Khazar Journal of Water and Environment 2026, 1, 1-14

Khazar Journal of Water and Environment

e-ISSN: 3150-0188
khazarjournal.com

KJWE

Shoreline Change Detection in Bandar Anzali (2015–2025) Using Landsat-8 Spectral Indices and Machine Learning: Implications for Coastal Management and Port Sustainability

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ARTICLE INFO
Research Article
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Received: 26 February 2026 / Revised: 22 April 2026 / Accepted: 04 May 2026 / Online: 05 August 2026

Cite this article as
Kazaria, K. & Hasanlou, M. (2026). Shoreline Change Detection in Bandar Anzali (2015–2025) Using Landsat-8 Spectral Indices and Machine Learning: Implications for Coastal Management and Port Sustainability. Khazar Journal of Water and Environment, 1, 1-14

ABSTRACT

Bandar Anzali, situated on the southern Khazar (Caspian) coast, is one of Iran's most significant maritime hubs for trade, tourism, and fisheries. In recent years, the area has experienced pronounced sedimentation and shoreline progradation, particularly during summer months when hydrodynamic activity declines and sediment delivery from upstream sources increases. These geomorphological shifts threaten port operations, navigability, and coastal infrastructure, underscoring the need for precise shoreline monitoring to support sustainable coastal management. This study applied satellite-derived spectral indices—NDWI, MNDWI, and NDVI—from Landsat 8 imagery to classify water and non-water surfaces in the Anzali coastal zone over 11 summers from 2015 to 2025. To improve classification accuracy, Random Forest and Support Vector Machine (SVM) algorithms were trained using representative land–water samples, surface reflectance bands, and spectral indices. The SVM model, implemented with an RBF kernel, demonstrated greater ability to detect subtle shoreline transitions and shallow, sediment-laden waters. Shoreline displacement was quantified using Net Shoreline Movement (NSM) and End Point Rate (EPR) derived from the classified water masks. Random Forest produced an NSM of 147.7 m and an EPR of 14.77 m/yr, while SVM yielded an NSM of 146.8 m and an EPR of 14.68 m/yr. The minimal discrepancy between the two models indicates high consistency in capturing shoreline advance, with SVM offering slightly finer delineation in transitional zones. These results confirm ongoing sedimentation and shoreline growth in the Anzali system, particularly near the port entrance and lagoon margins, with direct implications for dredging, port accessibility, and ecological stability. Integrating spectral indices, machine learning classification, and quantitative shoreline metrics provides a robust framework for monitoring sediment-prone coasts. It supports strategic planning for resilience in economically critical regions such as Bandar Anzali.

Keywords: Bandar Anzali, Change Detection, Landsat-8, Random Forest, Shoreline, SVM

1. Introduction

Coastal zones are constantly shaped by the dynamic interactions between land and sea, leading to both short-term fluctuations and long-term transformations. Understanding beach morphology has therefore become a central focus in coastal engineering research. Effective management and regulation of shoreline change and behaviour are critical not only for the success of marine infrastructure projects but also for the implementation of integrated coastal zone management strategies in these sensitive environments (Alemi Safaval et al., 2018).

The Anzali region on the southern coast of the Khazar Sea has been the focus of wave modelling and prediction efforts. To estimate and forecast significant wave height, two models were applied: Random Forest and Support Vector Machine (SVM). Field measurements of wind and wave parameters collected by the Anzali buoy over a defined observation period served as the dataset for training and validation. The integration of physical and machine learning approaches offers a comprehensive framework for analysing wave dynamics, improving prediction accuracy, and supporting sustainable coastal management in one of the Khazar Sea's most economically and ecologically critical zones (Khoshravan & Mammadov, 2017; Lotfollahi Yaghin et al., 2025).

Coastlines represent crucial natural boundaries where land and ocean meet, and their precise mapping plays a key role in coastal planning, environmental assessment, and climate resilience efforts. With the rapid progress of remote sensing technologies and the growing accessibility of diverse datasets—including satellite images, UAV (unmanned aerial vehicle) observations, and synthetic aperture radar (SAR) imagery—researchers can now achieve more detailed and dynamic delineation of shoreline features (Khurram et al., 2025).

