



HAL
open science

Deep and machine learning methods for the (semi-)automatic extraction of sandy shoreline and erosion risk assessment basing on remote sensing data (case of Jerba island -Tunisia)

Amina Boussetta, Simona Niculescu, Soumia Bengoufa, Mohamed Faouzi
Zagrarni

► To cite this version:

Amina Boussetta, Simona Niculescu, Soumia Bengoufa, Mohamed Faouzi Zagrarni. Deep and machine learning methods for the (semi-)automatic extraction of sandy shoreline and erosion risk assessment basing on remote sensing data (case of Jerba island -Tunisia). *Remote Sensing Applications: Society and Environment*, 2023, 32, pp.101084. 10.1016/j.rsase.2023.101084 . hal-04281261

HAL Id: hal-04281261

<https://hal.science/hal-04281261>

Submitted on 27 Nov 2023

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution - NonCommercial 4.0 International License

1 **Deep and machine learning methods for the (semi-)automatic extraction of sandy**
2 **shoreline and erosion risk assessment basing on remote sensing data (case of Jerba**
3 **Island -Tunisia)**

4 Amina Boussetta^{a,*}, Simona Niculescu^{b, c}, Soumia Bengoufa^b, Mohamed Faouzi Zagrarni^a

5 ^aU.R Applied Hydrosciences UR13ES81, Institut Supérieur des Sciences et Techniques des
6 Eaux de Gabès (ISSTEG), University of Gabès, Tunisia

7 ^bUniv Brest, CNRS, Nantes Université, Université de Rennes, LETG, UMR 6554, F-29280
8 Plouzané, France

9 ^c Institut universitaire de France (IUF)

10 **Abstract**

11 Against the backdrop of the environmental crisis, the socio-economic, ecological and
12 cultural importance of the coastal zone calls for greater awareness of how coastal resources
13 function, evolve, are managed and enhanced. This study aims to develop a high-performance
14 (semi-)automatic coastal monitoring method based on Landsat-5 and Sentinel-2 multispectral
15 satellite images for spatiotemporal analysis of shoreline changes and erosion risk assessment
16 along Jerba Island (Tunisia) using remote sensing data and geospatial tools. A comparative
17 study between the band ratioing (BR) method and the pixel-based image analysis (PBIA) and
18 object-based image analysis (OBIA) methods has led to the development of machine learning
19 (ML), random forest (RF), deep learning (DL) and convolutional neural network (CNN)
20 algorithms. Using these classification methods, 15 different shorelines were successively
21 detected in 1989, 2015 and 2023 and then compared with a digitized reference shoreline from
22 the Landsat-5 and Sentinel-2 images. Following a quantitative evaluation, the accuracy of the
23 classification model shows that the combined CNN-OBIA approach provided the least accurate
24 results, with an overall accuracy (OA) index of 67%, while the OBIA-RF classification method
25 provided the most accurate results (OA of 95%). This comparative study identified an accurate
26 and improved extraction method for quantifying changes in the position of the shoreline on the
27 east coast of Jerba Island, enabling managers to make better decisions on coastal protection and
28 adaptation to climate change.

29 **Keywords:** Machine learning; deep learning, erosion, Landsat-TM, Sentinel-2.

30 **1. Introduction**

31 Coastal zones are highly dynamic environments in a perpetual evolution of their natural and
32 anthropogenic origins, generated directly or indirectly by human interventions (Yan, 2023).
33 Factors such as winds, waves, tides, storms or sea-level variations can influence them. In
34 response to these variations, the coastal fringe undergoes temporal and spatial changes
35 (Zagórski *et al.*, 2020). It is generally perceived as either a form of erosion or an accumulation
36 of sediments (Paskoff, 1984). Erosion is thus a natural process that has always shaped the
37 morphology of the coastal fringe and leads to a net change in the sediment budget. The main
38 natural factors for this loss of sediment budget are a combination of material scarcity since the
39 end of the post-glacial transgression, hydrometeorological conditions and sea-level rise
40 (Sanlaville, 2001).

41 Most sandy shorelines in coastal areas are eroding, which is a cause for great concern. A
42 study of satellite shoreline data by Luijendijk *et al.*, (2018) for the 33-year period from 1984 to
43 2016 indicates that 24% of the world's sandy beaches are eroding at a rate of more than 0.5 m
44 per year, while 28% are accreting and 48% are stable. According to studies carried out by
45 Serbaji *et al.*, (2023) on erosion modeling, Tunisia presents a severe risk of coastal erosion,
46 showing that 6.43% of the country's total surface area is affected by a very high rate of erosion,
47 estimated at over 30 t/ha/year, and that 4.20% faces high average rates of erosion, ranging from
48 20 to 30 t/ha/year. In particular, the most eroded areas were identified in the south-west, center
49 and west of the country. At the regional level, the sandy coasts of Jerba Island in the Gulf of
50 Gabès in southeastern Tunisia are among the areas most affected by erosion. Boussetta *et al.*,
51 (2022a) recently confirmed this erosion trend, with values ranging from -2.87 to -8.42 m/year
52 between 1989 and 2021.

53 The shoreline is considered the boundary between land and a water surface (Boak and
54 Turner, 2005; Guariglia *et al.*, 2006; Sunder *et al.*, 2017). Shoreline monitoring needs to take
55 into account the spatiotemporal elements underlying the dynamic evolution of the boundary
56 between land and water. In order to estimate erosion rates, the precise extraction of the shoreline
57 remains a difficult task. Various methods have been used to extract and monitor shoreline
58 evolution (Ramesh and Singh, 2020). The most commonly used are manual identification
59 through visual interpretation (Zhao *et al.*, 2022), the thresholding approach (Aedla *et al.*, 2015;
60 McAllister *et al.*, 2022; Toure *et al.*, 2019), airborne LiDAR (Wang *et al.*, 2023), band ratios
61 (Boussetta *et al.*, 2022a; Görmüş *et al.*, 2021) and image classification; supervised and
62 unsupervised (Islam *et al.*, 2021; Souto-Ceccon *et al.*, 2023; Yang *et al.*, 2022).

63 Over the past decade, approaches to monitoring coastal erosion and shoreline evolution have
64 focused on the spatiotemporal analysis of satellite images. The current trend is towards
65 developing ML and artificial intelligence techniques, such as the CNN model, which can
66 support automated shoreline extraction (Görmüş et al., 2021; Tsiakos and Chalkias, 2023).

67 ML and DL algorithms, such as neural networks and random forests (RF), have recently
68 been successfully adopted for remote sensing applications (Bengoufa et al., 2021a; Dang et al.,
69 2022; Erdem et al., 2021; Niculescu et al., 2018; Seale et al., 2022), and have the potential to
70 improve our understanding of coastline evolution (Gomez-de la Pena et al., 2023). However,
71 limited research has focused on tasks related to shoreline detection, mainly due to the various
72 morphological features of the shoreline that need to be considered, especially in large-scale
73 monitoring scenarios (Seale et al., 2022). Furthermore, Toure et al., (2019) claimed that the
74 relevance of these methods for shoreline detection had not been sufficiently investigated, and a
75 limited number of studies have assessed the accuracy of these classification approaches based
76 on various new algorithms. Recently, Tsiakos and Chalkias (2023) have argued that using
77 neural networks and deep learning (DL) approaches should be expanded as they can support
78 different land and water segmentation models and coastal zone classification.

79 Bengoufa et al., (2021a) studied the contribution of several ML algorithms and their
80 accuracy in detecting the shoreline of Mostaganem (Algeria). This research focused on a small
81 section of the coastline and used very high-resolution images (Pleiades), which produced very
82 good results. However, these very high-resolution images are costly and difficult to obtain for
83 third-world countries that need an open source of data to effectively monitor the environmental
84 status of their coastlines. In addition, their research did not include an estimation of the erosion
85 rate, which is the main reason for the shoreline extraction process. We have proposed this
86 research paper to overcome these limitations and as an update and improvement to the work of
87 Bengoufa et al., (2021a) in another complex geographical area using open-source data.

88 In this context, this study aims to highlight and facilitate the understanding of different
89 approaches based on deep and shallow (semi-)automatic learning applied to coastal erosion and
90 shoreline change monitoring using 1989, 2015 and 2023 medium- and high-resolution
91 multispectral optical images, and in particular open access images (Landsat-5 TM and Sentinel-
92 2 MSI), providing details on their performance, strengths and weaknesses.

93 Therefore, this study focused on algorithmic development by comparing the effectiveness of
94 the RF algorithm, which is considered a powerful ensemble training technique (Demir et al.,

95 2017; Millard and Richardson, 2015; Rodriguez-Galiano et al., 2012); and the CNN, which is
96 theoretically superior to DL algorithms, and has been successful in classifying remote sensing
97 images (Zhu et al., 2017). Furthermore, this contribution aims to show the potential of OBIA
98 classification method in predicting shoreline evolution, and therefore, a more exhaustive search
99 of parameters could be useful to find the best performing ML model on the study site.

100 This study allows conclusions to be drawn from new perspectives on multitemporal and
101 multisensory satellite imagery processing. It thus presents a detailed long-term analysis of the
102 evolution of the shoreline of the east coast of Jerba Island with very high accuracy, and validated
103 mainly by in situ observations.

104 2. Study area

105 Jerba, located in southeastern Tunisia at northern latitude between $33^{\circ}57'0.56''$ and
106 $33^{\circ}37'46.82''$ and an eastern longitude between $10^{\circ}45'38.43''$ and $11^{\circ}3'53.802''$, is considered
107 the largest island in North Africa. The choice of our study site was based on its ecological
108 importance. It hosts three wetlands of international importance listed by the Ramsar Convention
109 on 7 November 2007, namely the Rass Rmel site, which was the subject of our study. It is the
110 region's leading tourist destination thanks to its beautiful sandy beaches on the east coast
111 (Figure 1).

112 Jerba is part of the Mediterranean Gulf of Gabès and is characterized by a microtidal regime,
113 with the most frequent tidal range on the coast being about 0.2 m for neap tides and 1.1 m for
114 spring tides. Geographically, the region is characterized by low-lying land with an average
115 topography of 20m and a gentle slope between 0° and 2.29° . The low topography extends into
116 the submarine zone, with an extensive shallow continental shelf with a -10m isobath averaging
117 3km from the shore. The low-lying shoreline of the eastern parts of Jerba is characterized by
118 very fine sediments and sandy beaches, which are most affected by changes in shoreline
119 configuration. These characteristics make the island highly vulnerable to coastal erosion.

