Fusion-Based Water Extraction Using Multiple Spectral Water Indices for Accurate Wetland Mapping

Serdar Selim[1,*], Emine Kahraman[2] and Atticus E. L. Stovall[3]

[1]Akdeniz University Faculty of Science Department of Space Sciences and Technologies, 07058 Antalya/Türkiye

[2]Akdeniz University Serik G.S.S. Vocational School, Department of Landscape and Ornamental Plants, 07058 Antalya/Türkiye

[3]Earth System Science Interdisciplinary Center (ESSIC), University of Maryland, 5825 University Research Ct Ste, 4001, College Park, MD 20740, USA

Abstract: Accurate delineation of water surfaces using remote sensing data is essential for water resource monitoring, hydrological analyses, and the assessment of environmental changes. This study proposes a fusion-based approach that combines the strengths of the Normalized Difference Water Index (NDWI), Modified Normalized Difference Water Index (mNDWI), and Automated Water Extraction Index (AWEI), which are widely used for water surface and shoreline delineation from Sentinel-2 imagery. The Alakır Reservoir Lake, located in Antalya Province, Türkiye, was selected as the study area, and Sentinel-2 imagery acquired in 2026 was used. NDWI, mNDWI, and AWEI were first calculated separately, and their outputs were subsequently integrated using a fusion technique to delineate the water surface and shoreline. For accuracy assessment, a reference shoreline was manually delineated from a Sentinel-2 composite image acquired on the same date. A total of 2,048 sample points was generated at 5 m intervals along the reference shoreline, and the shortest distances from these points to the shorelines derived by each method were calculated. The methods were compared in terms of mean positional error, standard deviation, and maximum error. Under the conditions investigated in this study, the fusion approach yielded relatively low positional errors, with a mean error of 7.25 m and a standard deviation of 10.03 m. The corresponding values were 10.36 m and 14.68 m for NDWI, 10.89 m and 13.87 m for mNDWI, and 8.25 m and 11.20 m for AWEI. The results indicate that the proposed fusion approach has the potential to provide relatively accurate and stable shoreline delineation compared with individual index methods, particularly in shoreline transition zones under the investigated conditions.

Keywords: Data fusion, Remote sensing, Sentinel-2, Shoreline delineation, Water indices, Wetland mapping.

1. INTRODUCTION

Global climate change, rapid population growth, urbanization, the expansion of agricultural activities, and increasing pressures on natural resources have made the sustainable management of water resources more important than ever worldwide [1]. Changes in precipitation regimes, prolonged droughts, increasing frequency of flood events, and rising temperatures have significant impacts, particularly on surface water resources and wetland ecosystems [2]. In this context, regular monitoring of water resources in terms of both quantity and quality has emerged as a fundamental requirement for developing climate change adaptation strategies and ensuring the sustainable use of natural resources [3].

Wetlands encompass diverse ecosystems such as lakes, rivers, deltas, lagoons, marshes, and reed beds, and are among the most valuable natural areas in the world in terms of biological diversity [4]. These ecosystems provide habitats for numerous plant and animal species and deliver critical ecosystem services, including carbon storage, flood regulation, groundwater recharge, natural water purification, and climate regulation [4-5]. In addition, wetlands generate significant economic value through activities such as agriculture, fisheries, recreation, and tourism [6]. However, in recent years, many wetlands have undergone substantial changes in their spatial extent and ecological structure due to climate change, land-use changes, uncontrolled urbanization, and anthropogenic interventions [7-8]. Consequently, regular monitoring of temporal changes in wetlands, along with their conservation and sustainable management, has become a fundamental component of environmental planning. Since monitoring extensive wetland areas through conventional field surveys is time-consuming and costly, remote sensing technologies have been increasingly used for this purpose in recent years [9-10]. In particular, satellite systems such as Sentinel-2 and Landsat, which provide high spatial and temporal resolution, enable the rapid, cost-effective, and repeatable detection of surface water changes over large areas [11]. Automated water extraction from satellite imagery provides significant advantages for scientific research, water resource management, environmental impact assessments, flood risk analyses, wetland restoration, and land-use planning. Up-to-date and reliable water

*Address correspondence to this author at the Akdeniz University Faculty of Science Department of Space Sciences and Technologies, 07058 Antalya/Türkiye;
E-mail: serdarselim@akdeniz.edu.tr

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surface maps enable decision-makers and planners to make more informed decisions regarding the conservation and sustainable management of natural resources [11-12].

Spectral water indices are among the most widely used methods for the automatic delineation of water surfaces from satellite imagery [13-14]. Indices such as the Normalized Difference Water Index (NDWI), Modified Normalized Difference Water Index (MNDWI), and Automated Water Extraction Index (AWEI), which exploit the reflectance characteristics of different spectral bands, have demonstrated successful performance in distinguishing water from non-water areas [15-16]. However, a single water index cannot be expected to perform equally well under all land surface conditions. In wetlands, factors such as reeds, aquatic vegetation, turbid water, shadow effects, and shallow water areas can substantially influence the performance of different indices [17-18]. Therefore, fusion approaches that integrate the strengths of different water indices have emerged as an important research topic for achieving more accurate and stable water extraction [19-21].