SAR imagery, collected through airborne platforms or remote sensing satellites, provides valuable data for examining diverse features on the Earth's surface, such as coastlines. Coastal regions hold significant economic value and are among the most densely inhabited areas worldwide. The growing human activity along these zones, coupled with the continual transformation of shorelines, has driven researchers to evaluate the rate and nature of these changes. Advances in remote sensing have further enabled the detection of coastlines through a range of image processing and analytical techniques, with segmentation methods playing a central role (Ciecholewski, 2024).

Selecting the appropriate remote sensing data for monitoring land cover and coastal environments is not always straightforward, given the broad range of systems in use today. To evaluate and compare both analogue and digital platforms, researchers typically rely on four categories of resolution: spatial, spectral, radiometric, and temporal. Among these, spatial resolution refers to the level of detail or clarity with which features on the Earth's surface can be distinguished (Klemas, 2011).

In recent years, a wide range of tools and methodologies have been employed to monitor coastal erosion and shoreline dynamics. Central to these efforts are geographic information systems (GIS), which encompass both proprietary platforms such as ESRI ArcGIS and the Digital Shoreline Analysis System, as well as open-source alternatives like QGIS and the Open Digital Shoreline Analysis System. These systems enable the organization and generation of geospatial datasets that can be further integrated into diverse programming environments for advanced analysis. Over the past decade, shoreline change detection has increasingly focused on the spatiotemporal examination of high-resolution satellite imagery. Beyond traditional remote sensing approaches, the rise of machine learning and artificial intelligence has introduced new possibilities for large-scale, automated shoreline extraction. These advanced techniques not only streamline the processing of complex environmental datasets but also reveal patterns and trends that may remain hidden through conventional methods. Moreover, they contribute to the production of precise habitat maps and the development of predictive models, offering valuable insights into how coastal ecosystems may adapt under varying environmental pressures (Tsiakos & Chalkias, 2023).

Advances in remote sensing and digital image processing have led to the development of modern techniques for shoreline extraction, including the Normalized Difference Water Index (NDWI), edge-based detection approaches, and contour vectorization methods. NDWI, calculated from Sentinel-2 imagery, serves as a robust spectral measure for separating water bodies from terrestrial surfaces. When integrated with segmentation and contour delineation workflows in platforms such as Google Earth Engine (GEE) and Python, these methods demonstrate strong potential for automated, large-scale shoreline monitoring. Despite this progress, limited research has focused on tailoring such integrations to smaller coastal settings like Ramsar wetlands, where fine-resolution analysis is essential to capture subtle geomorphological variations (Kuleli et al., 2011).

Spectral indices such as NDWI, when combined with automated image processing techniques, enable precise separation of water and land features. High-resolution satellite imagery, particularly from missions like Sentinel-2, offers a reliable foundation for detecting subtle geomorphological changes along coastlines. The integration of spectral indices with advanced processing tools in platforms such as ArcGIS Pro or Python-based workflows creates a robust framework for automated shoreline extraction. This approach not only complements conventional field-based methods—such as GNSS RTK receivers, LiDAR, or photogrammetry—but also enhances efficiency in applications that require frequent measurements, including bathymetric monitoring. Automated shoreline detection thus represents a valuable tool for improving accuracy, consistency, and scalability in coastal research and management (Specht, 2024).

The shoreline represents one of the most dynamic features of the Earth's surface, continuously shifting under the influence of natural and anthropogenic factors. Its significance lies not only in its environmental role but also in its economic value. To investigate long-term shoreline dynamics, the south-eastern coast of Bangladesh was analysed over the period 1980–2020 at decadal intervals. Automatic shoreline extraction was performed using a set of generic edge detection algorithms, including Threshold, Sobel, Prewitt, Roberts, and Canny, with the latter demonstrating superior accuracy in delineating coastal boundaries. For quantitative assessment, the Digital Shoreline

Analysis System (DSAS) was employed, applying three statistical indicators: Net Shoreline Movement (NSM), End Point Rate (EPR), and Linear Regression Rate (LRR). These metrics provided a comprehensive evaluation of shoreline displacement, capturing both accretion and erosion trends across the study area (Hossain et al., 2021).

