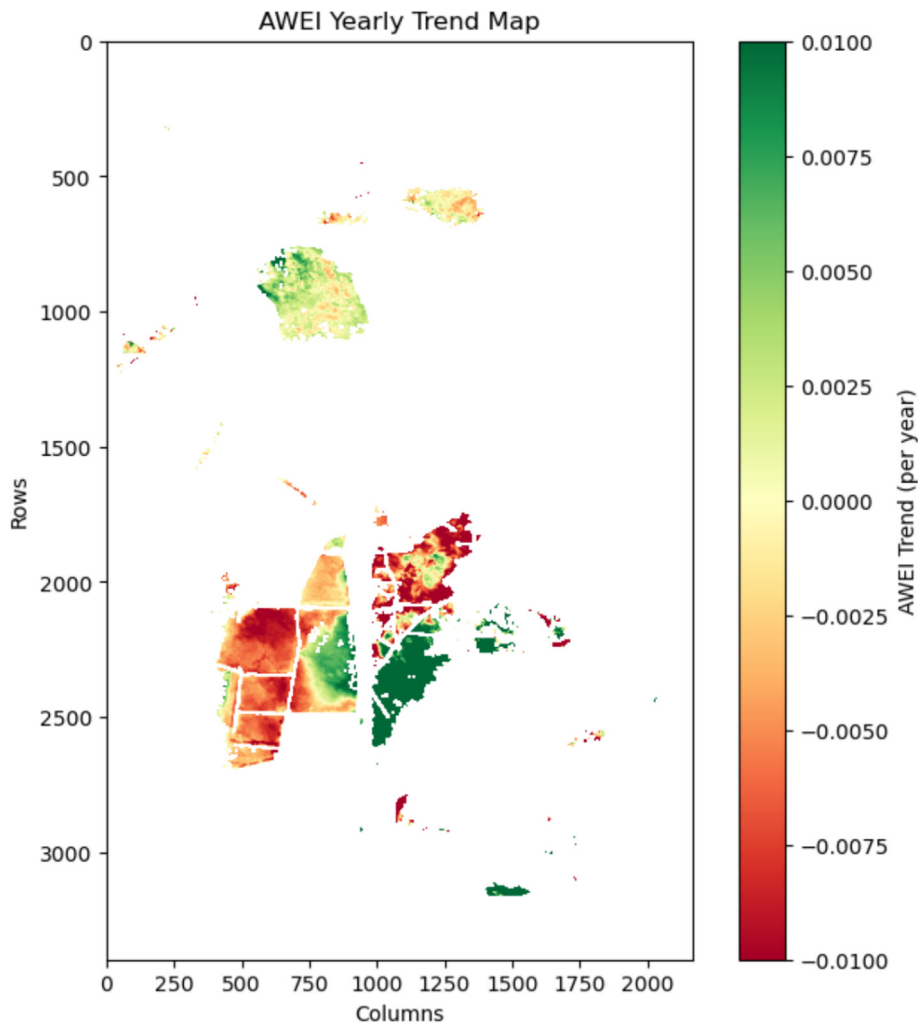


Fig. 12. AWEInsh yearly trend map (2000–2024) for summer illustrating spatial patterns of aquatic ecosystem changes derived using linear regression analysis.

agement strategies. The findings of this study highlight the necessity for improved transboundary water governance, conservation initiatives, and sustainable water allocation policies. While this study focused on the efficiency of spectral water indices for long-term monitoring due to their simplicity and operational feasibility, future research could integrate machine learning algorithms (e.g., Random Forest, Support Vector Machines, or deep learning models) to evaluate and compare their performance in complex wetland environments. These data-driven approaches could enhance classification accuracy, particularly in heterogeneous landscapes. Furthermore, to better understand the driving forces behind surface water changes, it is essential to incorporate regional hydrological data (such as rainfall, evaporation rates, and dam discharge records). This should be complemented by data on human activities, including irrigation practices, land use changes, and infrastructure development. Such multidisciplinary integration would enable a more quantitative and causal analysis of wetland degradation, which is critical for guiding evidence-based restoration and policymaking. Incorporating multi-sensor remote sensing techniques, such as radar

and hyperspectral data, may also enhance the detection of water bodies under challenging conditions, including cloud cover or dense vegetation. Overall, this study reinforces the importance of continuous satellite-based monitoring and calls for collaborative, data-informed strategies to ensure the long-term sustainability of the Hawizeh Marshes.