In this study, three spectral water indices widely used in the literature, namely the Normalized Difference Water Index (NDWI), Modified Normalized Difference Water Index (MNDWI), and Automated Water Extraction Index (AWEI), were jointly evaluated for the automatic delineation of wetlands using Sentinel-2 satellite imagery, and a novel water extraction approach based on the fusion of these indices was proposed. However, existing studies have predominantly focused on the use of a single water index or the separate evaluation of multiple indices, while approaches that integrate the complementary characteristics of different spectral water indices for the automatic delineation of wetlands remain limited. In this study, the proposed Fusion Water Index (FWI) approach integrates the complementary sensitivities of NDWI, MNDWI, and AWEI under different spectral and environmental conditions, thereby aiming to overcome the limitations of methods based on a single index. In this respect, FWI provides a novel fusion-based approach that integrates information derived from multiple water indices and is intended to achieve more reliable water-surface delineation, particularly in complex wetland environments. First, each water index was calculated separately, and a single integrated water map was subsequently generated using the selected fusion method. The resulting water maps were compared with those derived from individual indices through accuracy assessments, and the performance of the proposed approach in wetland delineation was evaluated. The primary contribution of this study is the development of a more reliable water extraction method that exploits the complementary characteristics of different spectral water indices rather than relying on a single index for the automatic delineation of wetlands. The proposed approach is expected to improve the accuracy of water surface delineation, particularly in complex wetland ecosystems. Furthermore, the results are expected to provide valuable data support for wetland inventories, temporal change analyses, sustainable water resource management, environmental monitoring, and spatial planning processes, thereby supporting management and decision-making for local governments.

2. MATERIAL AND METHODS

2.1. Study Area

Alakır Reservoir, located within the administrative boundaries of Antalya Province at 36°26'0.81"N and 30°14'37.44"E, was selected as the study area (Figure **1**). The reservoir, constructed on the Alakır Stream, is one of the region’s important surface water resources for irrigation and energy production [22]. The reservoir has an irregular shoreline geometry due to its topographic characteristics and temporal variations in water level, comprising narrow bays, irregular inlets and protrusions, and shoreline sections of varying widths. This heterogeneous shoreline structure represents an important morphological characteristic that complicates the accurate delineation of water surface boundaries.

The area surrounding the reservoir comprises various land cover and land use classes. Forest areas, maquis and shrub formations, agricultural lands, bare soil surfaces, and sparsely distributed settlement areas are present along the shoreline [23]. In particular, moist soils, alluvial surfaces, and sparse vegetation within the coastal zone may affect the performance of water indices by causing the spectral characteristics of water and land surfaces to become more similar. Alakır Reservoir includes deep open-water areas as well as shallow shoreline zones and transitional areas affected by seasonal variations in water level. In the northern part of the reservoir, shallow and muddy areas and moist surfaces that are periodically exposed due to changes in water level exhibit characteristics that may lead to misclassification during water extraction. In contrast, deeper water bodies dominate the central and southern sections of the reservoir, where the water–land boundary is more clearly defined. The coexistence of both deep and shallow water areas within the study area enables the performance of different spectral water indices to be evaluated under various hydrological and environmental conditions.

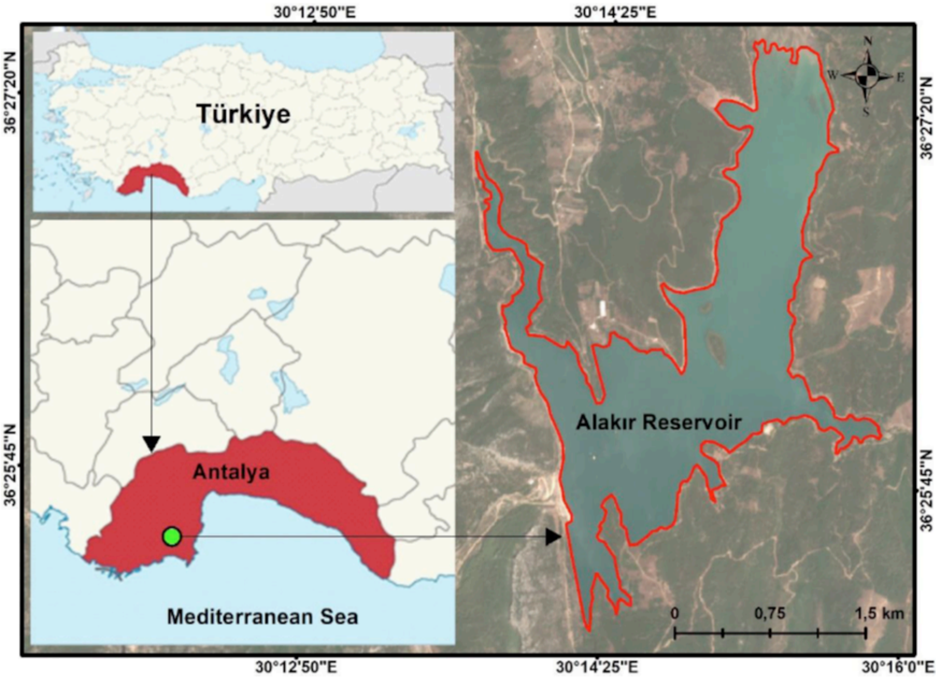

Figure 1: Study area location.