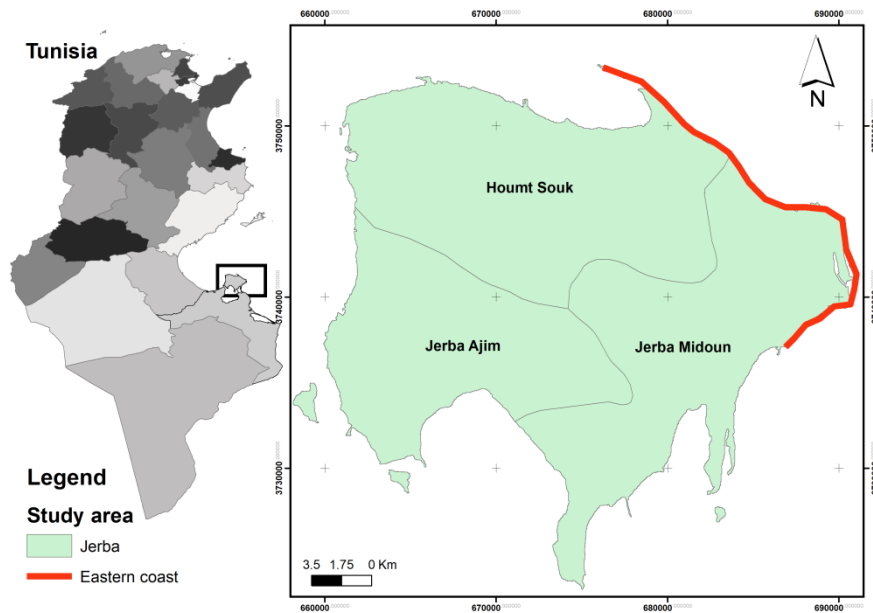
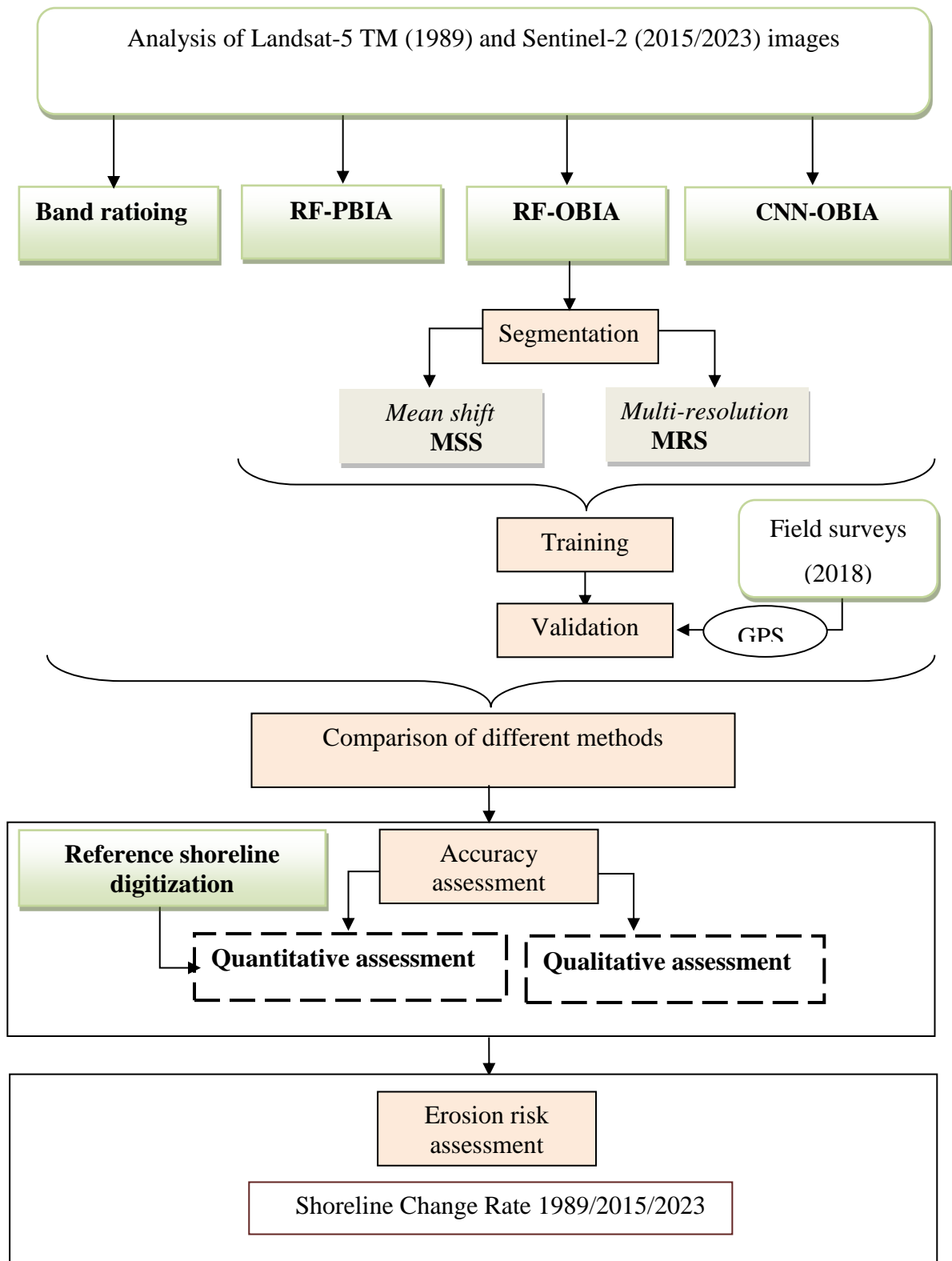


Fig. 1. Jerba Island, south-east Tunisia, selected as the study area

3. Material and methods

The first step of our approach was to analyze the geographical and geomorphological context of the study area through environmental analysis. In 2018, several field surveys were carried out at different times, which allowed us to observe the different signs of coastal erosion and visualize the morphological changes along the shoreline. This analysis identified the land-water boundary for its usefulness and reliability.

Secondly, this study aims to assess the methodological contribution of these approaches to (semi-)automatic shoreline extraction. Thus, a comparative study between four (semi-)automatic methods of band ratioing (BR) and supervised classification, namely, pixel-based image classification (PBIA), object-based image analysis (OBIA), an integrated CNN-OBIA approach and manual digitization.



138

139

140

141

Fig. 2. Flow chart of the comparative study between different classification methods and machine learning algorithms using multi-resolution, multisensor images.

142 **3.1.Data Acquisition**

143 The determination of shorelines using satellite images from a wide range of satellites,
 144 including Landsat (Wicaksono and Wicaksono, 2019) and Sentinel (Abdelhady et al., 2022),
 145 is becoming increasingly common due to improvements in image resolution, acquisition rates
 146 and availability. A Landsat Thematic Mapper (TM) image with a resolution of 30m was used
 147 for the year 1989. This was downloaded for free in GeoTIFF format from the United States
 148 Geological Survey (USGS) Earth Explorer portal (<http://www.earthexplorer.usgs.org>). Two
 149 high-resolution Sentinel-2 images with a MultiSpectral Instrument (MSI) sensor and 2A
 150 processing level were downloaded via the CNES Theia platform (free access; Muscate -
 151 Distribution Workshop) with 13 spectral bands of different spatial resolutions ranging from 10
 152 to 60 m. Bands B2, B3, B4 and B8 have a resolution of 10 m. Bands B5, B6, B7 and B8 have
 153 a resolution of 20 m, while bands B1, B9 and B10 have a spatial resolution of 60 m.

154 The Sentinel-2 mission provides an alternative source of optical remote sensing that is
 155 globally covered and freely accessible (Wang et al., 2018). High spatial resolution (10 m) data
 156 from the Sentinel-2 satellite is mainly used for mapping coastal areas. For the present work,
 157 images with the ‘flat reflectance’ band were selected. In this case, the Sentinel images are
 158 corrected for slope effects, and all the satellite images used had zero cloud cover.

159 **Table 1. Satellite images used**

Acquisition date	Acquisition time	Satellite and sensor	Resolution (m)	Bands used(µm)
07 January 1989	09:19:53	Landsat-5 TM	30*30	B1: 0,45 - 0,52 (Blue) B2: 0,52 - 0,6 (Green) B3: 0,63 - 0,69 (Red) B5: 1,55 - 1,75 (Mid-Infrared)
08 December 2015	10:20:05	Sentinel-2A MSI	10*10	B2=Blue B3=Green B4=Red B8=Near-infrared
10 January 2023	10:11:24	Sentinel-2A MSI		

160

161

162 **3.2. Preprocessing**

163 The preprocessing of the Landsat-5 TM scene begins with radiometric correction, where the
164 pixel values refer to the same physical units. As a preprocessing tool, QGIS 3.10 provides the
165 Semi-Automatic Classification plugin, which ensures a one-step attenuation of atmospheric
166 effects, compensation for differences in shooting conditions and sensor calibration. The next
167 step is geometric correction, which uses ground control points (GCPs). Using a global
168 positioning system (GPS), more than 30 well-distributed bitter points were carefully identified
169 in situ at permanent landmarks.

170 The *flat reflectance* bands of the Sentinel-2 images were already corrected and then further
171 corrected for terrain slope. Using European Space Agency's Sentinel Applications Platform
172 software (SNAP), a subset of four bands (B2/B3/B4/B8) was created.

173 **3.3. Shoreline detection and extraction using machine learning methods (random** 174 **forest algorithm)**

175 The principle of supervised classification with ML methods is to assign a class to each point
176 selected from a set of possible classes. The data set (pixel or object) must be grouped into
177 several subsets to create classes. This grouping is done based on similarity criteria. A
178 comparative study (Figure 2) assessed the suitability of supervised image classification
179 methods, namely PBI and OBIA, as well as ML and DL algorithms for shoreline detection
180 and extraction.

181 **3.3.1. Sampling process**

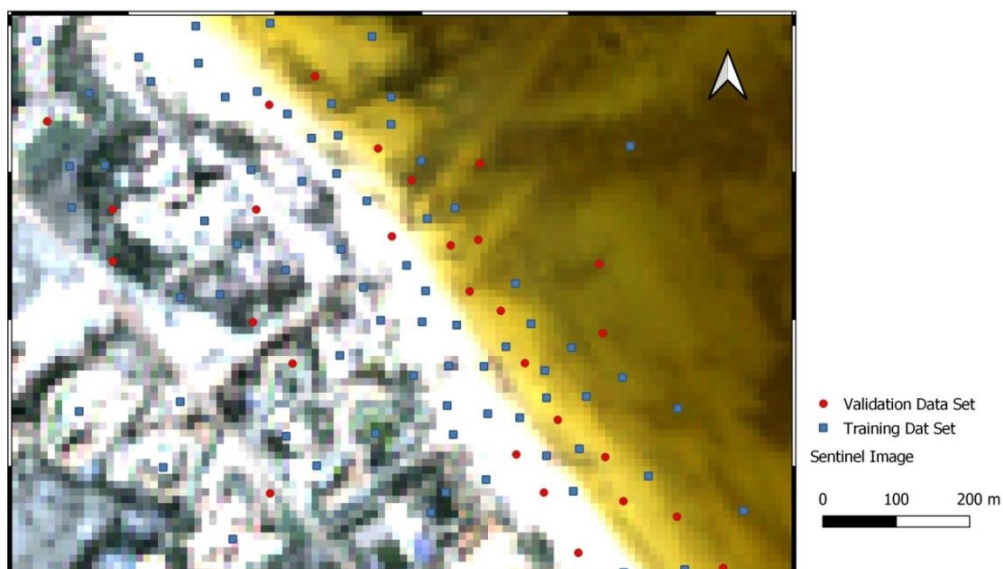
182 It is necessary to have a good knowledge of land use to instruct the treatment system. For
183 this, we need ground-truth data. Ground truth is a guaranteed set of exact data on observed land
184 use obtained through close observations in the field. Furthermore, the selection of samples is
185 always based on very high-resolution Google Earth images with the same dates as the satellite
186 images.

187 On this basis, certain regions of interest (ROI) were defined to highlight the land-water
188 boundary. The classes are as follows: for the Sentinel image: (1) water, (2) land, (3) urban and
189 (4) vegetation; for the Landsat image: (1) water, (2) land, (3) vegetation and (4) other. The
190 water class represents shallow coastal waters. The land class represents a beach consisting of

191 homogeneous sandy material. The boundary between this class and the water is maintained as
192 the target fault to be extracted, the shoreline.

