Monitoring shallow coastal environment using Landsat/altimetry data under rapid sea-level change

Mehrdad Jeihouni, A.A. Kakroodi*, Saeid Hamzeh

Dept. of Remote Sensing and GIS, Faculty of Geography, University of Tehran, Azin Alley, 50, Vezal Str, Tehran, Iran

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**ABSTRACT**

The Caspian Sea (CS) is the largest enclosed inland body of water and eminent for its rapid sea-level change. From 1929 to 1955, rapid cyclic changes with amplitudes of 3 m led to the formation of large submerged and emerged areas. The present study seeks to incorporate multi-source sensor data such as the Landsat time-series data (i.e., MSS, TM, ETM+ and OLI) alongside radar altimetry products (i.e., TOPEX, Jason-1, OSTM, Jason-3) as a means for extracting morphological features (Gorgan Bay and Gomishan lagoon) of the southeastern shorelines of the Caspian Sea, as well as to investigate changes in the shoreline for a given period of 42 years (1975-2016). We also employ Particle Swarm Optimization (PSO) algorithm as an automated method to extract shoreline change in shallow marine environments. Over the past century, the CS has experienced a lowstand in 1977 and a highstand in 1995. Despite an approximate 1.5 m drop in sea-level from 1995 to 2015, Gorgan Bay and Gomishan lagoon, with depths of 4.5 and 2.5 m, appear to have outlasted and emerged, respectively. PSO is a highly efficient method capable of defining shorelines and extracting water bodies. The surface area estimations using the PSO method are consistent with corresponding reference values, with an average error of 1.73% and a high coefficient of determination ($R^2 = 0.99$). Differences between calculated and reference areas were mainly observed in muddy and swamp sectors of the study area. This study highlights the key role of satellite time-series data in shoreline monitoring and management under rapid sea-level change conditions. Moreover, the study demonstrates the capabilities of the PSO algorithm as an automated and accurate method for shoreline detection.

**1. Introduction**

The Caspian Sea (CS) is the largest enclosed inland body of water on Earth, with a surface area of 371,000 km$^2$, characterized by rapid sea-level change. Caspian Sea level (CSL) has had large fluctuations and has experienced a ~3 m sea-level fall between 1929 and 1977, which was much higher than global sea-level change (Kroonenberg et al., 2007; Kakroodi et al., 2012, 2014; 2015; Haghani and Leory, 2016; Ramezani et al., 2016). After 1977, CSL began to rise at a rate one hundred times faster than the present eustatic sea-level, followed by a total rise of ~2.7 m from 1978 to 1995 (Kroonenberg et al., 2007; Kakroodi, 2012; Naderi Beni et al., 2013; Kakroodi et al., 2015). These sea-level fluctuations resulted in the formation of back-barrier lagoons, as one of the most significant responses of the coastal area to rapid sea-level rise (Kroonenberg et al., 2000, 2007; Kakroodi et al., 2014a,b) and shoreline change (Le Cozannet et al., 2014; Kakroodi et al., 2014a,b). Considering such fluctuations, in collaboration with the existence of tide-gauge data from the middle of the 19th century, makes the CS an excellent “natural laboratory” for the study of coastal responses to rapid sea-level changes (Kaplin and Selivanov, 1995).

Shoreline is the physical interface between land and water (Donlan et al., 1980). The shoreline position changes continually through the course of time (Boak and Turner, 2005) and is considered one of the most important dynamic processes in coastal areas (Mills et al., 2005). Accordingly, shoreline and shoreline change maps are critical in assessing coastal hazards (Marfai et al., 2008). Therefore, approaches to shoreline change detection and shoreline extraction have become the main focus of numerous environmental and remote sensing studies (Ramirez-Cuesta et al., 2016; Kuleli et al., 2011; Pardo-Pascual et al., 2012; Li and Gong, 2016; Kermani et al., 2016; Dean and Houston, 2016; García-Rubio et al., 2015; Almonacid-Caballer et al., 2016; Ford and Kench, 2015; Mann and Westphal, 2016; Simarro et al., 2015; Testut et al., 2016; Moussaid et al., 2015; Ghosh et al., 2015).