These characteristics make Alakır Reservoir a suitable study area for assessing the accuracy of different spectral water indices and fusion-based approaches. The complex shoreline geometry, diverse land cover types, and variable water depth conditions of the reservoir provide an appropriate setting for testing the proposed method under different environmental conditions and evaluating its reliability.

2.2. Data Sets

The Sentinel-2 MultiSpectral Instrument (MSI) satellite imagery provided by the European Space Agency (ESA) under the Copernicus Programme was used as the primary data source in this study. Sentinel-2 data are among the optical remote sensing datasets widely used for the delineation and monitoring of water surfaces due to their visible and near-infrared bands with a spatial resolution of 10 m and high temporal resolution [24]. A freely available Sentinel-2A Level-2A Surface Reflectance product acquired on 4 July 2026 was used in the study. Since the cloud cover over the study area was 0%, spectral uncertainties caused by clouds and cloud shadows did not affect the data quality. The use of the atmospherically corrected Level-2A product enabled direct analysis of the spectral reflectance values. The visible (Blue, Green, and Red), near-infrared (NIR), and short-wave infrared (SWIR) bands of the Sentinel-2 imagery were used in the study. These bands constituted the primary data source for spectrally distinguishing water surfaces from the surrounding land cover types [25]. For the accuracy assessment of the results derived from the satellite imagery, a reference shoreline was delineated based on expert visual interpretation of a natural-color Sentinel-2 composite image acquired on the same date (RGB: Band 4–Band 3–Band 2). This reference dataset was used as the primary comparison data for assessing the positional accuracy of the methods. The main characteristics of the Sentinel-2 imagery used in the study are presented in Table **1**.

2.3. Methods

In this study, three spectral water indices widely used in the literature for water surface delineation from Sentinel-2 imagery, namely the Normalized Difference Water Index (NDWI), Modified Normalized Difference Water Index (mNDWI), and Automated Water Extraction Index for Shadow (AWEIsh), were jointly evaluated, and an approach based on the fusion of their outputs was applied. The primary objective of the proposed method was to integrate the strengths of different spectral indices in delineating water surfaces into a single result, thereby generating a more reliable

Table 1: Specifications of the Sentinel-2 MSI Dataset used in this Study

Satellite	Sensor	Product Level	Tile (MGRS)	Acquisition Date	Spatial Resolution	Cloud Cover (Study Area)
Sentinel-2	MSI	Level-2A	T36STF	04 July 2026	10 m	0%

and stable water surface map. The overall workflow of the study is presented in Figure **2**.

In the first stage, an atmospherically corrected Sentinel-2 Level-2A Surface Reflectance image was used. The analyses utilized the visible bands (Blue, Green, and Red), near-infrared (NIR), and short-wave infrared (SWIR) bands. Since the image used in the study had 0% cloud cover over the study area, cloud and cloud-shadow masking was not required. While the visible bands of Sentinel-2 imagery have a spatial resolution of 10 m, the SWIR bands used in this study (Bands 11 and 12) have a spatial resolution of 20 m. To enable the combined use of bands with different spatial resolutions in spectral index calculations and to ensure pixel-level geometric consistency, the 20 m SWIR bands were resampled to a spatial resolution of 10 m using the bilinear resampling method [26]. Since bilinear resampling calculates new pixel values based on the weighted average of four neighboring pixels, it preserves spectral continuity in continuous reflectance data and provides smoother transitions than the nearest neighbor method, thereby reducing spectral distortions [27-28]. Thus, all bands were processed at a common spatial resolution, resulting in a pixel-wise consistent dataset for subsequent analyses.

In the second stage, three of the most widely used spectral water indices for water surface delineation were calculated separately. First, the NDWI proposed by McFeeters (1996) [29] (Equation 1) was calculated based on the spectral difference between the green and near-infrared bands.

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

Although NDWI produces effective results for the delineation of open water surfaces, it may cause certain built-up areas, moist soils, and some artificial surfaces to be misclassified as water [30]. To reduce these limitations, the Modified Normalized Difference Water Index (mNDWI), developed by Xu (2006) [31], was also calculated (Equation 2). By using the short-wave infrared (SWIR) band instead of the near-infrared (NIR) band, mNDWI reduces the spectral influence of built-up surfaces and bare soils, thereby enhancing the distinction between water and land surfaces [32].