The objective of this study is to investigate shoreline dynamics and sedimentation processes in Bandar Anzali for 11 years between June and August, through a satellite-based monitoring framework. To achieve this, spectral indices such as NDWI, MNDWI, and NDVI will be employed to delineate water and non-water classes. At the same time, machine learning classifiers—Random Forest and Support Vector Machine (SVM)—will be applied to enhance classification accuracy. Furthermore, quantitative shoreline displacement metrics, including NSM and EPR, will be utilized to assess spatial and temporal patterns of shoreline change. By integrating these approaches, the study aims to provide a comprehensive understanding of coastal dynamics and deliver practical insights for sustainable port management and resilience in this economically vital region.

2. Materials and Methods

2.1. Study Area

The Khazar Sea, the world's largest enclosed inland water body, covers an area of about 372,000 square kilometres, accounting for approximately 40–44% of global lacustrine waters. Along its margins, sandy coastlines dominate, driving rapid and dynamic changes in shoreline morphology. These conditions highlight the importance of advanced monitoring techniques, where remote sensing provides reliable tools for detecting coastal transformations and supporting effective management strategies. Bandar Anzali is located on the southern shore of the Khazar Sea in Gilan Province, Iran, at coordinates 37°28′15″N and 49°28′12″E. The city's coastline extends approximately 17 km, encompassing port facilities as well as the adjacent lagoon system. This coastal zone holds considerable strategic importance due to several factors: (1) It hosts one of Iran's most critical seaports, supporting major activities in trade, tourism, and fisheries. (2) The region experiences high sedimentation rates driven by river inflows and reduced hydrodynamic energy during summer, resulting in notable shoreline progradation. (3) The port entrance and associated breakwaters significantly influence sediment deposition patterns, necessitating continuous dredging and monitoring to maintain navigability. (4) The Anzali Lagoon represents a key wetland ecosystem, highly sensitive to sedimentation and water-quality variations, and supports diverse biological communities. Figure 1 shows the location of Bandar Anzali within Iran, highlighting its position along the southern Khazar coastline.

Figure 1. Geographical position of Bandar Anzali in Iran

Recent studies highlight that the southern shores of the Khazar Sea exhibit varying responses to both the construction of port structures and fluctuations in Khazar Sea level (KSL). The regions surrounding Amirabad and Astara ports have experienced the greatest displacements, with precise measurements revealing notable sedimentation and erosion rates. Similarly, the beaches adjacent to Nowshahr and Anzali ports have undergone substantial sedimentation changes, whereas the coast of Fereydunkenar has shown only minimal erosion. In particular, the construction of new breakwaters in Anzali Port has significantly altered the hydrodynamic regime of the Anzali International Lagoon. Already vulnerable to sediment inflows from mountainous catchments, the lagoon now faces further disruption as satellite image analyses demonstrate that the breakwaters impede the natural transfer of sediments from the lagoon to the sea (Khoshravan et al., 2023; Alemi Safaval et al., 2023).

Figure 2 illustrates the elevation characteristics of Bandar Anzali, showing a mean altitude of –27 m, with elevation values ranging from a minimum of –45 m to a maximum of –11 m. This figure highlights the spatial distribution of elevation across the coastal area, offering a clearer depiction of local topographic variation and low-lying terrain. These elevation patterns provide essential context for understanding geomorphological processes and hydrodynamic behavior in the region, particularly in relation to sediment transport and shoreline change.

Figure 2. Bathymetric map of Bandar Anzali (37.45° N , 49.45° E)

2.2. Data

Landsat-8, equipped with the Operational Land Imager (OLI) sensor, provides satellite imagery with enhanced radiometric precision. The OLI sensor, developed by Ball Aerospace & Technologies Corporation, captures data with a 12-bit dynamic range (4096 grey levels), a substantial improvement over the 8-bit instruments of earlier Landsat missions (256 grey levels). This higher radiometric resolution results in an increased signal-to-noise ratio, enabling more accurate characterization of land and water surfaces. For this study, Landsat-8 Collection 2, Level-2 (L2SP) surface reflectance products were used, which have been atmospherically corrected using the LaSRC (Land Surface Reflectance Code) algorithm. These pre-processed data eliminate the need for additional atmospheric correction, ensuring spectrally consistent measurements for detecting subtle shoreline transitions and sediment-affected zones. There are nine spectral bands acquired by the Operational Land Imager (OLI) sensor, and their specifications are summarized in Table 1.