Remote sensing-based approaches to shoreline and water body extraction have indeed become widespread, extending to methods including: visual interpretation and shoreline extraction (Ford, 2013;
Moussaid et al., 2015; Testut et al., 2016; Jonah et al., 2016), supervised and unsupervised classification (Frazier and Page, 2000; Borrels et al., 2011; Tourian et al., 2015; García-Rubio et al., 2015), Principal Component Analysis (PCA) (Lira, 2006), Tasseled Cap Transformation (TCT) (Ouma and Tateishi, 2006; Arsanjani et al., 2015; Fisher et al., 2016), band rationing and water indices (Jain et al., 2006; McFeeters, 1996; Xu et al., 2006; Davranche et al., 2010; Duan and Bastiaanssen, 2013; Ozturk and Sesi, 2015; Li and Gong, 2016), image segmentation based on PCA variants (Lira, 2006), and single band slicing (Jain et al., 2005; Frazier and Page, 2000). The latter is exceptionally effective and commonly used due to its simplicity as well as low computational costs (Ryu et al., 2002). The main objective of this approach is to find an appropriate point in the histogram of the images. In other words, it can be formulated as an optimization problem which can be solved through the employment of optimization techniques.

Particle Swarm Optimization (PSO), proposed by Kennedy and Eberhart (1995), is based on the principles of swarm intelligence and is an extremely simple yet effective algorithm for solving a wide range of optimization problems (Eberhart and Kennedy, 1995). In point of fact, PSO has been highlighted as a new and agreeable optimization technique for solving various problems and is broadly employed in different domains (Vellasques et al., 2013; Uguz et al., 2015; Zhou et al., 2016), especially for the case of non-remote-sensing image segmentation (Zhang et al., 2011; Chander et al., 2011; Maitra and Chatterjee, 2008; Feng et al., 2005; Ghamisi et al., 2012 Benaichouche et al., 2013). The PSO algorithm starts with an initial population (a number of particles), wherein each particle represents a random solution. Each particle also has a random velocity and position and can move within the search space (e.g., histogram of the images or between pixels), while keeping a record of its own search experiences as well as its companions’, in order to reach the global optimum. Finding the global optimum is equivalent to maximizing the inter-class variance and minimizing the intra-class variance based on pixel values or intensity levels (Ghamisi et al., 2012). Accordingly, the PSO algorithm can be used for shoreline detection.

The objectives of this study are as follows: (1) long-term monitoring of shallow environments during the last 42 years from 1975 to 2016, as well to cover most parts of the sea-level cycle by means of altimetry and optical remote sensing data, (2) assessment of the relation between CS level fluctuation and the coastal morphological change (Gorgan Bay and Gomishan lagoon), and (3) propose a novel approach for shoreline detection and water body extraction based on PSO algorithm.

2. Materials and methods

2.1. Study area

The CS is bounded by five countries; Iran, Azerbaijan, Russia, Kazakhstan and Turkmenistan. The south Caspian basin is considered the deepest part of the CS with a depth of 1025 m (Kroonenberg et al., 2000; Kakroodi et al., 2012). The southeastern CS has a semi-arid climate with mean annual precipitation of 350 mm (Kakroodi et al., 2012). The Gorgan and Qareh Su rivers flow to the CS in this part. The CS has no tide (Kroonenberg et al., 2000; Hoogendoorn et al., 2005; Firoozfar et al., 2012; Kakroodi et al., 2012; Beni et al., 2013) and rapid sea-level change plays a crucial role in controlling the coastal morphology (Kakroodi, 2012). Present CSL is ~27 m below global sea-level (bsl) and has had large sea-level fluctuations (Fig. 1) during the last decade. The study area comprises of the southeastern Iranian section of the CS (Fig. 2). Offshore and onshore gradient in the southeastern CS is rather gentle (Kakroodi et al., 2012). The area is characterized by two well-known coastal morphologies, namely the Gorgan Bay and the Gomishan lagoon, which are separated from the CS by a spit or barrier.

The schematic presentation of shoreline and coastal morphological features in 1999 and 2015 has been depicted in Fig. 3. Gorgan Bay is located in the southeast corner of the CS and is separated from the water body by the prominent Miankaleh Spit (Kakroodi et al., 2012, 2015). The bay extends to 60 km in length, with an average width of 12 km (Araghi et al., 2014). The bay’s average depth is 1.84 m, varying from 0.62 to 4.12 m (Bastami et al., 2012) and has a muddy bottom (Scott, 1995). Gorgan Bay is characterized by its notable economic and ecological contributions to fishing and recreation (Araghi et al., 2014).