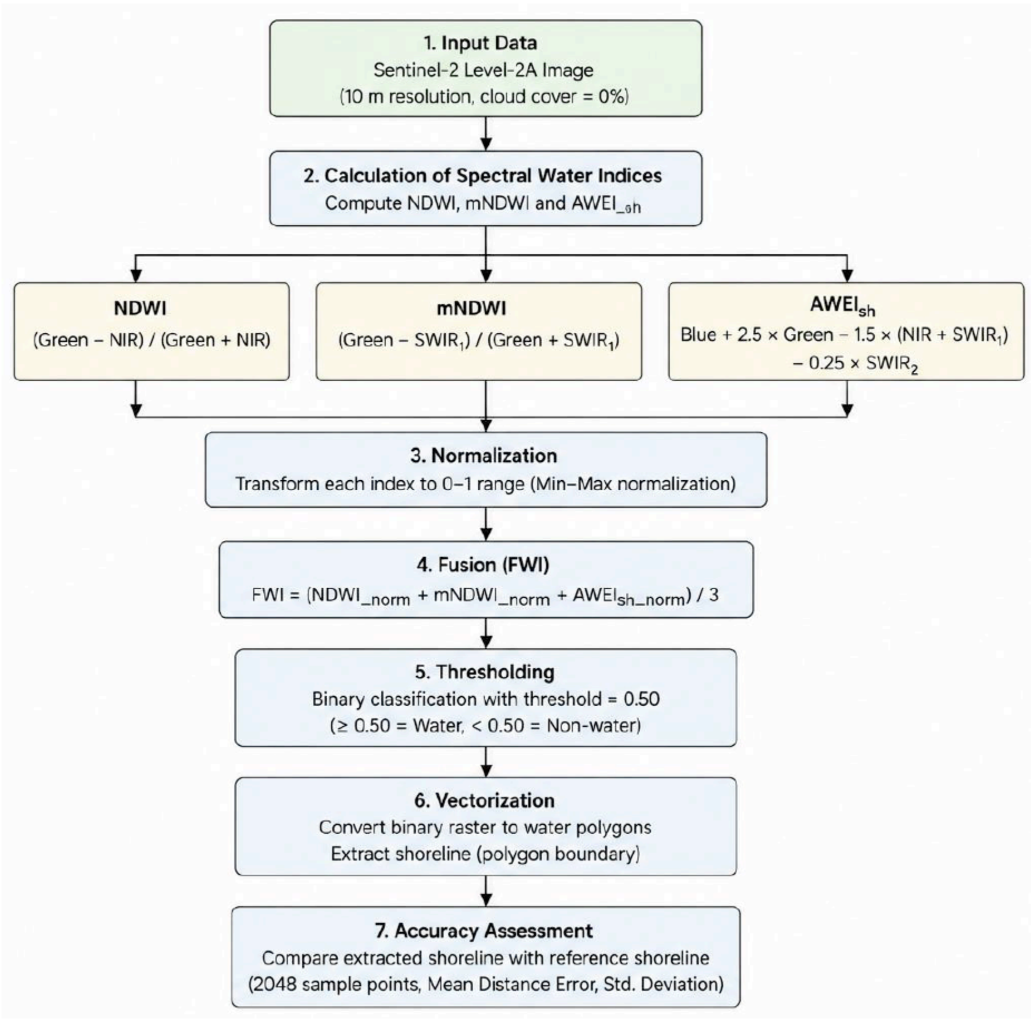

Figure 2: Method flowchart.

$$\mathrm{mNDWI} = \frac{Green - SWIR_1}{Green + SWIR_1} \quad (2)$$

Subsequently, the AWEIsh index proposed by Feyisa *et al*. (2014) [33] was calculated (Equation 3). AWEIsh was developed to improve water–land discrimination, particularly in areas affected by topographic shadows and surfaces with low reflectance, and substantially reduces the influence of shadows compared with other spectral indices [34].

$$AWEI_{sh} = Blue + 2.5xGreen - 1.5x(NIR + SWIR_1) - 0.25xSWIR_2 \quad (3)$$

In the third stage, all index rasters were transformed to a 0–1 range using min–max normalization [35] to enable the values obtained from different spectral indices to be evaluated on a common scale (Equation 4).

$$I_{norm} = \frac{I - I_{min}}{I_{max} - I_{min}} \quad (4)$$

Here, I_{norm}; represents the normalized pixel value, *I;* represents the original index value, I_{min}; represents the minimum value in the corresponding index raster and I_{max} , represents the maximum value in the corresponding index raster. This procedure ensured that indices with different value ranges contributed equally during the fusion stage.

In the fourth stage, the three normalized spectral indices were considered equally important without applying any weighting, and a fusion raster was generated by calculating their arithmetic mean (Equation 5).

$$\mathrm{FWI} = (NDWI_{norm} + mNDWI_{norm} + AWEIsh_{norm})/3 \quad (5)$$

The rationale behind this approach is that each spectral index offers advantages under different environmental conditions. While NDWI performs effectively in delineating open water areas, mNDWI reduces misclassifications caused by built-up areas and bare soils, whereas AWEIsh provides more reliable results in areas strongly affected by shadows [17, 24, 34]. Equal weighting of the indices prevents any single method from becoming dominant and allows the complementary characteristics of all three methods to be utilized collectively. However, a limitation of the equal-weighting approach is that it assumes that the contributions and discriminative capabilities of the three indices are comparable across different environmental conditions, which may not always be the case. Data-driven weighting schemes may potentially provide improved performance for specific study areas or environmental conditions. In this study, equal weighting was preferred to avoid assigning an a priori advantage to any individual index and to ensure that the complementary information provided by all three indices was incorporated equally into the fusion process.