Table 1. Overview of the spectral band specifications for the OLI instrument

Band	Description	Wavelength (μm)
Band 1	Coastal Aerosol	0.43-0.45
Band 2	Blue	0.45-0.51
Band 3	Green	0.53-0.59
Band 4	Red	0.64-0.67
Band 5	Near-Infrared	0.85-0.88
Band 6	SWIR 1	1.57-1.65
Band 7	SWIR 2	2.11-2.29
Band 8	Panchromatic	0.5-0.68
Band 9	Cirrus	1.36-1.38

Landsat-8 Collection 2, Level-2 surface reflectance imagery with 30-meter resolution, was used to monitor shoreline dynamics over the summer months (June–August) for selected years between 2015 and 2025. This seasonal window was chosen to minimize hydrodynamic variability and maximize sediment visibility. Images with less than 20% cloud cover were filtered, and a median composite was generated for each year to reduce atmospheric noise and temporal anomalies.

2.3. Research Methodology

Figure 3 illustrates the methodological framework adopted in this study. The approach focuses on the classification of water and land areas using satellite imagery, employing two machine learning algorithms including Random Forest (RF) and Support Vector Machine (SVM). These algorithms were selected due to their proven efficiency in handling complex geospatial datasets and their ability to achieve high accuracy in land–water separation tasks. The diagram provides a step-by-step representation of the workflow, from data preprocessing and feature extraction to model training and classification, thereby highlighting the analytical process underlying the study.

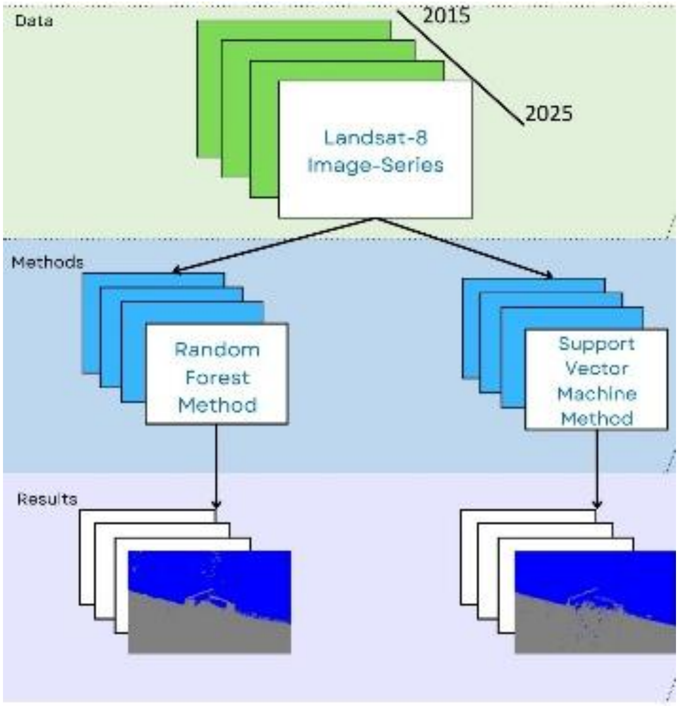


Figure 3. Methodological workflow for the study

Landsat-8 Collection 2, Level-2 (L2SP) surface reflectance products were used in this study. These pre-processed data have been atmospherically corrected using the LaSRC algorithm, eliminating the need for additional atmospheric correction. The surface reflectance values were directly used to compute spectral indices (NDWI, MNDWI, NDVI) for water/land classification in the Bandar Anzali coastal zone.

$$NDWI = \frac{(Green\ Band - NIR\ Band)}{(Green\ Band + NIR\ Band)} \quad (1)$$

The Normalized Difference Water Index (NDWI) is designed to enhance the separation of water bodies from land by exploiting the spectral contrast between the green and near-infrared bands, making it particularly effective in detecting open water features (McFEETERS, 1996). The Modified NDWI (MNDWI) improves upon this approach by replacing the near-infrared band with shortwave infrared, which significantly reduces confusion with built-up areas and sediment-laden waters. Together, these indices provide robust tools for delineating water boundaries in coastal and urban environments, especially where turbidity or complex land cover may challenge conventional classification methods (Jiang et al., 2014).