Gomishan lagoon is located on the eastern coast of the CS in the southeast (Scott, 1995). This south-north oriented shallow lagoon was formed as a result of landward movement of a narrow barrier caused by a rapid sea-level rise after 1977 (Kakroodi et al., 2015). Gomishan lagoon is a large shallow area with an average depth of 1 m and a maximum depth of 2.50 m (Patimar et al., 2009). During the rapid CSL fall between 1929 and 1977, the lagoon entirely dried out, with the coastline moving several kilometers seaward (Kakroodi et al., 2012). Rapid sea-level rise between 1977 and 1995 breached the sand barrier, resulting in the formation of a new lagoon which extended further towards the mainland (Kakroodi et al., 2015). Moreover, Gomishan lagoon has a very gentle slope both onshore and offshore, which makes it very sensitive to sea-level fluctuations (Kakroodi et al., 2012).

2.2. Data

2.2.1. Landsat imagery

This study aims to monitor the shallow marine environments in low-angle coasts using available Landsat data for the longest possible time period in order to cover most of the sea-level cycle. A total of twenty four images were acquired from Landsat satellites series (2, 5, 7 and 8) including Multi-Spectral Scanner (MSS), Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+), and Operational Land Imager (OLI) sensors to provide adequate data to cover the 42 year study period (between 1975 and 2016) (Table 1). The dataset consists of two main data periods; 1) long-term monitoring data from 21 images (1975–2016) and 2) seasonal monitoring data from four images for the year 2000. Interestingly, Gorgan Bay and Gomishan lagoon could be covered with a single scene of Landsat satellite series. All Level 1 Terrain-Corrected (LIT) images were acquired from United States Geological Service (USGS) database (http://earthexplorer.usgs.gov/). LIT products are radiometrically calibrated, geometrically terrain-corrected and orthorectified using ground control points and digital elevation model (DEM) to obtain correct relief displacement. Based on a report by NASA, LIT products are georeferenced with a geodetic accuracy of more than 0.44 pixels (13.4 m) (NASA, 2012), which renders them suitable for pixel-level time-series analysis (USGS, 2017). These products have been broadly used in many studies (Li et al., 2015; Feyisa et al., 2014; Zhu et al., 2016; Nitze and Grosse, 2016; Olthof et al., 2015; Li and Gong, 2016).

2.2.2. Satellite altimetry data

Satellite altimetry is a technique often applied to estimate surface levels of water bodies (Duan and Bastiaanssen, 2013). Satellite altimetry databases are generally used in water resource studies (Duan and Bastiaanssen, 2013; Sima and Tajrishy, 2013; Tourian et al., 2015). One of the most common types of satellite altimetry database is the Global Reservoir and Lake Monitor (GRLM) database, prepared by the USDA Foreign Agricultural Service (USDA/FAS) in collaboration with NASA and the University of Maryland (USDA, 2017b). The GRLM altimetry database is available at https://www.pecad.fas.usda.gov/cropexplorer/global_reservoir/. The project utilizes near-real-time data from the Jason-3 mission, as well as recorded data from the Jason-2/OSTM, Jason-1, TOPEX/POSEIDON, and ENVISAT missions to collect time-series of water level variations data for some of the world’s lakes and reservoirs from 1992 for operational applications (USDA, 2017b). The altimetry data for the CS were collected from multiple satellites including; TOPEX, Jason1, OSTM, Jason3 (Fig. 1 b). The satellites have a 10-day revisit period.
2.3. Shoreline detection

Various methods have been proposed for shoreline detection and water body extraction, however, this study sought to employ visual interpretation and careful manual digitization as the most suitable and accurate approach consistent with the objective of this study. However, this approach might be time-consuming and tedious (Duan and Bastiaanssen, 2013). Accordingly, all shorelines, shallow environments and landforms (spits) were extracted by means of visual interpretation and manual digitization.

Shoreline can be delineated by a single band in the Infrared domain, since the water reflectance is close to zero in this domain. But the near-infrared (NIR) domain is relatively transparent to clear water (Ryu et al., 2002) and sensitive to turbidity (Frazier and Page, 2000) which limits the use of single band in the NIR domain. Conversely, in the shortwave infrared (SWIR) domain (1.55–1.75 μm), energy is strongly absorbed by water and is therefore minimally sensitive to water plant materials, suspended sediments (Olthof et al., 2015) and turbidity (Frazier and Page, 2000). For this reason, the Landsat SWIR1 band is suitable for separating land from water and delineating shorelines (Frazier and Page, 2000; Olthof et al., 2015; Ryu et al., 2002). This study employed SWIR1 bands for different years as a means for shoreline detection and water body extraction with consideration of swamps in the study region, which in turn were validated using false color composite (FCC).