193 The sampling step is essential for supervised classification, either for OBIA or PBIA. Indeed,
194 good classification requires representative and suitable samples (Sabat-Tomala et al., 2020). A
195 training sample is necessary for training and developing classification models. The sampling
196 technique consists of taking the number of classes in each sample, making it possible to deal
197 with class imbalance (Sertel et al., 2022). The validation step of the model was done using
198 ground-truth points (validation samples) collected in situ using the GPS. This step is crucial for
199 assessing the accuracy of the assisted classification and capturing the accuracy metrics (see the
200 accuracy assessment section 4.1.4.1).

201 The training and validation samples (about 850 samples) must be selected in areas highly
202 representative of the objects on Landsat-5 for 1989 and Sentinel-2 images for 2015 and 2023;
203 these areas should be highly reflective to compensate for possible confusion (Puissant et al.,
204 2014). It was also necessary to select these samples separately to avoid overlap between the
205 two sets in the same areas (Figure 3). In the remote sensing literature and statistics, a certain
206 number of representative samples of the objects to be classified is needed to avoid over- or
207 under-learning certain objects. For all classifications, 80% of the samples were used to train
208 and tune the ML algorithms, while 20% of the validation samples were used as a test set.



210 Fig. 3. Illustration of the distribution of validation and training samples on a Sentinel-2 image

211 3.3.2. Object-Based Image Analysis (OBIA)

212 OBIA is based on image objects consisting of pixels with homogeneous information
213 (Hossain and Chen, 2019). This method provides spatial information as well as spectral, textural
214 and contextual features as a basis for classification. It subdivides the image into homogeneous
215 regions called image objects or segments (Benz *et al.*, 2004). The OBIA approach comprises
216 three main stages: image segmentation, classification and validation.

217 **3.3.2.1. Segmentation**

218 Segmentation is the most crucial process in OBIA (Deliry *et al.*, 2021). Its principle is to
219 automatically divide images into thousands of non-overlapping superpixels (Yang *et al.*, 2020).
220 The result is well-defined regions or features of an object that can be distinguished. In the field
221 of remote sensing, there are several segmentation algorithms. Our study compares two
222 segmentation algorithms that were applied to segment coastal land cover types in order to
223 extract water/land boundaries: mean shift segmentation (MSS) and multi-resolution
224 segmentation (MRS).

225 ***Meanshift image segmentation (MSS)***

226 The main idea behind this algorithm is to divide the image into highly correlated segments.
227 The Orfeo Tool Box (OTB), an open-source software package, was used to apply MSS. Three
228 parameters need to be determined: spatial radius (sr) used to determine the neighborhood
229 boundaries, range radius (rr) for defining the width in spectral space, and minimum region size
230 (mrs) to be maintained after clustering (Varo-Martínez and Navarro-Cerrillo, 2021). In our case,
231 13 trials were conducted. The parameters were set after cross-validation based on the
232 segmentation models that achieved the highest overall accuracy (OA).

233 ***Multi-resolution image segmentation (MRS)***

234 The MRS is one of the most widely used segmentation algorithms in the literature and was
235 chosen for its proven accuracy in wetland classification (Hossain and Chen, 2019; Merchant,
236 2020; Yan *et al.*, 2021). The main objective of this algorithm is to reduce average pixel
237 heterogeneity as much as possible (Incekara *et al.*, 2018). The MRS was implemented using the
238 eCognition© Definiens Developer software. In order to obtain the expected results, three
239 parameters had to be chosen empirically to demonstrate the morphology of the objects: scale
240 parameter (Sc), representing the weighting between a colour factor (or spectral factor) and a
241 shape factor, designated by the weight w shape/w colour; shape (Sp), defined as the maximum

242 heterogeneity allowed within the objects; and compactness (C_p), making the object more or
243 less regular, denoted by the weight $w_{\text{compt}}/w_{\text{smooth}}$.

244 Parameters were determined based on trial and error as well as the visual interpretation. In
245 addition, the near-infrared (NIR) band of the Sentinel images and the mid-infrared (MIR) band
246 of the Landsat image were more weighted (value of 10) than the other RGB bands (value of 1),
247 as this region of the electromagnetic spectrum is known to enhance the detection of the
248 land/water interface due to the inherent optical properties of water (Valderrama-Landeros and
249 Flores-de-Santiago, 2019).

250 **3.3.2.2. Classification**

251 Classification is divided into two stages: training and prediction, and was done using
252 eCognition software and an RF classifier (see *Random Forest Classifier* section)

253 **3.3.3. Pixel-Based Image Analysis (PBIA)**

254 The concept of the traditional PBIA method is based on the spectral information of satellite
255 images. It involves assigning a thematic class to each pixel (Guo et al., 2021) by assessing the
256 degree of similarity of a pixel's spectrum to reference spectra for surface features
257 (Shayeganpour et al., 2021). PBIA was applied to detect the shoreline using the open-source
258 software OTB.

259 The method consists of three steps. The first is classification using the RF algorithm,
260 followed by validation and vectorization (see *Random Forest classifier* section). This approach
261 produces raster maps with a 'salt and pepper' appearance (Mollick et al., 2023). Using Mapla's
262 Classification Map Regularization tool, smoothing was performed to transform 'isolated' pixels
263 into the majority of surrounding pixels. The result of the classification was then converted from
264 raster to vector format using the Polygonize Raster to Vector tool in QGIS. It consists of
265 obtaining class boundaries to extract the shoreline. The extracted boundary was a raw vector
266 layered with high-frequency noise.

267 ***Random Forest Classifier***

268 The various approaches involved the evaluation of PBIA and OBIA based on an RF-
269 supervised ML classifier. This type of model has several advantages, including the non-
270 parametric nature of the algorithm, high classification accuracy and the ability to identify
271 important variables and predict missing values (Jhonnerie et al., 2015).

272 Given the performance and automatic aspect of the method, which requires only a few
273 parameters to be set, quantifying the importance of the variables is one of the most crucial
274 aspects of the model applied (Ramesh and Singh, 2020). Two parameters were examined: the
275 maximum number of trees in the forest (Ntree) and the minimum number of samples in each
276 node (Mtry). Published literature has highlighted that the RF classifier is more sensitive to the
277 Mtry parameter than the Ntree parameter (Gonçalves et al., 2020). The RF parameters were
278 configured with Ntree and Mtry set values after cross-validation. We therefore tested different
279 scenarios using the spectral bands (B1/B2/B3/B5) for the Landsat-5 TM image (1989) and
280 (B2/B3/B4/B8) for the Sentinel-2 images (2015/2023). The iteration parameters that performed
281 best in terms of OA were finally used to produce the final classification images. From the
282 various Mtry values tested, the values of 30 and 50 were selected for PBIA-RF and OBIA-RF,
283 respectively. Next, class prediction of the objects was performed using the *vector classifier* tool
284 of the OTB software for the OBIA approach, and the *image classifier* tool for PBIA approach.

285 **3.4. Shoreline detection and extraction using a deep learning model (CNN)**

286 The convolutional neural network (CNN; Fukushima, 1988) is a highly responsive
287 supervised DL algorithm. CNN is a powerful recognition algorithm widely used in pattern
288 recognition and image processing that has the ability to learn autonomously and perform
289 information extraction efficiently, quickly and reproducibly. However, the CNN-based method
290 is more complex than other methods and requires purer images (Zhang et al., 2016; Zhu et al.,
291 2017). Its architecture consists of convolutional, pooling and fully connected layers.

292 We used the new combination of CNN with the OBIA using the MRS approach developed
293 by Bengoufa et al., (2021b) for rocky shoreline extraction and Bengoufa et al., (2023) for the
294 extraction of shoreline biological indicators. We adapted this approach for the extraction of
295 water/land boundaries. The aim is to implement a shoreline extraction method that integrates
296 the benefits of CNN model output, namely CNN probability, with the robustness of the OBIA
297 approach.

298 As well, for the classification process, our CNN architecture was fed with 2×2 sample patch
299 sizes. Given this small size, the number of hidden layers was 1, with a convolution kernel size
300 of 1×1 . A max-pooling layer with a kernel size of 1×1 was used after the first convolution
301 layer. Max-pooling's role is to merge features that are semantically similar (Bengoufa et al.,
302 2021a). This is a non-linear top-down sampling technique that uses the maximum value of each
303 cluster in the previous layer to reduce the loss of information in subsequent convolution layers.

304 In addition, the use of patch sizes of 50 and 5,000 training steps resulted in excellent
305 performance. The learning rate parameter was set to 0.0006 after trial-and-error tests. Then
306 different feature maps were generated.

307 The MRS was used for image segmentation. A class hierarchy was applied for all classes
308 according to a linear cohesion function (x, y) , with a maximum value equal to one (1) and a
309 minimum equal to zero (0). The resulting objects from this segmentation were trained and
310 classified based on a combination of neighbourhood, spatial features and similarity in the CNN
311 probability (CNN application output), which can bring advantages in automatic data extraction
312 and high-precision prediction. The resulting polygons (objects) were converted to polyline
313 format to select and extract the target shoreline.

314 **3.5.Detection and extraction of the shoreline using the band ratioing method**

315 Boussetta et al., (2022a) used the BR method to automatically extract the sandy shoreline of
316 Jerba Island and obtained good results. To evaluate the accuracy of the machine and DL
317 methods used here, we compare their results with those of the BR method.

318 For the BR method, the ratio between the visible NIR and MIR was calculated,
319 corresponding to band 5/band 2 (MIR/green) in the case of Landsat TM (1989) and band 8/band
320 2 (NIR/green) in the case of Sentinel-2 images (2015–2023), as the NIR and MIR wavelengths
321 are strongly absorbed by water and reflected by soil (Alesheikh et al., 2007; Cui and Li, 2011).
322 This initial BR processing was followed by three steps: reclassification and vectorization using
323 tools from the IDRISI Selva system and smoothing, performed using ArcGIS software
324 (Boussetta et al., 2022a).

325 **3.6.Sensitivity and accuracy assessment**

326 **3.6.1. Qualitative assessment**

327 The qualitative evaluation of our methods was based on the visual adoption of classification
328 maps. This assessment allowed us to gain an in-depth understanding of the process. It includes
329 both the why and the how and allows us to delve deeper into topics of interest and explore
330 subtleties.

331 **3.6.2. Quantitative assessment**

332 **3.6.2.1. Confusion matrices and metrics**

333 A confusion matrix was calculated to assess classification quality and detect confusion
334 between well- and poorly-classified pixels. The main indices calculated from the generated

335 matrix are the kappa index developed by Cohen (Cohen, 1960), which provides global measures
336 of quality, and the OA index, which reflects classification performance. A visual assessment of
337 the classification was combined with this numerical calculation to identify the sources of error.
338 The accuracy percentage ranges from 0 to 1, with values close to 1 corresponding to very good
339 OA. An index greater than 0.6 is considered good and an index greater than 0.8 is considered
340 very well.

341 **3.6.2.2. Comparison between extracted and reference shorelines**

342 A reference shoreline was used to accurately assess the different methods used here. All
343 detected shorelines were imported into ArcMap 10.4. The results of the (semi-)automatic
344 extraction were then compared with the results of the manual digitization of the shoreline used
345 as the reference. Manual digitization of the shoreline leverages the judgement and interpretation
346 of scientists to identify the land-sea boundary, compared to computer-based classification
347 methods (Matin and Hasan, 2021; Sreekesh et al., 2020).