$$MNDWI = \frac{(Green\ Band - SWIR\ 1\ Band)}{(Green\ Band + SWIR\ 1\ Band)} \tag{2}$$

The Normalized Difference Vegetation Index (NDVI) is a widely used spectral indicator of vegetation cover and health. It leverages the strong reflectance of vegetation in the near-infrared band and its absorption in the red band, producing values that distinguish dense, healthy vegetation from barren land, built-up areas, or water. In coastal studies, NDVI helps separate vegetated land from non-vegetated zones, improving shoreline delineation when combined with water indices such as NDWI and MNDWI (Abdi, 2024).

$$NDVI = \frac{(NIR\ Band - Red\ Band)}{(NIR\ Band + Red\ Band)} \tag{3}$$

Four surface reflectance bands—Green (SR_B3), Red (SR_B4), Near-Infrared (SR_B5), and Shortwave Infrared 1 (SR_B6)—were first scaled using the standard Landsat-8 scaling factor (0.0000275) and additive offset (−0.2) to convert digital numbers to physically meaningful surface reflectance values. Following radiometric calibration, three spectral indices were computed to enhance the separation of water and land features and to support subsequent classification tasks.

To address the temporal aspect, only summer (June–August) Landsat-8 scenes were included in the analysis for each year. For each summer season, a composite mean image was generated to reduce variability and ensure a consistent temporal scale across the study period. This approach provided a fixed temporal reference for each year, allowing for reliable inter-annual comparison of shoreline changes. Imagery from other months exhibited extensive cloud contamination, rendering them unsuitable for shoreline extraction. Additionally, the summer period corresponds to reduced hydrodynamic activity in the Khazar Sea, during which sediment deposition and shoreline progradation are most evident. Focusing on this season, therefore, ensured both higher-quality imagery and more reliable detection of sediment-driven shoreline changes.

In the initial workflow, two representative training regions were manually delineated through visual (optical) examination of the Landsat-8 imagery: one encompassing lagoon and open-sea waters, and the other covering coastal margins and adjacent land surfaces. The selection of training regions was based on a priori knowledge of the study area, ensuring that spectrally distinct and representative zones were included for both water and land classes.

From each region, 2,500 pixels were sampled at 30-m resolution and assigned binary labels of water (class = 1) or land (class = 0). The samples were then merged into a unified training dataset, and a frequency histogram was generated to verify that the class distribution was balanced before model training. This balanced sampling approach prevented class imbalance issues and ensured that both classifiers were equally trained on water and land signatures.