2.4. Particle Swarm Optimization (PSO)

Determining the optimal threshold for image values of the SWIR band domain (1.55–1.75 μm) in order to separate water from land is perhaps the most crucial part of shoreline detection and water body extraction. Finding the optimal threshold value is formulated as an optimization problem, which can be solved through the application of the PSO algorithm.

PSO is a metaheuristic approach (Marini and Walczak, 2015), wherein the initial particles represent candidate solutions within the search space and the aim is to find an optimal solution by exploring the search space. Each particle keeps track of its own coordinates while moving through the search space. As particles move throughout the search space, each particle stores the current best solution that is called personal best (pbest), in terms of fitness, and interact and share their experiences with their surrounding particles. The overall best solution in each step is called the global best (gbest). Each particle tries to find the optimal solution based on pbest and gbest in the search space. In the first phase, particles are generated at random locations with random velocities. Then, with each iteration of the algorithm, the velocity and pbest of each particle and the overall gbest are updated, and particles, in turn, update their coordinates within the search space as they try to find an optimal solution. The motion equation of the \( i \)th particle is:

\[
x_i(t + 1) = x_i(t) + v_i(t + 1)
\]

where \( t \) and \( t + 1 \) are two successive iterations and \( v_i \) indicates the velocity of the \( i \)th particle. The velocity equation of the \( i \)th particle (\( v_i \)) is:

\[
v_i(t + 1) = w v_i(t) + c_1 r_1 \left( p_{best} - x_i(t) \right) + c_2 r_2 \left( g_{best} - x_i(t) \right)
\]

Where \( w \) is the inertia weight used for balancing the global and the local search (Shi and Eberhart, 1998), \( c_1 \) and \( c_2 \) are acceleration constants in the range of \([0,4]\), \( c_1 \) is the cognitive coefficient and determines the impact of pbest on the search process, \( c_2 \) is the social coefficient and determines the impact of gbest on the search process (Benaichouche et al., 2013; Marini and Walczak, 2015), \( r_1 \) and \( r_2 \) are uniform random values between 0 and 1. For specific detail on theories and application of PSO refer to (Kennedy and Eberhart, 1995; Eberhart and Kennedy, 1995; Ghamisi et al., 2012; Marini and Walczak, 2015).

In this study, particle positions were initialized randomly within the search space and their initial velocities were set to zero, with \( c_1 \) and \( c_2 \)
Fig. 2. Study area; Gorgan Bay, Gomishan Lagoon, Miankaleh and Gomishan Spit.

Fig. 3. The schema of land, swamp, lagoon, spit, washover and coastline during highstand and lowstand periods in 1999 and 2015.
values set at 1.5 (Ghamisi et al., 2012). The algorithm repeats Eqs. (1) and (2), all the while considering the values of pbest and gbest in each iteration, until certain termination conditions are met, such as a pre-specified number of iterations or a pre-defined number of iterations without achieving better results. A brief summary of the proposed PSO algorithm is presented in Fig. 4.

3. Results

To give an overview of the changes in marine shallow environments and coastal morphological features during the given 42-year period, all areas are shown in Table 2 and graphically displayed in Fig. 5. The bay varied in area from a minimum value of 299.16 km² in 1977 and 1992, respectively. Corresponding values for the Miankaleh spit occurred in 1975 and 2015 with a minimum area of 109.99 km² and maximum area of 177.02 km² in 1994 and 2013, respectively, and the lagoon was entirely dried out in 2015.

3.1. Gorgan Bay and Miankaleh spit

A 72% increase can be seen in the bay area from lowstand to highstand. Shrinkage and expansion of the bay surface area were calculated and have been shown alongside CS fluctuations in Fig. 6. Considering the surface area variations during 1975–1977, the area of Gorgan Bay has decreased by about 30 km², which is shown in tan color. Fig. 6 also points to another important issue, which is the relation between shrinkage and expansion with CSL variations. The bay’s shrinkage and expansion are highly matched with trends in water level fluctuation. When the trend is positive, the bay’s area increases and expansion occurs (e.g., 2000–2001), but when the trend is negative the area decreases, resulting in shrinkage (e.g., 1994–1999). This is due to the direct connection between the CS and the bay.