4.6. Policy implications and management recommendations

The hydrological trends identified in this study have clear implications for the management of the Hawizeh Marshes, particularly in the context of transboundary governance. The substantial loss of surface water, spatial concentration of degradation hotspots, and seasonal patterns revealed through remote sensing can support more informed and targeted policy actions. For example, the identification of peak (January) and minimum (July) water periods provides a foundation for adjusting upstream water releases through adaptive seasonal allocation, especially during dry periods. Moreover, the spatial trend maps derived from multi-year analysis can guide the prioritiza-

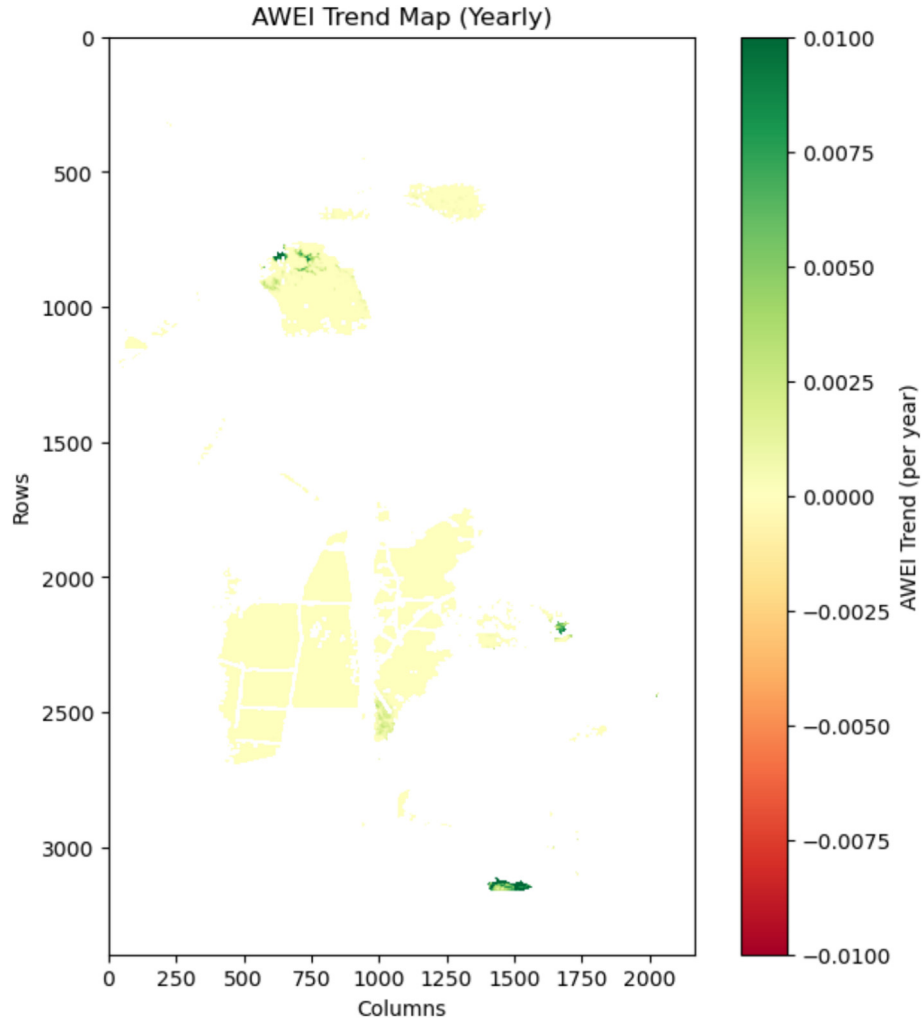


Fig. 13. AWEInsh yearly trend map (2000–2024) for summer illustrating spatial patterns of aquatic ecosystem changes derived using linear Support Vector Regression (SVR).