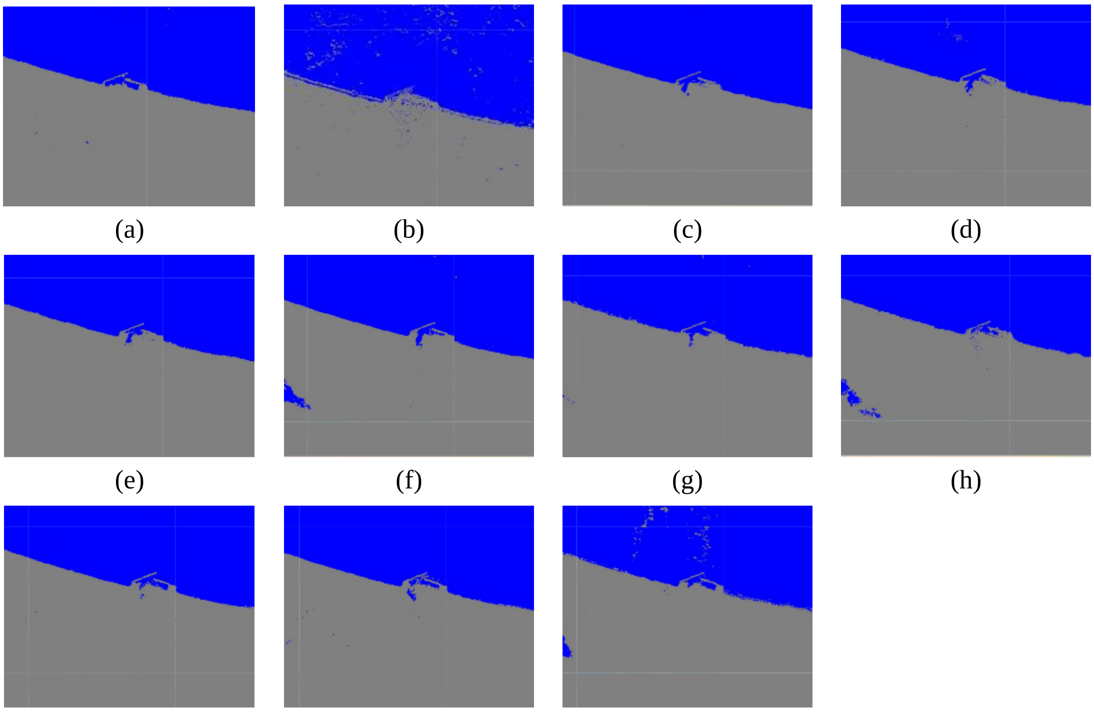
Two machine learning classifiers were implemented in the Google Earth Engine (GEE) platform: A Support Vector Machine (SVM) with Radial Basis Function (RBF) kernel and a Random Forest (RF) with 100 decision trees. The SVM hyperparameters were set to gamma = 0.5 and cost = 10, a configuration optimized for capturing subtle nonlinear boundaries between water and land in transitional zones influenced by sedimentation. The RF classifier, as an ensemble method, builds multiple decision trees and aggregates their outputs, providing robustness against noise and overfitting. The number of trees was set to 100, a standard value that balances computational efficiency with classification performance.

Both models were trained using the same input features, including calibrated spectral bands (Green, Red, NIR, SWIR1) and derived spectral indices (NDWI, MNDWI, NDVI). The trained models were applied to the composite summer images to produce binary water/land classifications for each year.

3. Results and Discussions

The classification results revealed distinct spatial patterns of water and land distribution across the Bandar Anzali coastal zone. The SVM classifier, with its RBF kernel configuration, effectively delineated water–land boundaries, particularly in transitional zones where spectral signatures were ambiguous due to sediment influence. The RF classifier, leveraging its ensemble learning approach, provided robust and stable classifications across the entire time series, effectively handling the spectral heterogeneity characteristic of the study area.

Figure 4 shows the shoreline classification maps of Bandar Anzali for 11 years, but derived using the SVM method. The trained SVM model was applied to the composite image, producing a binary classification where each pixel was assigned as water (blue) or land (grey). The SVM outputs emphasize finer transitions along shallow water zones and sediment-affected regions, capturing subtle shoreline shifts more precisely. In the second workflow, two rectangular training regions were defined: one representing lagoon/sea waters and the other representing urban or terrestrial zones. Again, 2,500 pixels were sampled from each region at 30 m resolution, labelled as water (1) or land (0), and merged into a unified training dataset. Class distribution was checked using a frequency histogram to ensure balanced representation.