The Miankaleh spit shrinkage and expansion is highly matched with water level fluctuation as well, with the exception that when the trend of CSL is positive the area decreases and shrinkage occurs (e.g., 2008–2009), but when the CSL trend is negative the area increases and expansion takes place (e.g., 2010–2011). This in turn is due to the direct impact of CSL fluctuations on Miankaleh. The relation of the Gorgan Bay area and Miankaleh spit area with CSL is linear with high coefficients of determination (R²) of 0.92 and 0.83, respectively (Fig. 7). CSL has a direct relation with bay area and a reverse relation with Miankaleh area. Based on the fitted linear models, the area of bay and spit can be estimated as a function of CSL.

3.2. Gomishan lagoon

The Gomishan lagoon has undergone dramatic changes as a result of CSL fluctuations. Fig. 8a presents the lagoon size during a 30-year period. The lagoon’s surface area has varied from 171 km² in 1994 to 58 km² in 2014 and it entirely dried out in 2015 (Fig. 8b). As evident from Fig. 8b, variations in lagoon area are highly dependent on CSL fluctuations. This dramatic change is clear in its seasonal trend as well.
January was the lowstand and July was the highstand period of the CS in 2000. The lagoon's surface area has increased from 130 km² in January was the lowstand and July was the highstand period of the CS in 2000. The lagoon's surface area has increased from 130 km² in January 2000 to 165 km² in July 2000. This change contributes to a 27% increase in area over the course of 6 months. Shrinkage and expansion of lagoon surface area were calculated between study years. In 2000. The lagoon's surface area has increased from 130 km² in January 2000 to 165 km² in July 2000. This change contributes to a

<table>
<thead>
<tr>
<th>Year</th>
<th>Gorgan Bay</th>
<th>Gorgan Spit</th>
<th>Gomishan Lagoon</th>
<th>Gomishan Spit</th>
<th>Gomishan Modern Beach</th>
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<tr>
<td>1975</td>
<td>328.80</td>
<td>0</td>
<td>0</td>
<td>109.99</td>
<td>0</td>
</tr>
<tr>
<td>1977</td>
<td>299.16</td>
<td>−29.63</td>
<td>−29.63</td>
<td>119.88</td>
<td>9.88</td>
</tr>
<tr>
<td>1986</td>
<td>413.76</td>
<td>114.59</td>
<td>84.95</td>
<td>160.50</td>
<td>40.61</td>
</tr>
<tr>
<td>1987</td>
<td>421.11</td>
<td>7.35</td>
<td>92.31</td>
<td>169.94</td>
<td>9.43</td>
</tr>
<tr>
<td>1989</td>
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<td>10.81</td>
<td>103.12</td>
<td>164.49</td>
<td>−5.44</td>
</tr>
<tr>
<td>1991</td>
<td>509.80</td>
<td>77.87</td>
<td>181.00</td>
<td>151.26</td>
<td>−13.22</td>
</tr>
<tr>
<td>1992</td>
<td>515.80</td>
<td>6.00</td>
<td>187.00</td>
<td>142.19</td>
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</tr>
<tr>
<td>1993</td>
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<td>−8.65</td>
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<td>144.92</td>
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<td>142.03</td>
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<td>167.35</td>
<td>141.11</td>
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<td>155.79</td>
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<td>147.04</td>
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<td>2009</td>
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<td>9.17</td>
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<td>142.66</td>
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<td>2010</td>
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<td>17.01</td>
<td>112.89</td>
<td>170.27</td>
<td>−6.75</td>
</tr>
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</table>

Table 2
Area of water bodies and land forms (spit and modern beach) in Gorgan Bay and Gomishan lagoon from 1975 to 2016.
relation between lagoon seasonal surface area and CSL is also polynomial with a high $R^2$ of 0.99. Variations in the lagoon spit and modern beach were also assessed on both annual and seasonal (the year 2000) scales and were, similar to the lagoon, highly dependent on CSL fluctuations. As a matter of fact, coastal morphological features were also affected by CSL fluctuations, a change which was clearly observed in their seasonal trend as well. The Gomishan spit area has varied from 26 km² in 1987 to 7 km² in 2001 then increased to 30 km² in 2013. The relation between the Gomishan spit area and CSL was modeled by a linear model with a high coefficient of determination. The linear relation indicates that Gomishan spit was directly affected by CSL fluctuations. Likewise, this change is seen in its seasonal trend but with more subtle changes. The spit area also had a descending trend in 2000. The spit modern beach has varied in area from 17 km² in 1987 to 3.9 km² in 2014, which corresponds to a 77% decrease in area for the given period.