348 The digitization of the shorelines was performed manually from the Sentinel-2 and Landsat-
349 5 images, as the separation of land surfaces and water bodies could be easily detected when
350 visually inspecting the images. After digitizing the shorelines for the years 1989, 2015 and
351 2023, respectively, these digitized shorelines are used as a reference for calculating the net
352 shoreline movement (NSM; equation 3) relative to the shoreline extracted from (semi-)
353 automatic classification techniques. The shoreline change rates along the coastal zone were then
354 calculated using the DSAS version 5.0 extension developed by the USGS.

$$355 \quad \quad \quad NSM = time_{oldest} - time_{recent} \text{ (Eq. 3)}$$

356 In addition, the shoreline change rate expressed by the end point rate (EPR) was calculated
357 using the extracted shorelines from each method and compared with the EPR obtained using
358 the digitized shorelines (reference shorelines). This could include assessing the chosen
359 method's impact on the final erosion risk assessment.

360 **3.7. Estimation of erosion rate (shoreline change rate)**

361 The extracted shorelines are stored in a personal geodatabase in vector form. First, the buffer
362 method was used to establish a baseline roughly parallel to the shoreline at an offshore distance
363 of 200 m from the source. This shoreline was then used to draw 689 perpendicular transects

364 with a spacing of 30 m. The distance between two shorelines on a transect represents the change
365 in the shoreline between their corresponding points of intersection.

366 In order to determine long-term shoreline change statistics over a 34-year period (1989–
367 2023), the EPR method was used with the Digital Shoreline Analysis System (DSAS) in
368 ArcGIS10.4.1 software. The EPR method (equation 1) is calculated by dividing the distance of
369 shoreline movement by the time elapsed between the oldest and the most recent shoreline
370 (Himmelstoss et al., 2018).

$$371 \quad EPR = NSM/T(\text{Eq. 1})$$

372 The erosion rate cannot be estimated without taking into account the total sources of error
373 ($E\alpha$), namely the error associated with remote sensing data processing (RMSe), the error of the
374 automatic shoreline extraction from Landsat and Sentinel data based on the method used (MEe)
375 and the uncertainty of the EPR calculations (EPRunc), according to the following equation 2:

$$376 \quad E\alpha = \sqrt{RMSe^2 + MEe^2 + EPRunc^2} \quad (\text{Eq.2})$$

377 **4. Results**

378 Multisensor analyses using high spatial resolution optical images were used to compare
379 different methods (BR, ML and DL techniques) for (semi-)automatic shoreline extraction and
380 erosion risk assessment. The results were evaluated in terms of operator experience (qualitative
381 and visual assessment) and performance and suitability through statistical analysis (quantitative
382 assessment).

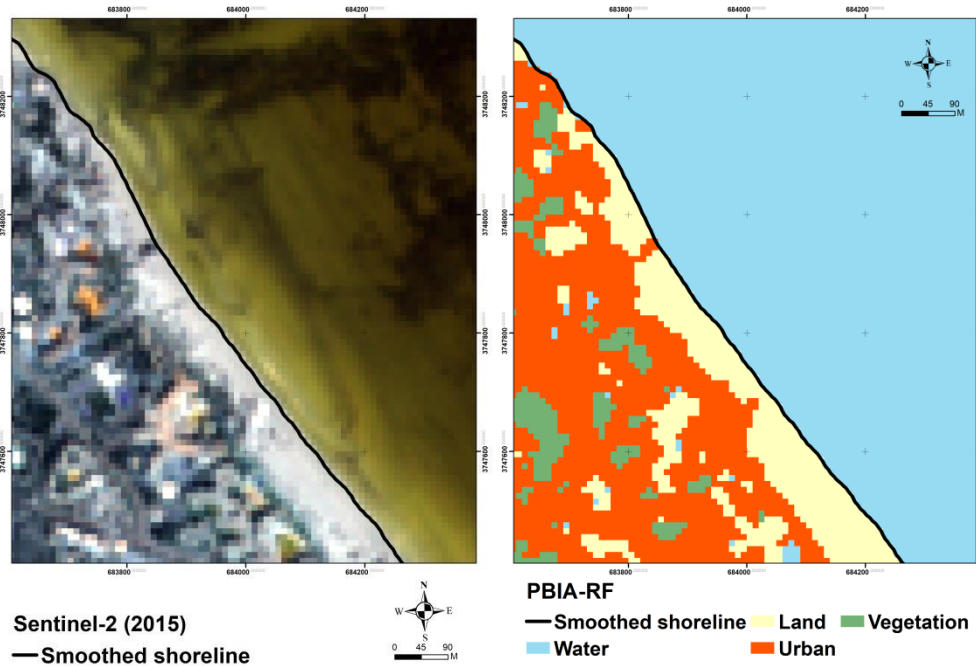
383 **4.1. Shoreline detection using machine learning algorithms**

384 Here, we present the results of the accuracy evaluation of all the methods used (PBIA-RF,
385 OBIA-RF, CNN-OBIA and BR), together with the classification outputs for each method. The
386 parameter fitting was done empirically.

387 **4.1.1. Random Forest classification using PBIA (PBIA-RF)**

388 Five classes were differentiated using the PBIA-RF approach for the Sentinel-2 composite
389 images: water (1), land (2), urban (3) and vegetation (4; Figure 4), and four classes were
390 identified on the Landsat-5 image (Figure 5): water (1), land (2), vegetation (3) and other (4).

391 The classification accuracy was evaluated using the confusion matrix to assess the quality
392 of the predictions (Šiljeg et al., 2022). The calculated confusion matrix includes commission
393 errors, i.e., pixels included in other thematic classes after classification, and omission errors,
394 i.e., thematic pixels lost after classification. The kappa index was equal to 0.87, meaning 87%
395 of the ground-truth variables were correctly classified. The ground-truth classes correspond to
396 the classes defined in the matrix column, and the classes of the classification result correspond
397 to the rows of the matrix.

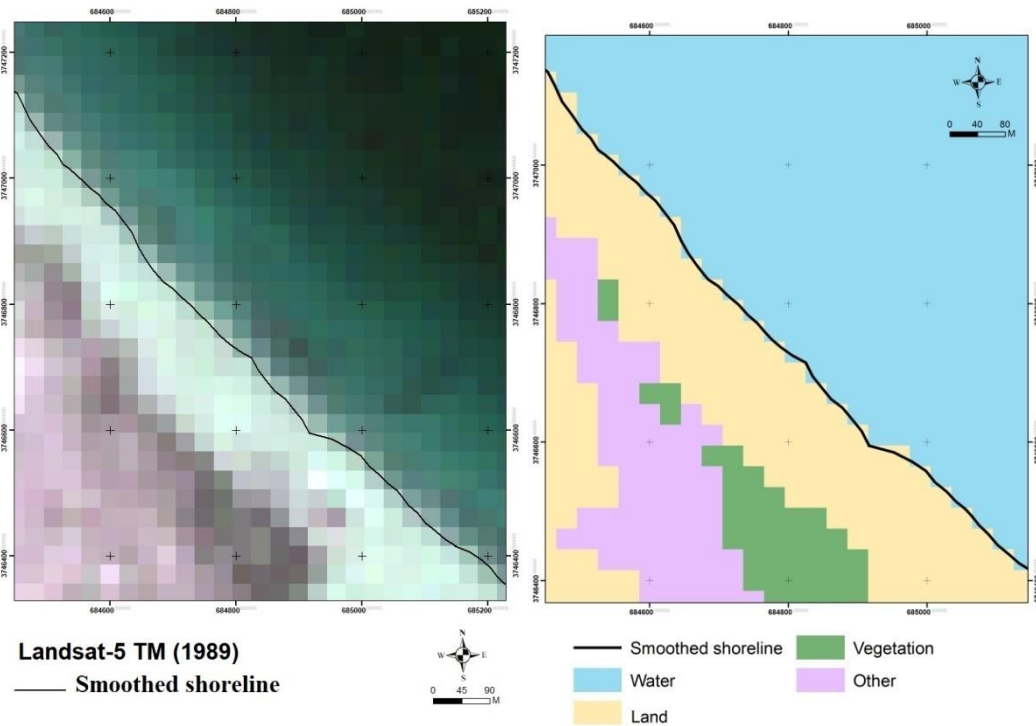


398

399

400

Fig. 4. PBIA classification maps using the RF algorithm Sentinel-2 image 08/12/2015



401

402 **Fig. 5. PBI A classification maps using the RF algorithm Landsat-5 image 08/21/1989**

403

404 **4.1.2. Object Based Image Analysis using RF and CNN**

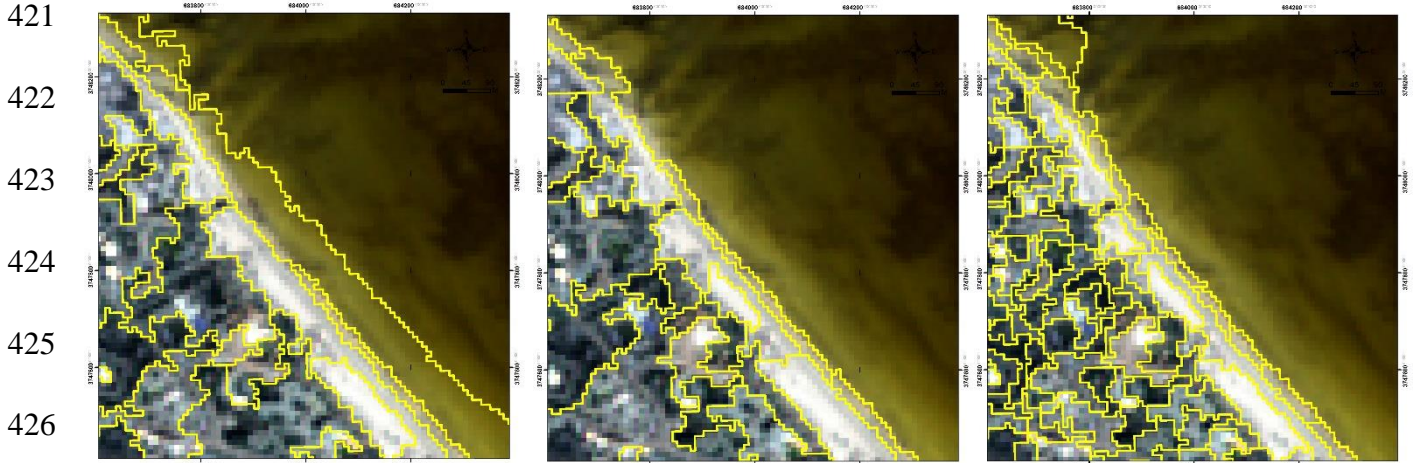
405 **4.1.2.1. MSS segmentation**

406 Several segmentation tests were carried out, and the different parameters generated entirely
 407 different results. Based on visual inspection and the most suitable OA, the parameters of the
 408 MSS segmentation algorithms applied to Sentinel and Landsat images were optimized and set.
 409 Table 6 provides an overview of the results of the various parameter values and tests performed
 410 on Sentinel 2023 images.