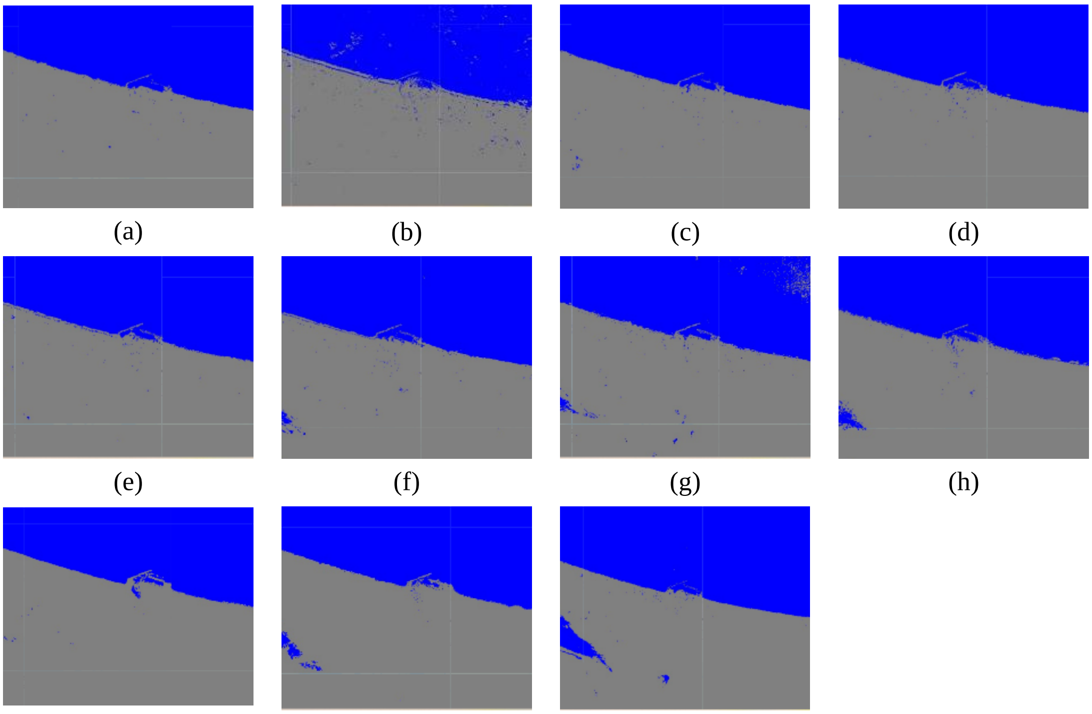


(a) (b) (c) (d) (e) (f) (g) (h) (i) (j) (k)

Figure 4. Shoreline classification results derived from the SVM method, showing shoreline dynamics in Bandar Anzali across the period 2015–2025, (a-k)

Random Forest classifier with 100 decision trees was trained using the same input features (spectral bands + indices). RF, as an ensemble method, builds multiple decision trees and aggregates their outputs, providing robustness against noise and overfitting. This made it particularly effective in handling heterogeneous land cover and spectral variability in the Anzali coastal zone.

Figure 5 presents the shoreline classification maps of Bandar Anzali between 2015 and 2025, generated using the Random Forest method. The grey areas represent land, while the blue areas indicate water. By comparing the yearly outputs, the figure highlights the gradual advancement of the shoreline and sediment deposition near the port entrance and lagoon margins. The RF classifier provides a robust and stable delineation of water–land boundaries across the entire time series, making large-scale shoreline changes clearly visible. The results were visualised in Google Earth Engine, pre-processed, and subsequently exported to Google Drive for further shoreline analysis in QGIS. After generating the classified water and land masks from Landsat-8 imagery using machine learning methods, the shoreline positions were extracted to evaluate long-term coastal changes in Bandar Anzali.



(a) (b) (c) (d)
(e) (f) (g) (h)
(i) (j) (k)

Figure 5. Shoreline positions extracted using the RF method, highlighting changes in Bandar Anzali from 2015-2025 (a-k)

To quantitatively assess shoreline dynamics, two standard indicators were applied: (1) Net Shoreline Movement (NSM), and (2) End Point Rate (EPR).

$$NSM = oldest_{year_{distance}} - newest_{year_{distance}} \quad (4)$$

NSM measures the linear displacement of the shoreline between the earliest and latest positions along defined transects. In Bandar Anzali, the Random Forest classification yielded an NSM of 147.7 meters, while the SVM classification produced a very similar value of 146.8 meters.

$$EPR = \frac{NSM}{oldest_{shoreline_{year}} - newest_{shoreline_{year}}} \quad (5)$$

The End Point Rate (EPR), defined as the Net Shoreline Movement normalized by the duration of the study period, provides a measure of the average annual shoreline displacement. Over the 11-year interval, the Random Forest–derived shoreline exhibited an EPR of 14.77 m/yr, indicating a steady and measurable shoreline advance. The SVM-derived shoreline produced a nearly identical EPR of 14.68 m/yr, reinforcing the consistency between the two classification approaches. The close agreement in these values suggests that both models capture the long-term progradation trend with high reliability, despite their differing sensitivities to transitional water–land boundaries.