3.3. PSO method

PSO was employed for extracting the area of the Gomishan lagoon from SWIR domain (1.55–1.75 μm) for each year and water surface area was calculated annually. A total of 17 SWIR images were processed, each of which belonged to one year of the given study period. Reference surface areas derived from previous visual digitization (sections 2.3 and 3.2) were used to assess and validate the PSO-estimated areas. A brief schema of the proposed PSO method and results is presented in Fig. 11. As can be observed, the figure shows the histogram thresholds (Fig. 11b) and compares the extracted shoreline with reference boundary (Fig. 11d). It also demonstrates the erroneous areas in three different sections with different amounts of error (Fig. 11 e, f and g). Reference area, estimated areas, and estimation errors are presented in Table 3. Moreover, the relation between the estimated area of the Gomishan lagoon and the reference area was also assessed (Fig. 12).

4. Discussion

Apart from recent global eustatic sea-level rise and its impact on the coastal zone (Phillips, 2018) with changes around 3.4 ± 0.4 mm/year as well as accelerated future sea-level rise (Sweet et al., 2017), the CS experiences a much higher rise in sea-level, at a rate one hundred times faster than the present eustatic sea-level (Kakroodi et al., 2012, 2014, 2015). This in turn results in a variety of coastal responses to rapid sea-level change. Generally, there is a relation between sea-level and accretion/erosion rates as mentioned by Carrasco et al. (2016), which become stable after 80 years in consideration of a constant sea-level rise from 3 to 10 mm/year. However, the CS is completely different in this regard and can hardly be modeled due to unexpected rapid sea-level change.

Coastal morphological features such as lagoons, although valuable components of ecosystems due to their critical productive roles, are extremely difficult to manage and are accompanied by many challenges (Gaertner-Mazouni and De Wit, 2012). Accordingly, continuous monitoring of shallow marine environments under sea-level fluctuations plays a key role in the sustainable development of coastal areas worldwide. Shallow environments, such as the study area, have experienced eremitical changes because of CSL fluctuations. The following discusses three periods of sea-level change commencing from 1929 to 1977 with a ∼3 m sea-level fall, from 1977 to 1995 with a ∼3 m sea-level rise and 1995-2016, with a trend of sea-level fall around ∼1.5 m using time-series data from Landsat and altimetry datasets.

4.1. Changes in shallow marine environments during rapid sea-level fall between 1929 and 1977

From the year 1929–1977 the CS has experienced a rapid fall in sea-level of ∼3 m. Based on the historical dataset presented by Kakroodi et al. (2012) the study area includes two lagoons which extended.
further inland. Unfortunately, there is no further data to monitor until 1977. Based on MSS data in 1977, two lagoons emerged under rapid sea-level fall. In the year 1977 the lagoon was completely dried out and the bay was separated from the CS because of sea-level fall.

4.2. Changes in shallow marine environments during rapid sea-level rise between 1977 and 1995

The CS has also experienced a rapid sea-level rise from 1977 to 1995; the highstand was during 1995 with a rise of \( \sim 3 \) m. This rapid sea-level rise resulted in the formation of lagoonal environments, which extended further to the mainland. In the year 1992 the bay had the largest area and expanded to about 216 km\(^2\), and gained a maximum depth of about 4.5 m compared to 1977. The bay expanded westwards, which indicates that the bay decreased in depth from east to west.

After 1977, during the rapid sea-level rise period, the Gomishan lagoon started to form and expand again. The lagoon experienced its maximum area in 1994 and expanded to about 111 km\(^2\) (Table 2) and gained a maximum depth of 2.5 m.

4.3. Changes in shallow marine environments during rapid sea-level fall between 1995 and 2016

Considering \( \sim 1.5 \) m of sea-level change between 1995 and 2016, two important morphological features were monitored; the Gorgan Bay and Gomishan lagoon. Although there was a minor sea-level rise in 2005, the overall sea-level trend was descending. At the beginning of this period, the bay and lagoon had maximum depths of \( \sim 4.5 \) and \( \sim 2.5 \) m, respectively. However, they were entirely changed in regard to their formation, connection with marine waters, depth, and stored...