411 The variation of the segmentation parameters of the MSS algorithm is directly correlated
 412 with the type of object detected by visual observation. The smaller the value of the sr and mrs
 413 parameters, the greater the number of segments (objects) generated. On the other hand, the
 414 larger the value of the parameter rr, the greater the loss of information, resulting in blurred
 415 objects of interest. This situation was confusing due to the large amount of data. Therefore, the
 416 parameter values sr, rr and mrs of 10, 0.05 and 20, respectively, were determined to be the best
 417 configuration parameters for the Sentinel-2 image (Table 6). These parameters of the MSS

418 algorithm gave the best OA of 95%. For the Landsat-5 image, the parameters 10, 0.01 and 5
 419 showed the best OA of 92.7%.

420 **Table 2. Different MSS segmentation parameter values and test results for Sentinel-2023 images**



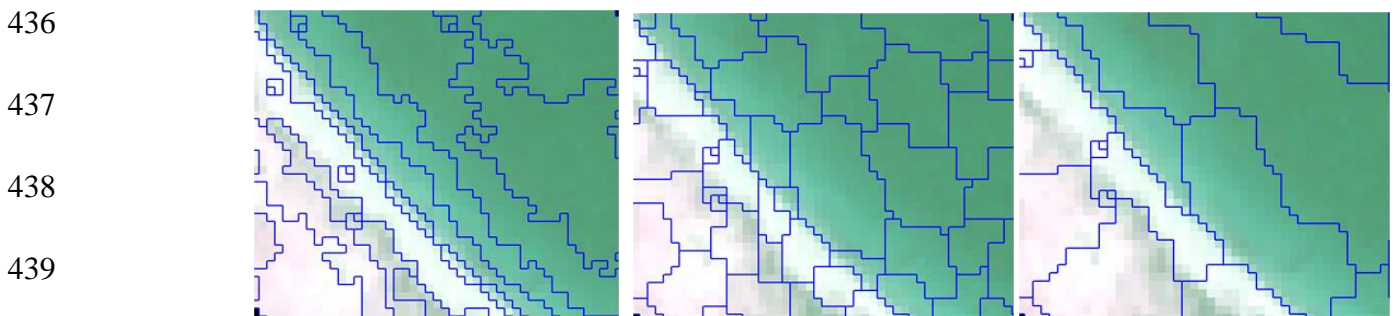
Parameters	Sr=30,rr=0.07, mrs=20	Sr=10, rr=0.1, mrs=50	Sr=10, rr=0.05, mrs=20
RF-OA (%)	75	82	95

427 **4.1.2.2. MRS segmentation**

428 The configuration tests (Table 7) applied to the multi-resolution segmentation (MRS)
 429 algorithm showed that the larger Sc, the larger the objects; the smaller Sp, the more objects are
 430 generated; and the larger Cp, the more objects are generated.

431 Therefore, values of 20, 0.1 and 0.5 were selected for Sc, Sp and Cp, respectively, for the
 432 Sentinel images. These configuration parameters were the best in terms of accuracy, achieving
 433 an OA of 96.3%. For the Landsat image, values of 0.9, 0 and 1 were selected for Sc, Sp and Cp,
 434 respectively, resulting in an OA of 94.6%.

435 **Table 3. Results of MRS parameter setting on Landsat-5 images**



Parameters	Sc=0.9, Sp=0, Cp=1	Sc=0.9, Sp=0.1, Cp=0.1	Sc=2, Sp=0.1, Cp=0.1
RF-OA (%)	94.6	87.3	79.2

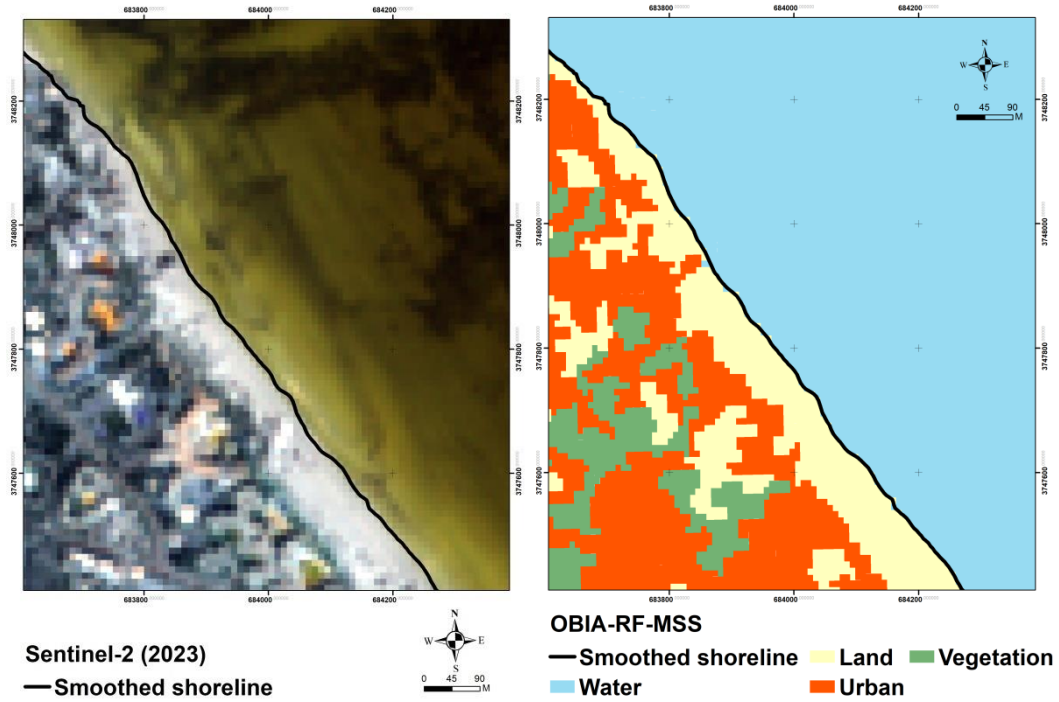
440 **4.1.2.3. Classification**

441 Similar to PBIA, four classes were identified for the Sentinel-2 images: water (1), land (2),
442 urban (3) and vegetation (4; Figure 6), and for Landsat-5 images, four classes were identified:
443 water (1), land (2), vegetation (3) and other (4; Figure 8). The use of different ML and DL
444 algorithms (RF and CNN) with different types of segmentation (MSS and MRS) made it
445 possible to determine the most suitable method for the satellite images used. Pronounced
446 differences between the different classes could be observed on the classification maps.

447 Zone (X) of the Sentinel-2 (2023) image is used as a test zone to estimate the limitations and
448 accuracy of the method (Figure 9). The RF algorithm represented this area (X) as an urban area,
449 while it was considered dry sand by the CNN algorithm. Verification in the field and against a
450 very high spatial resolution satellite image led to the visual observation that it was a building
451 well described by the RF algorithm. The maps clearly showed several errors, including the
452 misclassification of vegetation cover and urbanization. The CNN algorithm represented a large
453 amount of vegetation cover (class 3) interspersed with small areas of water (class 1). The RF
454 algorithm represented it as mainly dominated by an urban area (class 3) interspersed with
455 vegetation cover, even for the land class (class 2), which was represented inconsistently and
456 heterogeneously by the CNN, while it was represented evenly and homogeneously by the RF.

457 The same findings were shown in the Landsat image (Figure 8), where several errors were
458 seen. In particular, the incorrect classification of land (class 2) into other classes (class 4) and
459 the amount of vegetation (class 3) were almost absent from CNN.

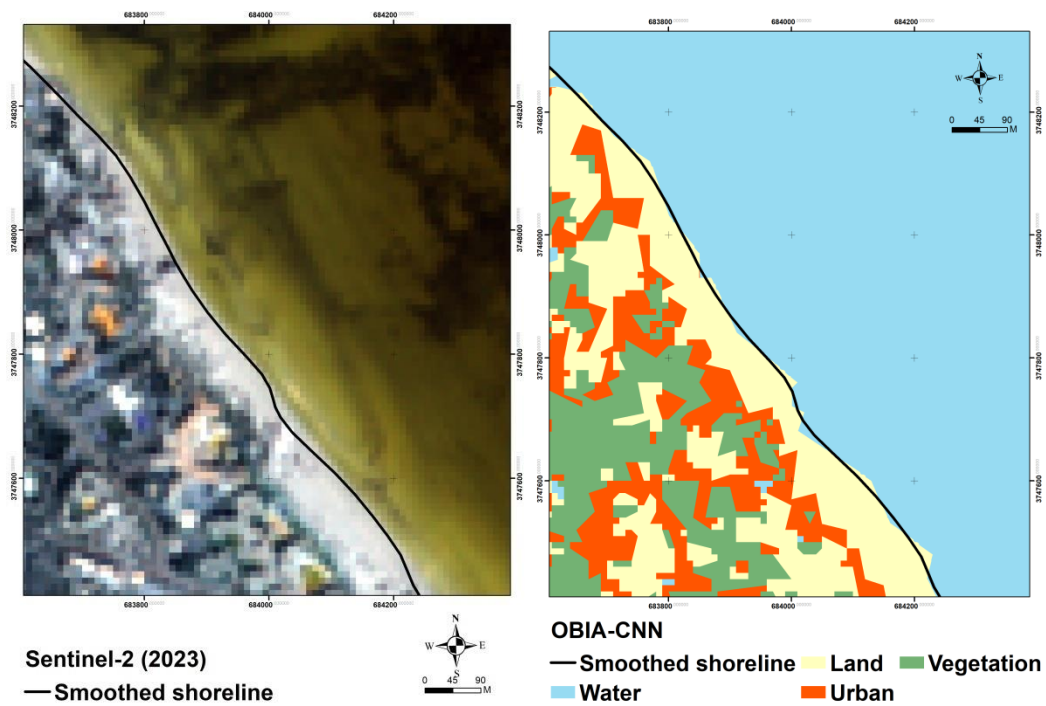
460 As a result, the RF-OBIA-MSS algorithm better reflects the reality on the ground. It seems
461 to have fewer ambiguities in the classifications and fewer errors for the wet sand class, which
462 is a fundamental class and thus considered an indicator of shoreline detection for sandy beaches.