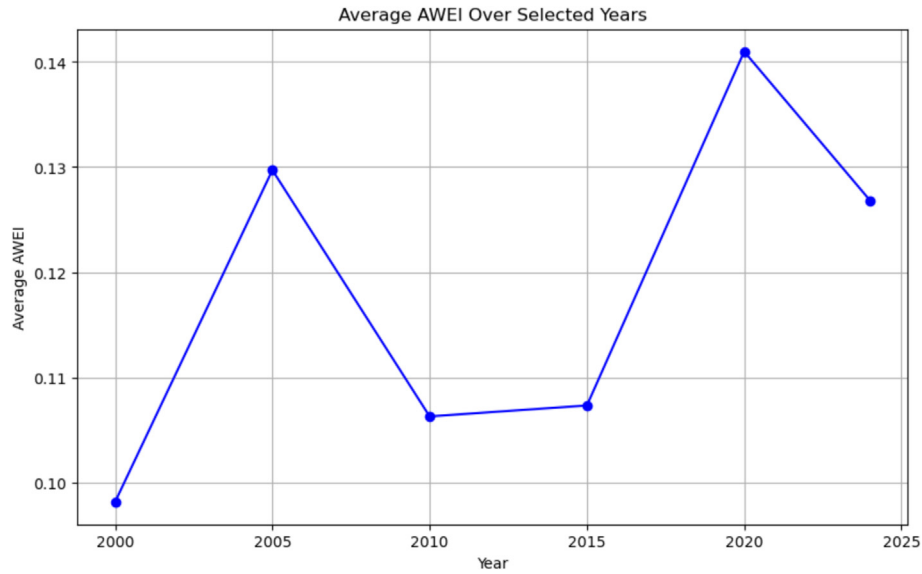


Fig. 14. Average AWEInsh during summer for selected years (2000–2024), showing temporal variation in aquatic ecosystem conditions.

Table 3

Changes in the area between 2020 and 2024 for water and non-water classes.

Class	WINTER				SUMMER			
	Area2020(km ²)	Area2024(km ²)	Change(km ²)	Change (%)	Area2020(km ²)	Area2024(km ²)	Change(km ²)	Change (%)
WATER	2028.3714	513.6039	−1514.76	−74.67	1411.0092	362.4624	−1048.5468	−74.31
NON-WATER	4605.9695	6120.7371	1514.7675	32.88	5223.3318	6271.8786	1048.5468	20.07

tion of restoration zones and infrastructure interventions. The operational ease of using indices such as AWEI (NSH) in cloud-based platforms also enables the development of a low-cost, shared monitoring system between Iran and Iraq. Establishing such a system would facilitate transparency, early warning, and cooperative management. Looking forward, the integration of remote sensing with institutional coordination mechanisms and regional water governance frameworks will be essential for translating these insights into effective and sustainable wetland conservation strategies.

5. Conclusion

This study provides a comprehensive assessment of hydrological changes in the Hawizeh Marshes from 2000 to 2024 using multi-temporal Landsat imagery and various water indices. By evaluating NDWI, MNDWI, AWEI (SH), and AWEI (NSH) against the Dynamic World water band, we identified AWEI (NSH) as the most accurate index for delineating water bodies in this complex wetland system. The findings reveal a substantial decline in water extent, particularly after 2010, with regression analysis confirming a persistent downward trend.

Seasonal trend analysis demonstrated that peak water presence occurs in January, while the lowest water extent occurs in July, aligning with known hydrological cycles and climatic influences. The results underscore the significant impact of anthropogenic interventions, including upstream water diversions, dam construction, and regional climate variability, on the marsh's sustainability. The observed 74.67 % reduction in water coverage between 2020 and 2024 further highlights the urgency for trans-boundary water management efforts. Given the alarming rate of wetland degradation, future conservation strategies must incorporate high-resolution remote sensing, hydrological modeling, and international cooperation to ensure the long-term sustainability of this ecologically vital wetland. This research not only advances our understanding of the spatiotemporal dynamics of the Hawizeh Marshes but also reinforces the importance of continuous satellite-based monitoring for effective wetland management and restoration.

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.

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