This study has some limitations that should be acknowledged. First, only summer (June–August) Landsat-8 scenes were used due to extensive cloud contamination in other months. While this approach ensured higher-quality imagery and more reliable shoreline detection, it limits the temporal analysis to a specific season. It may not capture shoreline dynamics occurring during the rest of the year. Second, the machine learning models were trained on a fixed number of pixels without independent validation using high-resolution ground-truth data or cross-validation strategies, which may affect the robustness of the classification accuracy.

4. Conclusions

Both NSM and EPR values are positive, indicating shoreline progradation in Bandar Anzali. This advancement is directly linked to increased sediment deposition, particularly near the port entrance and lagoon margins. Such sedimentation not only alters coastal morphology but also poses significant challenges for port operations, navigability, and dredging requirements.

Furthermore, during the summer months, reduced hydrodynamic activity and higher evaporation rates can lower water levels in the Khazar Sea. This seasonal decline in water surface elevation exacerbates the impact of sedimentation, further restricting navigable depth and intensifying the need for regular dredging and maintenance of navigational channels.

In addition to seasonal variations, the Khazar Sea has experienced a significant and persistent decline in water levels over the past decade (2015–2025). This long-term sea-level drop has been particularly pronounced in the southern basin, including the Bandar Anzali region. The combined effect of reduced water levels and ongoing sediment deposition has accelerated the observed shoreline advance, as falling water levels naturally expose more coastal land regardless of sediment input. Therefore, the detected shoreline progradation (NSM ~147 m) cannot be attributed solely to sediment accumulation but must also be considered in the context of regional water-level decline.

In conclusion, this study confirms that Bandar Anzali's shoreline has advanced steadily between 2015 and 2025 due to active sedimentation processes. The positive NSM and EPR values underscore the severity of this progradation. By demonstrating the effectiveness of combining Landsat-8 imagery, spectral indices, and machine learning classifiers, this research provides a scientifically grounded framework for sustainable coastal management. Such approaches are essential for safeguarding the economic and ecological functions of critical seaports along the Khazar Sea.

From a management perspective, the observed shoreline progradation in Bandar Anzali underscores the urgent need for comprehensive sediment management strategies. Regular dredging of navigation channels and port entrances must be prioritized to maintain maritime transport and ensure port accessibility. At the same time, continuous monitoring through satellite remote sensing and in-situ measurements can provide reliable data on sedimentation rates and shoreline dynamics, enabling proactive interventions. Engineering measures such as sediment traps or breakwaters may also help reduce deposition in critical areas, while predictive modeling tools can support long-term planning and risk reduction.

Equally important is integrating ecological considerations into management practices. Sediment control should be designed to protect lagoon ecosystems while sustaining port operations, avoiding excessive disturbance to habitats. Seasonal water level declines during summer, driven by evaporation, further exacerbate navigational risks, making adaptive strategies essential. A coordinated framework that combines engineering solutions, ecological safeguards, and institutional cooperation among local authorities and port stakeholders offers the most sustainable path forward to mitigate sedimentation impacts and secure the long-term functionality of Bandar Anzali and the lagoon system.

To enhance future studies on shoreline dynamics in the Anzali region, several paths can be pursued. First, incorporating multi-sensor satellite data, particularly Sentinel-2 (with 10-m resolution), could provide higher spatial detail and more frequent visit cycles, improving the accuracy of shoreline detection. Additionally, integrating tide gauge or satellite altimetry data with shoreline analysis would help to separate the effects of sea-level fluctuations from genuine sediment-driven coastal changes. Second, developing customized machine learning models with region-specific hyperparameters and training datasets tailored to the unique spectral characteristics of the southern Khazar coast could yield more accurate classification results. Implementing rigorous validation strategies, such as cross-validation and independent ground-truth data from high-resolution imagery or field surveys, would further strengthen the reliability of the results.

Author Declarations

Authors' contributions: Concept: K.K., Design: M.H., Data collection: K.K., Analysis: K.K. and M.H., Writing: K.K., Edit: M.H.

Conflict of interest/Competing interests: The author(s) declare no conflict of interest.

Ethics approval/declarations: No need/ Not applicable.

Funding: This research received no external funding.

Consent to participate: No need/ Not applicable.

Consent for publication: No need/ Not applicable.

Data availability: Data are available on request due to privacy or other restrictions.

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