463

464 Fig. 6. OBIA-RF-MSS classification maps applied to Sentinel-2 (2023)

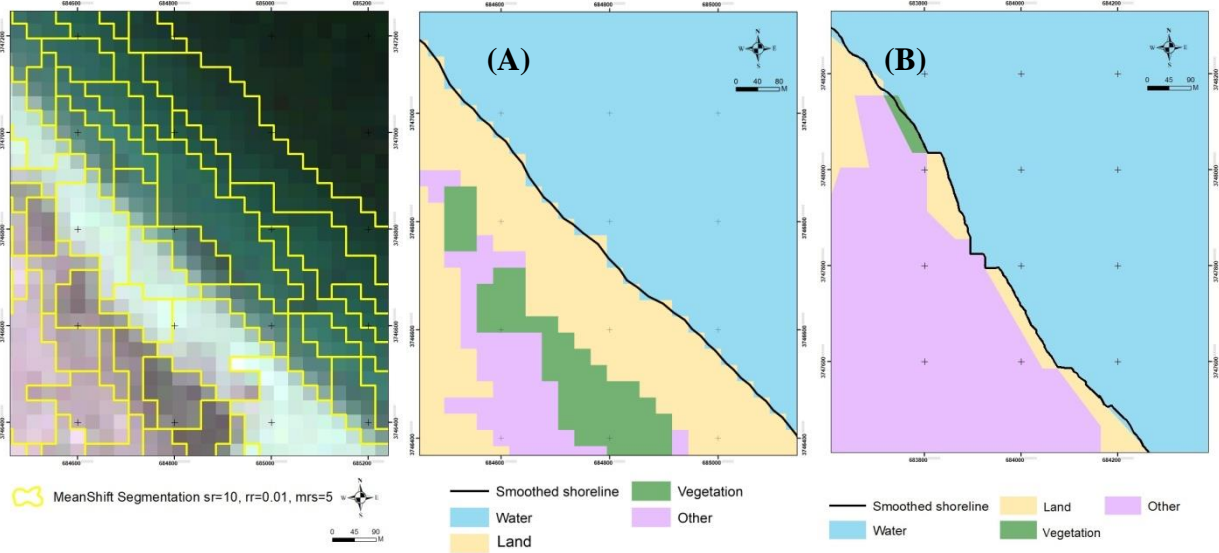
465



466

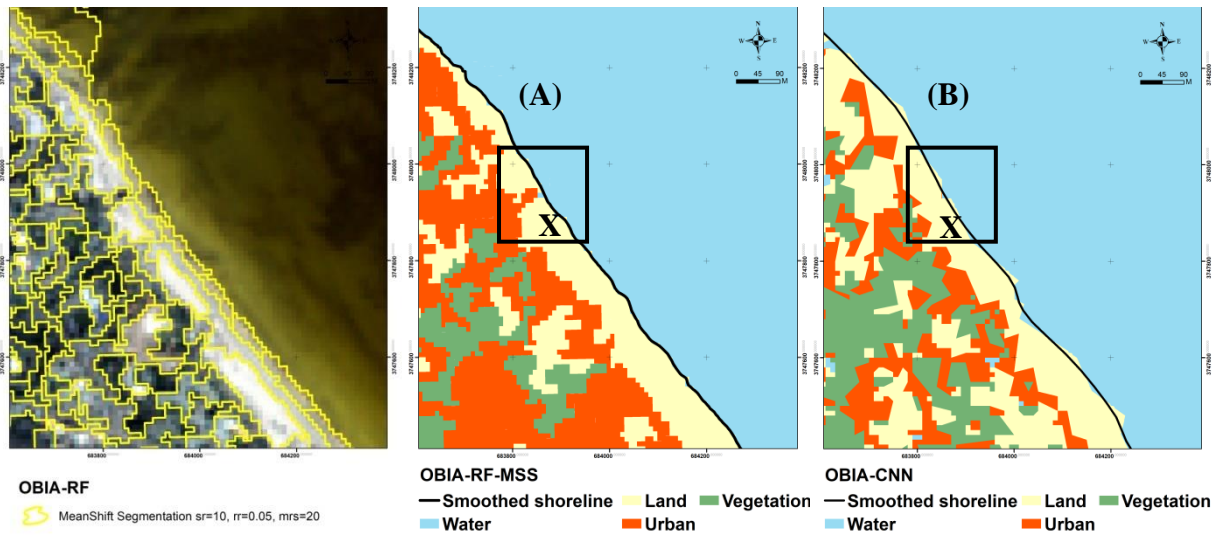
467 Fig. 7. CNN-OBIA classification maps applied to Sentinel-2 (2023)

468



469

Fig. 8. Comparison of OBIA classification results applied to Landsat 1989 images using RF (A) and CNN (B) algorithms.



470

471

Fig. 9. Comparison of OBIA classification results applied to the Sentinel-2023 image using the RF (A) and CNN (B) algorithms.

472 4.1.3. Qualitative assessment

473 The classifications showed a satisfactory visual representation of the land cover. However,
 474 when comparing the RF-ML algorithm, the PBIA and OBIA approaches resulted in slightly
 475 different profiles. There were clear differences between the approaches to the representation of
 476 the vegetation class and the urban class. Despite these slight differences in representation
 477 between the different image analysis approaches, the water class was well defined overall.

478 The land class was also well represented. In contrast, differences in the representation of the
 479 vegetation class between the approaches were particularly striking. While the PBIA-RF
 480 approach accurately represented the land class, the OBIA-RF approach produced the most

481 accurate representation of this same class along the shoreline. Since the boundary between land
 482 and water is the reference shoreline for shoreline detection, the OBIA-RF approach based on
 483 the MSS algorithm provided the best results.

484 **4.1.4. Quantitative assessment**

485 **4.1.4.1. Accuracy of the classification model**

486 The integrated approach based on a CNN and OBIA-DL model revealed the lowest kappa
 487 and global accuracy indices, with values below 0.8 and the lowest OA of 67%. This result is
 488 due to the high level of confusion between the different classes detected.

489 Since the kappa coefficient was above 0.8 for the classification approaches used (PBIA-RF
 490 and OBIA-RF; Table 8), the confusion matrix values have a high probability of validity. The
 491 PBIA and OBIA approaches both performed satisfactorily, with an OA above 85%. More
 492 specifically, OBIA-RF-MSS had the highest kappa index values of the other classification
 493 methods monitored. OBIA-RF achieved the highest OA of around 95%.

494 **Table 8. Accuracy of different classification methods, kappa index and overall accuracy**

	PBIA-RF			OBIA-RF-MSS			OBIA-RF-MRS			CNN-OBIA		
Image	1989	2015	2023	1989	2015	2023	1989	2015	2023	1989	2015	2023
Indice kappa	0.88	0.87	0.90	0.93	0.92	0.93	0.71	0.63	0.74	0.67	0.76	0.79
OA %	90%	89%	92%	92.7%	95%	95%	71%	69%	70%	67%	77%	78%

495

496 **4.1.4.2. Accuracy of shoreline extraction**

497 The comparison between the extracted shoreline and a digitized shoreline (reference) is
 498 presented in Table 9, which shows the NSM, which are the minimum, maximum and average
 499 (mean) distance calculations, namely the i) min, ii) max and iii) mean values. The mean distance
 500 is used as an ‘indicator ‘of the accuracy of the shoreline extraction method.

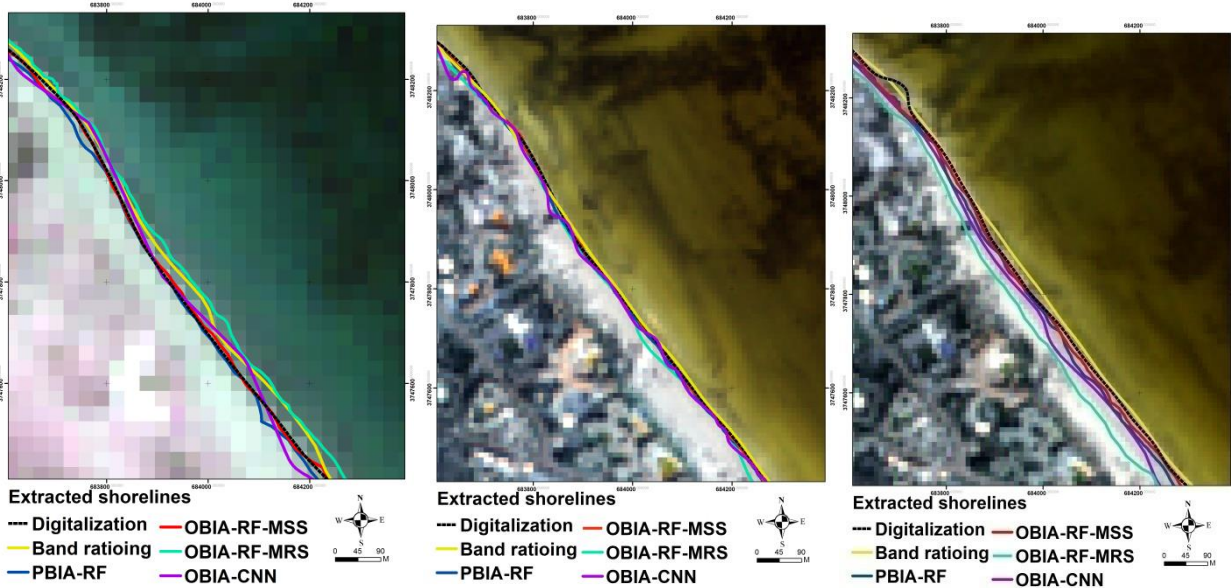
501 Using the PBIA approach, the RF algorithm resulted in a shoreline extraction with an
 502 average distance of 15.25 m for the Landsat image and 10 m for the Sentinel images.

503 Overall, the OBIA-RF-MSS approach generated shorelines with greater accuracy. It
 504 provided the most accurate shoreline extraction with mean distances of 7.8 m, 5.5 m and 6.09

505 m for Landsat-5 and Sentinel-2 images (2015, 2023), respectively. The BR approach produced
 506 shorelines with mean distances of 11.28 m, 7.7 m and 7.6 m for Landsat-5 (1989) and Sentinel-
 507 2 (2015, 2023) images, respectively.

508 The most significant distance values are observed with the combined CNN-OBIA approach,
 509 which has lower accuracy with mean distance values of 18.48 m, 8.14 m and 16 m for satellite
 510 images from 1989, 2015 and 2023, respectively. These distances prove that this (semi-
 511)automatic extraction method is completely ineffective in detecting the land/water boundary on
 512 Sentinel-2 and Landsat-5 TM images.

513 The final results of the methods used show that the OBIA-RF-MSS approach is the best for
 514 shoreline extraction. However, it should be noted that this small-scale detection is due to the
 515 high resolution of the Landsat and Sentinel images.



516
 517 **Fig. 10. Extracted shorelines from different methods (a) Landsat TM image 1989 (b) Sentinel-2 image 2015 (c) Sentinel-2**
 518 **image 2023**

519 **Table 9. Net shoreline movement (NSM) statistics based on DSAS calculations relative to the reference shoreline**

	Landsat-5 1989					Sentinel-2 2015					Sentinel-2 2023				
NSM	Ratio	PBIA -RF	OBIA -RF- MSS *	OBIA -RF- MRS	CNN- OBIA	Rati o	PBIA -RF	OBIA -RF- MSS	OBIA -RF- MRS **	CNN- OBIA	Ratio	PBIA- RF	OBIA- RF- MSS	OBIA -RF- MRS	CNN- OBIA
MIN	0.1	0.8	0.01	0.8	0.01	0.01	0.02	0.03	0.03	0.02	0.02	0.02	0.03	0.05	0.11
MAX	59	50.02	53	54	99.78	40	37.42	35.33	40	45	39	38.2	38.11	40	52
MEAN	11.28	15.25	7.8	10.11	18.48	7.7	10	5.5	8.5	8.14	7.6	10	6.09	8.01	16

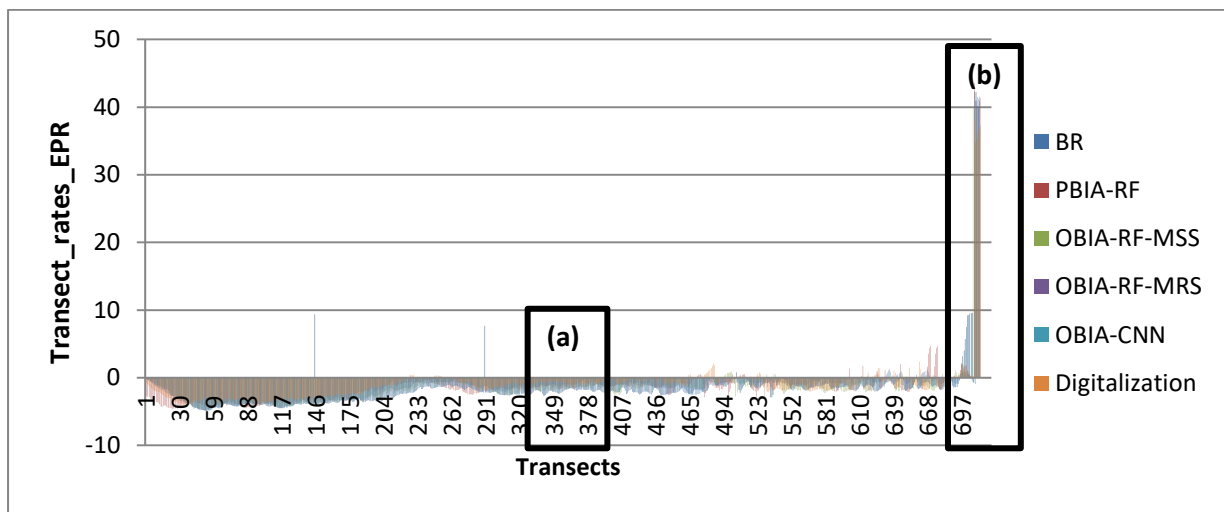
520 *Mean Shift Segmentation **Multi-resolution Segmentation

521 The various methods of BR, PBIA-RF, OBIA-RF-MSS, OBIA-RF-MRS, CNN-OBIA and
 522 digitization show the EPR, or the average rates of shoreline change, for the east coast of Jerba
 523 between 1989 and 2023 (Table 10). The graph (Figure 11) presents an overview of the different
 524 evolution rate values (EPR) results for each method used. Form Table 10 and Figure 11, we can
 525 note that OBIA-MSS with the RF algorithm obtained values closest to those of the EPR of the
 526 digitization method, which is our reference EPR used to evaluate the results. Therefore, OBIA-
 527 RF-MSS is more relevant than the other methods.