In the fifth stage, binary water–land classification was performed using the normalized spectral indices and the fusion raster. Since all rasters were normalized to the 0–1 range, a threshold value of 0.50 was used for classification. This threshold represents the midpoint of the normalized value range and provides a common and standardized decision criterion for distinguishing land from water, with lower index values representing land and higher values representing water. Accordingly, pixels with values of 0.50 or higher were classified as water surfaces, whereas pixels with values below 0.50 were classified as land surfaces. The use of the same threshold value for all methods enabled the results obtained from different approaches to be directly compared using a common classification criterion and minimized methodological differences arising from threshold selection. This approach allowed the comparison to focus on the performance of the spectral indices and the fusion approach in water surface extraction rather than on differences in threshold values. Nevertheless, a limitation of using a fixed threshold of 0.50 is that it may not represent the optimal threshold for separating water and land under all environmental and spectral conditions. In particular, the optimal threshold may vary in the presence of turbid water, shallow water, aquatic vegetation, shadows, and heterogeneous land-cover conditions. Therefore, the 0.50 threshold was not considered a universally optimal value in this study, but rather a standardized decision criterion adopted to ensure consistent and direct comparison among the different methods.

In the sixth stage, the resulting binary rasters were converted into vector format to generate water surface polygons, and the polygon boundaries were subsequently converted into shorelines. In the final stage, a reference shoreline was delineated based on expert visual interpretation of a natural-color Sentinel-2 image (RGB: 4-3-2) acquired on the same date. A total of 2,048 sample points were generated at 5 m intervals along the reference shoreline, and the shortest distance from each sample point to the shorelines derived by the respective methods was calculated. The positional performance of the methods was evaluated using the Mean Distance Error (MDE) and standard deviation. A lower mean error indicates that the predicted shoreline is closer to the reference shoreline, whereas a lower standard deviation indicates that the method produces more consistent and stable results across the study area.

3. RESULTS

The water surface boundaries derived using different spectral water indices in the study were first compared in terms of their spatial distribution and shoreline geometry. The results obtained using the NDWI, mNDWI, AWEI, and FWI methods are presented in Figure **3**, while the comparative view showing the results for the same study area together provides a clearer assessment of the differences in shoreline delineation among the methods.

To quantitatively compare the results presented in Figure **3**, the positional distance between the shoreline produced by each method and the reference shoreline was additionally calculated. For this purpose, the manually digitized reference shoreline derived from a natural-color composite (RGB: 4-3-2) of the Sentinel-2 image acquired on the same date was used as the reference. A total of 2,048 sample points were generated at 5 m intervals along the reference shoreline, and the shortest distance from each sample point to the shoreline derived by the corresponding method was calculated using the Near tool in ArcGIS Pro 3.2. Thus, the degree of deviation of the shoreline produced by each method from the reference position was quantitatively determined. Mean Distance Error, standard deviation, and maximum error values were used to assess positional accuracy. The results are presented in Table **2**.

The results presented in the table indicate clear differences among the four methods in terms of positional accuracy. The FWI method exhibited the lowest positional deviation, with a mean error of 7.25 m. The corresponding values were 8.25 m for AWEI, 10.36 m for NDWI, and 10.89 m for mNDWI. Accordingly, the mean distance of the FWI-derived