Fig. 7. The correlation between Gorgan Bay and Miankaleh area and Caspian Sea water level.

Fig. 8. Gomishan lagoon surface area between 1986 and 2015. a) size variation, and b) area variation with sea-level.
water volume in response to sea-level fall.

The Gomishan lagoon was formed by rapid sea-level rise between 1977 and 1995 and after that there was no permanent river discharge into the lagoon. This situation made the lagoon vulnerable. Based on the results, the lagoon area was controlled by CSL until 2009, after which the lagoon was not directly connected with the CS due to sea-level fall and started to dry out. The lagoon lasted for some years and was entirely dried out again in 2015.

The dry point of the lagoon could be predicted based on altimetry and the surface area extracted from the time-series dataset (Fig. 10). By considering the lagoon area as higher than 120 km², the relation between surface areas and water level can be modeled using a linear model. This seems logical considering that the CS was connected to the lagoon and fed it with water. However, after decreases in water levels

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Fig. 9. Shoreline change rate of Gomishan lagoon based on End Point Rates (EPR).

Fig. 10. The correlation between Gomishan Lagoon area and CSL, a) non-linear modeling of Gomishan lagoon area based on the 1992–2015 dataset that contains the real dry out point., b) non-linear modeling of Gomishan lagoon area based on 1992–2014 dataset to predict the Gomishan dry out point.
to $-26.55\text{ m}$, the relation between the CS and the lagoon was disconnected. Based on the generated non-linear model for CSL and lagoon area (Fig. 10a), which has a high coefficient of determination, the area can be estimated by relational equations based on water level. However, when assessing the relation for the period from 1992 to 2014 (excluding the lagoon dry point) using the polynomial model (Fig. 10b), model (b) indicated that the lagoon would be dried out at a water level of $-27.095\text{ m}$, whereas the lagoon was actually dried out at a water level of $-27.055\text{ m}$. The estimation method has an error of 0.14%, which is indicative of the high performance of the prediction model and proves that the lagoon’s dry out point was predictable.

The Gorgan Bay had its minimum area in 2015 when CSL dropped by $\sim 1.5\text{ m}$. Yet, the bay survived, since it was directly connected to the CS. Also some permanent rivers like the Qare Su, Bandar Qaz, No Kandeh, Jafa Kandeh and Ab Miranlu discharged water into the bay. The bay had a greater depth and more stored water as well, which increased its resistance to sea-level fall.

### 4.4. PSO extraction and its error

The PSO-estimated areas were validated based on reference surface areas that were previously derived using visual digitization. According to the validation results (Table 3), the average error was 1.73%. The estimated water body areas from PSO were in good agreement with reference areas with a high coefficient of determination ($R^2 = 0.99$) as presented in Fig. 12. Differences in area between calculated and reference areas are related to muddy and swamp regions in the study area and are clearly observable in FCCs in Fig. 11e, f, g. Swamp pixels behave similarly to water pixels with the exception of a lower absorbance rate compared to water pixels. Existence of these pixels in the scene...
Fig. 12. The relation and comparison between estimated and reference area.

alters the image histogram, therefore swamps and muddy pixels may be mistakenly labeled as water bodies. The PSO method is quite suitable for areas with dry and non-muddy (non-swampy) coasts, as shown in section B of Fig. 11, and can generate highly accurate results. Overall, the results indicate that the PSO method can be used as an automated method for shoreline detection and water body extraction from SWIR domain (1.55–1.75 µm).

5. Conclusion

The CS water level fluctuations have direct impacts on shallow marine environments and coastal morphological features. The Gorgan Bay and Gomishan lagoon are highly dependent on CSL due to the CS's critical role as their main water supply. Defining the relation between body area and water level leads to a practical non-linear model that could predict a water level at which the lagoon dried out. Moreover, this study highlights the role of PSO as a metaheuristic approach in shoreline detection and water body extraction.

The conclusions can be summarized as follows:

1. Application of PSO as an automated method for shoreline detection.
2. Gomishan lagoon emerged entirely (2.5 m depth, ~1.5 m sea-level fall).
3. Rapid coastal evolution observed under rapid sea-level change.
4. River discharge into the lagoon is important to the lagoon's survival; otherwise it will be controlled solely through sea-level changes.
5. Combined altimetry and satellite data enabled prediction of lagoon drying point.

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References