528 Table 10. Comparison of different End Point Rate of the shoreline extracted from the used methods

EPR (m/year)	BR	PBIA-RF	OBIA-RF-MSS*	OBIA-RF-MRS	CNN-OBIA	DIGITIZATION
MIN	-4.9	-4.62	-4.1	-4.82	-4.8	-4.06
MAX	+41.5	+43.2	+39.97	+43.5	+42.32	+39.32
MEAN	-1.38	-1.36	-0.8	-1.39	-1.8	-0.77

529 *Mean Shift Segmentation



530
 531 Fig. 11. The rate of change of sandy beaches (a) and sandy spit (b) on the east coast of Jerba Island between 1989 and
 532 2023

533 **4.2. Shoreline change rate: Erosion risk assessment**

534 Analysis of shoreline evolution over the 727 transects and after applying an overall margin
 535 of error for the methods adopted of about ± 2.38 m for sandy beaches and ± 3.16 m for the sandy
 536 spit revealed a clear trend of erosion throughout the entire study area, with the exception of the
 537 Rass Rmel sand spit, which experienced a sharp increase with a maximum evolution of about
 538 $+39.97$ m/year. The results of this study are shown in Figure 12. Positive (+) and negative (-)

539 EPR values indicate accretion and erosion, respectively, in a particular region on the island's
540 east coast.

541 **5. Discussion**

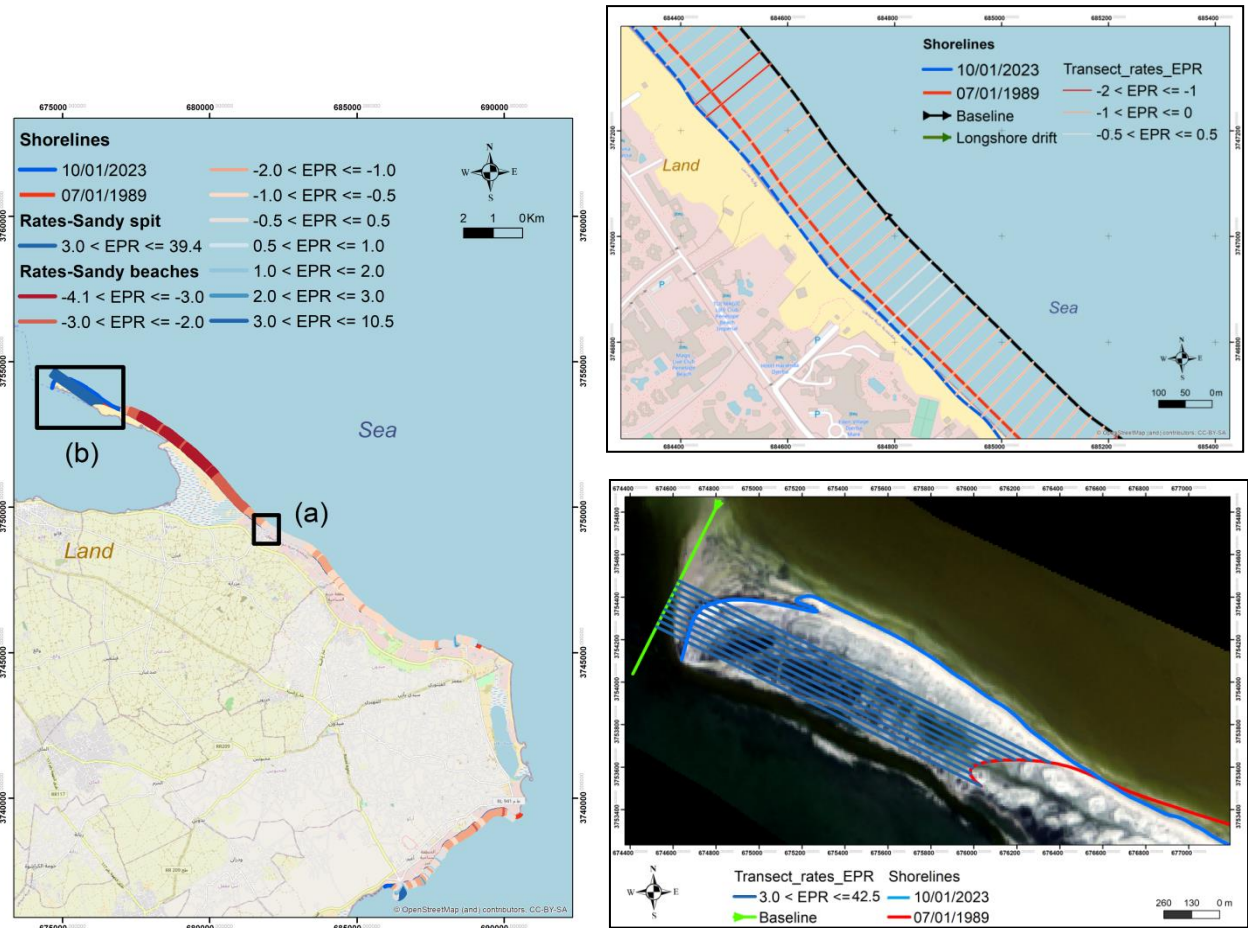


Fig. 12. The rate of change of shorelines extracted from OBIA-RF-MSS recorded with the EPR method in front of the Radisson Hotel on the east coast of Jerba (a) and for the sand spit at Rass Rmel (b)

542 Optical imagery has been found to be more feasible for capturing shoreline positions at
543 different spatial and temporal scales (Almonacid-Caballer et al., 2016; Hegde and Akshaya,
544 2015). The methodological approaches developed for shoreline extraction were based on high-
545 resolution open-source optical imagery, namely Landsat-5 TM (30 m) and Sentinel-2 (10
546 m). The aim was to analyze and assess the land cover and to extract and distinguish the different
547 classes.

548 Approaches based on band ratios are widely used in shoreline monitoring and extraction
549 studies (Tsiakos and Chalkias, 2023b). In the previous technology, green and NIR bands were
550 used to define threshold values separating water pixels from land pixels (Cham et al., 2020). In

551 the present work, the ratio method based on visible (band 2) and MIR-NIR (bands 5 and 8)
552 shows good results for shoreline detection. These results are similar to those obtained by Roy
553 et *al.*, (2018), which showed that the Band ratioing method yields significant results for the
554 delineation of the shoreline over a 25-year period.

555 In contrast, this method allows deficient detection of sandy shorelines on satellite imagery.
556 This simple and fast method does not require user intervention (Boussetta et *al.*, 2022a).
557 However, this approach has certain limitations and can lead to questionable results when
558 monitoring applications in a complex environment such as a sandy spit. BR is still a primary
559 method. With this in mind, the main objective of this work was to develop and compare methods
560 to define an effective and validated approach for more systematic and detailed monitoring of
561 coastal dynamics, taking advantage of the latest innovations in remote sensing, DL and shallow
562 ML.

563 **5.1.Images analysis for shoreline extraction**

564 A comparison of the three approaches to satellite image classification was carried out to
565 determine the best one. We tested two classification methods, OBIA and PBIA, to detect coastal
566 land cover types. The OBIA approach provided a more convergent representation of land cover.
567 This finding is consistent with the results of studies by Mollick et *al.*, (2023), who argued that
568 the accuracy of OBIA was 27% higher than that of PBIA. Furthermore, comparing the CNN-
569 OBIA approach with the ML algorithm-based OBIA approach indicates that the OBIA-RF
570 approach performs better than the CNN-OBIA approach and has higher accuracy. These results
571 differ from those obtained by the studies of Zaabar et *al.*, (2022), who showed that CNN
572 combined with object-based image analysis (OBIA), tested on Sentinel-2 spectral data, is the
573 best-performing method for detecting different land-use classes with an OA higher than that of
574 the OBIA-RF method by 0.9%.

575 If we compare the results of the method proposed in this article with those of Bengoufa et
576 *al.*, (2021a), who demonstrated that the OBIA-RF method using the MRS algorithm, applied to
577 very high-resolution images, performs best for shoreline extraction, this could be explained by
578 the very high resolution of the Pleiade images (2m) and the medium resolution of the Landsat-
579 5 TM and Sentinel-2 images (30 m and 10 m, respectively). Therefore, we can confirm that
580 such a result depends on the data used, the classes targeted, the choice of the reference shoreline,
581 and, above all, the user's experience.