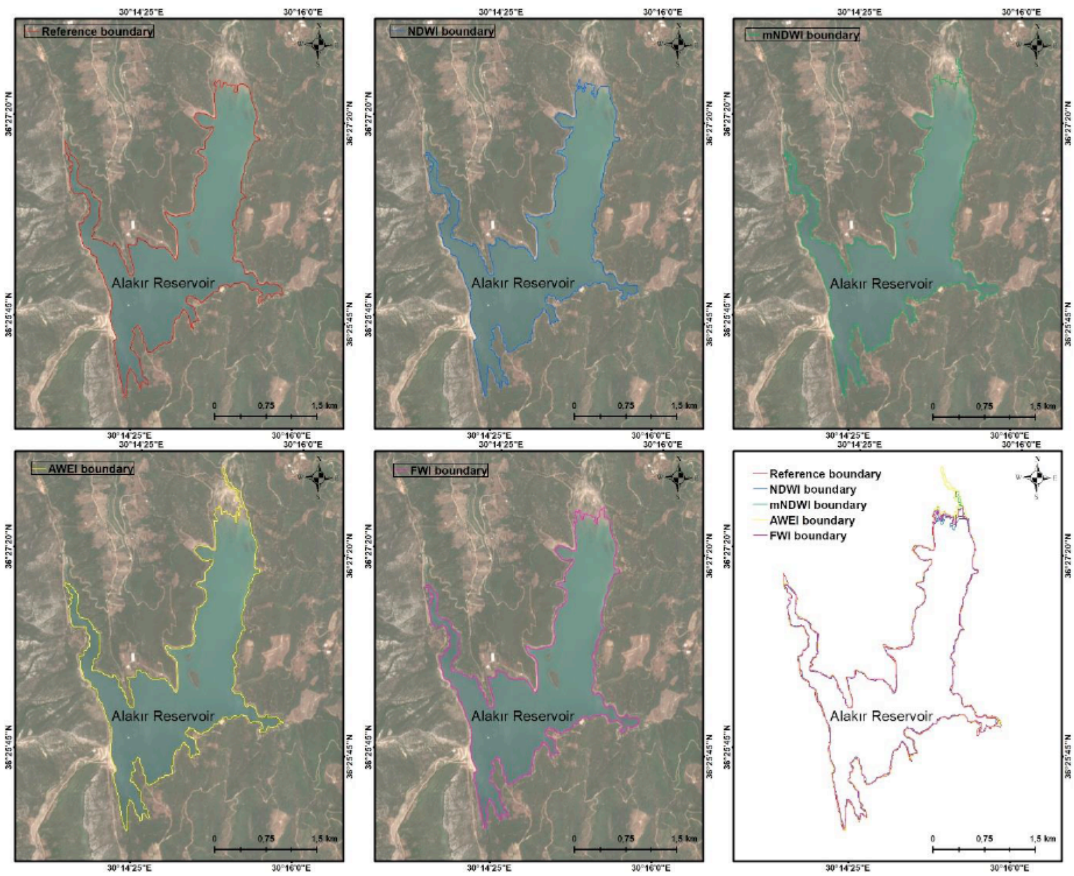

Figure 3: Water surface boundaries derived using the NDWI, mNDWI, AWEI, and FWI methods and comparison of the method results with the reference shoreline.

Table 2: Positional Accuracy Assessment of Water Boundary Extraction Methods Based on Distance from the Reference Shoreline

Method	Mean Distance Error (m)	Standard Deviation (m)	Maximum Error (m)
NDWI	10.36	14.68	175.41
mNDWI	10.89	13.87	166.79
AWEI	8.25	11.20	134.77
FWI	7.25	10.03	124.50

shoreline from the reference shoreline was approximately 1.00 m, 3.11 m, and 3.64 m lower than those of AWEI, NDWI, and mNDWI, respectively. This result indicates that the water–land boundary delineated by FWI was generally closer to the reference shoreline within the study area and that the method provided higher positional accuracy in shoreline delineation.

The standard deviation values used to assess the variability of the error distribution also indicate that FWI exhibited more consistent performance than the other methods. The standard deviation calculated for FWI was 10.03 m, which was lower than those obtained for AWEI (11.20 m), mNDWI (13.87 m), and NDWI (14.68 m). When evaluated together with the mean error, these results indicate that FWI produced lower overall positional deviation and exhibited less variability in error among the sample points. The highest standard deviation observed for NDWI suggests that this method exhibited greater deviations from the reference boundary in certain shoreline sections. Although the mean error of mNDWI was slightly higher than that of NDWI, its lower standard deviation indicates that the two methods had different error distribution characteristics.

Maximum error values provide additional information regarding the behavior of the methods, particularly in problematic shoreline sections. The fact that the maximum error values exceeded 100 m for all methods indicates that substantial positional deviations occurred in certain parts of the shoreline. The highest maximum error was recorded for NDWI at 175.41 m, followed by mNDWI at 166.79 m and AWEI at 134.77 m. In contrast, FWI had the lowest maximum error among the four methods, at 124.50 m. The maximum error of FWI was approximately 51 m lower than that of NDWI, indicating that the method produced more limited errors not only in terms of overall performance but also in areas characterized by the greatest deviations. The maximum error values were observed particularly in the northern part of the study area, where shallow water and periodically receding water levels occur. In these sections, reduced water depth, moist soils, and temporarily exposed surfaces may weaken the spectral distinction between water and land. Consequently, some methods may have classified water surfaces beyond the actual shoreline or failed to adequately delineate shallow water areas adjacent to the shoreline, resulting in high distance errors relative to the reference shoreline. This finding indicates that water indices relying more heavily on a single spectral characteristic may exhibit variable performance under heterogeneous shoreline conditions.

When the performance of the methods is evaluated collectively, FWI produced the lowest error values across all three assessment criteria. The mean error, standard deviation, and maximum error values of 7.25 m, 10.03 m, and 124.50 m, respectively, demonstrate that FWI provided a more spatially consistent delineation of the shoreline. AWEI exhibited the second-lowest mean error (8.25 m) and standard deviation (11.20 m) after FWI, whereas NDWI and mNDWI produced higher mean error values. However, the 10 m spatial resolution of Sentinel-2 and potential digitization uncertainties associated with the manually delineated reference shoreline should also be considered when evaluating differences in performance among the methods. Therefore, the observed error values reflect not only differences among the algorithms but also positional uncertainties associated with image resolution and reference data generation.

Overall, these findings demonstrate that FWI produced lower and more consistent errors than NDWI, mNDWI, and AWEI in the positional delineation of water surface boundaries within the study area. The lower maximum error observed particularly in sections characterized by shallow water–land transitions and heterogeneous shoreline conditions suggests that FWI may provide a more stable distinction between water and land surfaces in such problematic areas. However, these results do not indicate that FWI is universally superior across all study areas and environmental conditions; the findings should be interpreted within the context of the study area, the Sentinel-2 imagery used, and the shoreline conditions evaluated.

4. DISCUSSION

The results of this study demonstrate that the combined use of different spectral water indices through a fusion approach can improve the positional accuracy of shoreline extraction from Sentinel-2 imagery compared with the use of individual indices. The fact that the proposed FWI approach produced the lowest values for mean positional error, standard deviation, and maximum error indicates that different water indices can provide complementary information under heterogeneous surface conditions. This finding is consistent with previous studies reporting that the performance of water indices varies depending on the characteristics of the study area and environmental conditions [17, 36-38]. The higher performance of FWI is particularly relevant to the heterogeneous shoreline conditions of Alakır Reservoir. The study area includes various surface characteristics, such as open water, shallow water, moist soil, exposed sediment, and shoreline vegetation. Under such conditions, the spectral characteristics of water and land surfaces may become similar, limiting the performance of individual water indices. While NDWI exploits the spectral difference between the green and NIR bands, mNDWI uses SWIR information to reduce the influence of land and built-up surfaces, whereas AWEIsh is designed to reduce misclassifications caused by dark surfaces and shadows [29, 31, 33]. Therefore, the lower error values obtained with FWI suggest that combining different spectral responses can reduce the dependence on a single index. Similarly, Wen *et al*. (2021) [37] demonstrated that combining multiple water indices through an ensemble approach can provide more stable water classification than individual indices.

Among the individual indices, the lower positional error produced by AWEIsh compared with NDWI and mNDWI is also consistent with findings reported in the literature. AWEI has previously been shown to perform effectively in complex environments characterized by shadows and low-reflectance surfaces [17, 39]. However, the lower performance of AWEIsh compared with FWI indicates that the advantages of a single index may not be sufficient to represent all shoreline conditions. The superior performance of FWI suggests that jointly considering the different spectral characteristics captured by NDWI, mNDWI, and AWEIsh can provide an advantage, particularly in heterogeneous shoreline environments. This result is also consistent with studies reporting that no single water index consistently provides the best performance under different environmental conditions [36, 38-39].

An important distinction between this study and similar studies in the literature is the relatively simple and direct structure of the fusion process. Previous studies have employed data fusion approaches combining Sentinel-1 and Sentinel-2 data [40], while other studies have developed new water indices and more complex classification methods [41]. In contrast, this study used three widely applied water indices derived solely from Sentinel-2 data, and their normalized values were combined using equal weights. This resulted in an interpretable and reproducible approach that can be implemented without requiring an additional sensor, training data, or a complex classification model. Therefore, the primary contribution of this study is not the development of a new spectral index, but rather the integration of the complementary characteristics of existing indices into a single water extraction product through a simple fusion strategy.

The accuracy assessment approach employed in this study also provides an important distinction for shoreline extraction. Many previous studies have evaluated water extraction performance using pixel-based classification metrics such as overall accuracy, F1-score, Kappa, or confusion matrices [17, 37]. In this study, the shortest distances from sample points generated along the reference shoreline to the extracted shorelines were used. This approach directly evaluates the spatial accuracy of the water–land boundary rather than focusing solely on whether individual pixels were correctly classified as water or land. Such an approach increases the practical value of the method, particularly for hydrological analyses, shoreline change monitoring, and water surface area delineation, where the accurate spatial positioning of the shoreline is of particular importance. Nevertheless, the positional accuracy results should be interpreted by considering the uncertainties associated with both the 10 m spatial resolution of Sentinel-2 imagery and the manual delineation of the reference shoreline. The 10 m spatial resolution of Sentinel-2 may limit the precise representation of the actual shoreline, particularly along narrow shoreline zones, shallow-water areas, and gradual water–land transition zones. In addition, because the reference shoreline was manually delineated, the reference data may itself contain a certain degree of positional uncertainty associated with operator interpretation. Therefore, the lowest mean positional error of 7.25 m obtained by FWI should not be interpreted as an accuracy measure against a completely error-free or absolute reference shoreline. Differences among the methods should be interpreted within the context of these uncertainties, particularly when the magnitude of the observed positional errors is comparable to the spatial resolution of the Sentinel-2 imagery and the uncertainty associated with the delineation of the reference shoreline [42].

Nevertheless, the results should be interpreted within the context of several limitations. In this study, the three indices were assigned equal weights, and a threshold value of 0.50 was used for the fusion raster. Although this approach produced successful results for the analyzed image of Alakır Reservoir, equal weighting and the same threshold value cannot be assumed to be optimal for different lakes, wetlands, seasons, or water-level conditions. Previous studies have reported that the optimal threshold values of water indices may vary depending on environmental conditions and image characteristics [38]. Therefore, the present results for FWI should not be interpreted as evidence of universal superiority but rather as an indication of its performance under the study area and image conditions examined in this research.

The relatively high maximum error values observed for all methods indicate that shoreline transition zones remain an important challenge for water extraction. These high errors are likely associated with shallow water, moist sediment, exposed shoreline surfaces, and areas where the water–land transition occurs gradually. In such areas, reduced spectral differences between water and land can cause deviations from the actual shoreline position. The lower maximum error obtained with FWI indicates that the fusion approach can reduce such local uncertainties, although it does not completely eliminate them. This finding demonstrates that the method may offer a potential advantage not only in terms of overall accuracy but also in its performance in problematic shoreline sections. The persistence of relatively high maximum errors despite the improved performance of FWI highlights some important limitations of the proposed approach. In shallow-water and moist-soil areas, the spectral response of water may overlap with that of surrounding soil, sediment, and vegetation, making the water–land boundary difficult to delineate even when multiple indices are jointly considered. Similarly, gradual changes in water level and mixed pixels within shoreline transition zones may result in the simultaneous representation of water and land characteristics within a single 10 m pixel. These conditions can limit the advantage of FWI in exploiting the complementary information provided by different indices and may result in relatively high local positional errors in certain shoreline sections. Therefore, although FWI improves overall and mean positional accuracy, it may not be sufficient by itself for highly precise shoreline delineation in areas characterized by complex and gradual water–land transitions. This finding suggests that FWI may provide more reliable results along relatively distinct water/land boundaries, whereas its application in small-scale and highly complex shoreline environments could benefit from higher-resolution imagery or complementary sensor data.

Overall, the findings of this study demonstrate that the combined use of different spectral water indices can improve the reliability of Sentinel-2-based water surface and shoreline extraction. The lower positional errors produced by FWI compared with the individual NDWI, mNDWI, and AWEIsh methods support previous findings indicating that multi-index approaches can provide more stable results [37]. The primary novelty of this study lies in combining existing and widely used water indices through a simple, interpretable, and applicable equal-weight fusion approach and evaluating its performance directly in terms of shoreline positional accuracy. However, further testing across different dates, water levels, and wetland conditions, together with the adaptive determination of index weights and threshold values, is required to establish the generalizability of the proposed method.

5. CONCLUSION

In this study, a fusion-based approach integrating the outputs of NDWI, mNDWI, and AWEIsh was developed to improve the delineation of water surfaces and shorelines from Sentinel-2 satellite imagery and was evaluated using Alakır Reservoir as a case study. Under the study area and image conditions investigated, the results demonstrated that the proposed FWI method provided higher positional accuracy than the individual water indices. FWI produced the lowest error values across all evaluation metrics, with a mean positional error of 7.25 m, a standard deviation of 10.03 m, and a maximum error of 124.50 m. These results indicate that integrating the complementary characteristics of different spectral water indices can contribute to a more stable delineation of the water–land boundary, particularly under heterogeneous and complex shoreline conditions within the investigated study area.

An important finding of the study is that FWI outperformed the other methods not only in terms of mean error but also with respect to error variability and maximum deviation. This indicates that the proposed approach can reduce some of the uncertainties associated with individual indices in problematic shoreline sections characterized by shallow water, moist soil, sediment, and other transitional surfaces. However, the presence of relatively high maximum errors in certain shoreline sections for all methods demonstrates that the 10 m spatial resolution of Sentinel-2 and complex water–land transitions remain important limitations for shoreline extraction. Furthermore, because the reference shoreline used for the accuracy assessment was manually delineated, the reference data may itself contain a certain degree of positional uncertainty. Therefore, the observed error values should be interpreted by considering both the spatial resolution of Sentinel-2 and the uncertainty associated with the delineation of the reference shoreline. The main advantage of FWI is its reliance on the simple and interpretable integration of three widely used spectral water indices without requiring an additional sensor or a complex classification model. This characteristic makes the method a practical alternative for applications such as wetland inventory development, water surface area delineation, reservoir and lake monitoring, shoreline change detection, and temporal monitoring of water resources. The free and regular availability of Sentinel-2 data further supports the reproducibility of the method and its applicability to long-term time series.

Nevertheless, the results of this study are limited to a single study area and a single Sentinel-2 image acquired on one date. Therefore, FWI should be tested across different lakes and wetlands under varying seasonal conditions, water levels, turbidity levels, and land cover characteristics. Future studies could improve the generalizability of the method by replacing equal index weighting with data-driven or adaptive weighting approaches and by evaluating automatic threshold determination methods adapted to specific study conditions instead of using the fixed threshold value of 0.50. In addition, integrating FWI with Sentinel-1 radar data, higher-resolution satellite imagery, or unmanned aerial vehicle data could provide new opportunities for more precise delineation of complex and small-scale shoreline transitions. In this context, evaluating the performance of FWI using multi-temporal datasets would provide further insight into its potential for monitoring the temporal dynamics of wetlands, beyond its performance on a single image.

In conclusion, this study demonstrates that integrating different spectral water indices through a fusion approach can improve the positional accuracy of Sentinel-2-based water surface and shoreline extraction under the investigated conditions. The proposed FWI approach shows potential as a simple and interpretable approach for water surface and shoreline delineation under similar conditions; however, its broader applicability and superiority across different study areas, environmental conditions, and temporal settings cannot be established from the present single-site and single-date analysis. Further validation using multi-temporal and multi-site datasets is therefore required to assess its generalizability.

CONFLICT OF INTEREST STATEMENT

The Authors declares that there are no relevant financial or non-financial competing interests to report.

AUTHORS' CONTRIBUTION

Serdar SELİM: Conceptualization, supervision, methodology, data processing, formal analysis, investigation, visualization, and writing—original draft; **Emine KAHRAMAN:** Methodology, validation, interpretation of results, and writing and review; **Atticus E. L. STOVALL:** Validation, interpretation of results, and writing, review and editing.

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