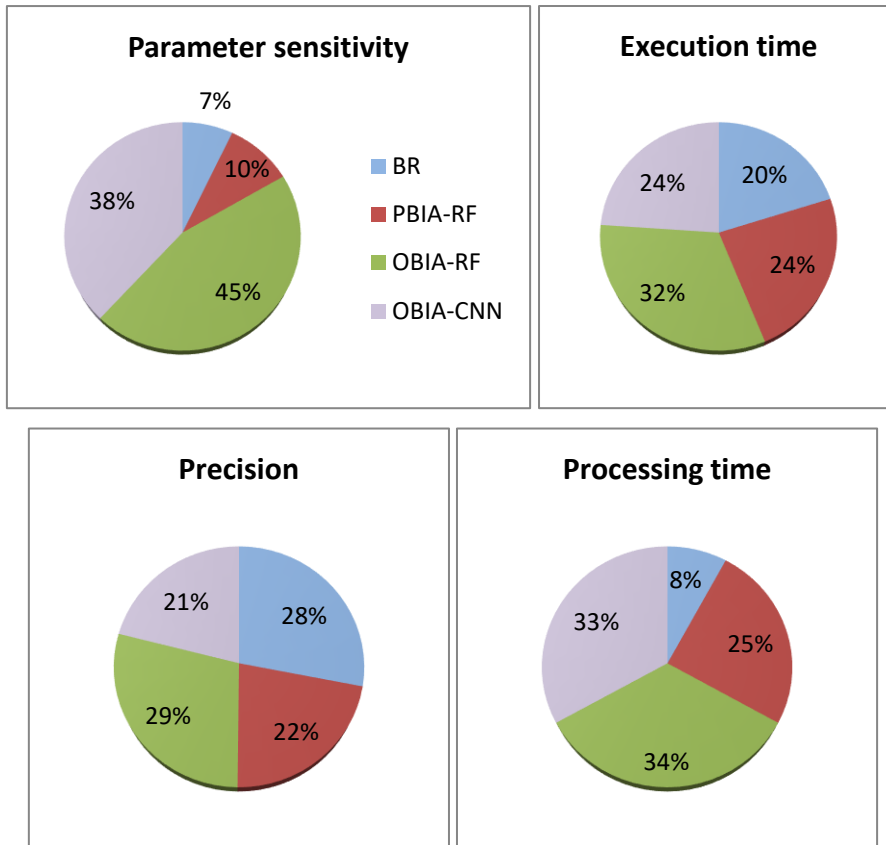
582 In OBIA, objects are extracted through segmentation processes that take into account the
583 spectral, textural and contextual information of similar pixels (Blaschke, 2010). Moreover,
584 despite the CNN algorithm's ability to improve classification by selecting input features and
585 OBIA, it is essential to consider the influence of different parameters on the segmentation
586 processes. To be sure, the OBIA method should be enhanced by optimizing the segmentation
587 parameters. Adjusting the parameters of the segmentation algorithms makes OBIA a subjective
588 task (Belgiu et al., 2014; Belgiu and Drăguț, 2014), which was confirmed in this work after a
589 good 10 adjustment attempts. However, cross-validation of Landsat and Sentinel-2 images
590 removed this subjectivity. According to the results obtained, OBIA from MSS improved the
591 classification and finally allowed a better shoreline extraction with a maximum OA value of
592 0.95 applied to the Sentinel-2 image.

593 It is important to note that the shorelines produced by all algorithms using the PBIA or OBIA
594 approaches showed satisfactory results overall, with some interpretation errors in certain
595 irregularly shaped coastal areas, especially for OBIA combined with CNN with a minimum OA
596 of 0.77. Contrary to the studies carried out by Bengoufa et al., (2021b) which showed that the
597 combination of the deep learning model and OBIA are very effective for the extraction of the
598 rocky shoreline using very high-resolution multispectral images. Also the results obtained with
599 the CNN algorithm contradict the conclusions of the work of Gomez-de la Pena et al., (2023),
600 which presented an in-depth research and description of deep learning model configurations
601 that proved effective for shoreline prediction.

602 **5.2. A method for automatic shoreline extraction: user-friendliness and accuracy**

603 The assessment of the performance of the methods applied to Landsat-5 and Sentinel-2
604 imagery reveals that shallow learning algorithms outperform DL techniques. OBIA-RF still has
605 the highest percentages for parameter sensitivity, execution time, processing time and accuracy.
606 In contrast, the BR method had the lowest percentages and a reasonable value for accuracy
607 (28%), compared to the other approaches. The latter gives good results and, above all, saves a
608 great deal of time. However, OBIA-RF brings added value in metric accuracy and extraction
609 capacity. These results are similar to those obtained by Sreekesh et al., (2020) who claimed that
610 this method proved robust, with 95-99% consistency in areas presenting complex coastal
611 geomorphological features (in our case the sandy spit), as well as when using satellite images
612 of variable spatial resolution (medium- and high-resolution).

613



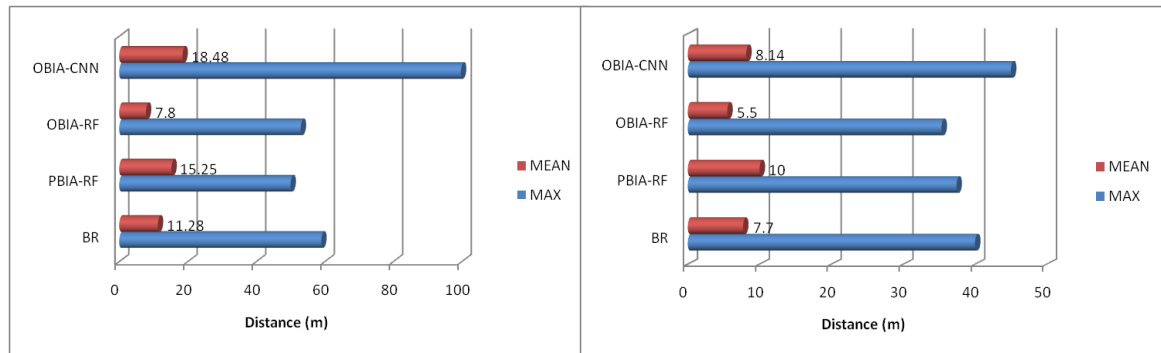
614

615

616

Fig. 13. Qualitative assessment of the performance of shoreline extraction methods

617 The shoreline extraction methods were continued by calculating the distances between the
618 shorelines. The average value was used as a baseline for comparison. This evaluation also
619 quantitatively shows the quality of each classification compared to another based on shorelines
620 extracted along the line of each land use feature. In Figures 14 (a) and 14 (b) below, a small
621 distance from the mean corresponds to a good classification, and vice versa. There is a clear
622 difference between OBIA and PBIA and between the ML (RF) and DL (CNN) algorithms for
623 land-water boundary classification. This difference proves that the OBIA-RF approach
624 classifies our thematic variables better than the other approaches, especially at the wet sand
625 class level.



626 **Fig. 14. Average and maximum distance between the extracted shoreline and the one digitized on the Landsat-1989 (a)**
 627 **and Sentinel 2015 (b) images**

628 The sandy beaches have been subject to severe shoreline recession over the last three decades
 629 (1989–2023), except for the Rass Rmel spit, which has experienced significant sediment
 630 accretion (+39.97 m/year between 1989–2023). This apparent trend towards erosion and
 631 accretion was well illustrated by the work of Boussetta et al., (2022a), where the DSAS results
 632 are conform to the real-world situation. The results of the retrospective analysis of the shoreline
 633 change, leads us to raise the alarm about the situation of the sandy beaches on the island of
 634 Jerba, given the exacerbation of the phenomenon of erosion. This phenomenon is changing the
 635 hydrological and the sediment transport balances which is causing landslides. This can have
 636 serious consequences for biodiversity, socio-economical security and for the humane safety
 637 living in the immediate vicinity of these environments. This situation is more complex for our
 638 study area, given that the island of Jerba is very frequented as it is an excellent tourist
 639 destination, where most of the socio-economic activities are located close to the shoreline. This
 640 requires immediate awareness by managers and the involved stakeholders, in order to draw up
 641 natural risk prevention plans, especially in the context of the acceleration of sea level rise due
 642 to climate warming and global environmental change. The latter are increasingly felt in island
 643 environments such as our study area, which makes it as naturally very vulnerable (Boussetta et
 644 al., 2022b).

645 Although the latter method has yielded good results, no study has provided statistics on the
 646 evolution rates of the different approaches. Therefore, this study is the first to provide, compare
 647 and, most importantly, validate the EPR, or the shoreline evolution rates, for the Jerba Island
 648 over a 34-year period. The outputs of this study could be a good tools for coastal management
 649 and risk mitigation.

650 **6. Conclusions**

651 The analysis of satellite images to determine an appropriate land cover detection method is
652 vital for extracting relevant information to monitor the evolution of the shoreline. Before
653 choosing the method of detecting and extracting the reference shoreline, it is important to
654 eliminate distortions due to the irregular shape of the land. Therefore, the radiometric and
655 geometric corrections were carried out thoroughly. In order to select the detection methods for
656 the different classes according to research needs, field visits and visual interpretations were
657 considered preparatory steps in this work. They allowed us to identify the objects and structures
658 in the field on the east coast of Jerba.

659 The comparison of the different classification techniques (BR, PBIA-RF, OBIA-RF and
660 CNN-OBIA) enabled us to understand their effectiveness and efficiency by comparing their
661 OA and kappa index statistics. The qualitative and quantitative evaluation and the validation
662 process using the digitization method produced the best results. The OBIA-RF-MSS
663 classification proved the most suitable, and the evaluation revealed that the real situation on the
664 field is clearly the same.

665 Whether the method is basic or evolved, developing new methodologies in line with the
666 available data and research objectives is critical. With this in mind, this study focused on
667 establishing an operational, perfectly reproducible and less subjective shoreline detection
668 method.

669 Using multitemporal, multisensory satellite imagery, we were able to determine a shoreline
670 of 22.8 km, or over 15% of the island's shoreline, with very high accuracy using the
671 methodology created in this study. Statistical analysis of the EPR method using the DSAS tool
672 allowed us to distinguish two types of situations. Some sites are experiencing general erosion
673 (sandy beaches), and others are experiencing progradation (the Rass Rmel sand spit). These
674 coastal forms are characterized by one or more eroding sectors: the upstream drifting part (the
675 tourist area), feeding the downstream drifting part (the Rass Rmel spit) and a prograding part
676 with occasional hook construction. In many places, erosion has become almost irreversible, and
677 restoring stability will not be easy.

678 This work demonstrates the potential of Landsat-5 TM and Sentinel-2 imagery for obtaining
679 shorelines from classifications on the sandy coasts of Jerba Island, where the indicator is the
680 land-water boundary. This research is considered the first in its field to be applied to the Jerba
681 study area, given its importance on a national scale. The final results should prove useful to
682 coastal managers of island environments, which will increase awareness of the environmental

683 problems on Jerba's east coast and facilitate the implementation of plans to combat coastal
684 erosion. Thanks to increased social awareness and data dissemination, this action will be much
685 easier.

686 **Credit authorship contribution statement**

687 **Amina BOUSSETTA**: Conceptualization, Acquisition of data, Methodology, Software,
688 Writing - Original Draft, Writing, Writing - Review & Editing. **Simona NICULESCU**:
689 Resources, Visualization, Funding acquisition, Writing - Review & Editing. **Soumia**
690 **BENGOUFA**: Validation, Writing - Original Draft, Writing - Review & Editing. **Mohamed**
691 **Faouzi ZAGRARNI**: Supervision, Project administration, Writing - Review & Editing.

692 **Acknowledgment**

693 The authors are very grateful to the CNES/ TOSCA project ID 7618.

694 **Funding**

695 This work was supported by the University of Gabès as part of a work-study award.

696 **References**

- 697 Abdelhady, H.U., Troy, C.D., Habib, A., Manish, R., 2022. A Simple, Fully Automated
698 Shoreline Detection Algorithm for High-Resolution Multi-Spectral Imagery. *Remote*
699 *Sens.* 14, 557. <https://doi.org/10.3390/rs14030557>
- 700 Aedla, R., Dwarakish, G.S., Reddy, D.V., 2015. Automatic Shoreline Detection and Change
701 Detection Analysis of Netravati-GurpurRivermouth Using Histogram Equalization and
702 Adaptive Thresholding Techniques. *Aquat. Procedia, INTERNATIONAL*
703 *CONFERENCE ON WATER RESOURCES, COASTAL AND OCEAN*
704 *ENGINEERING (ICWRCOE'15)* 4, 563–570.
705 <https://doi.org/10.1016/j.aqpro.2015.02.073>
- 706 Alesheikh, A.A., Ghorbanali, A., Nouri, N., 2007. Coastline change detection using remote
707 sensing. *Int. J. Environ. Sci. Technol.* 4, 61–66. <https://doi.org/10.1007/BF03325962>
- 708 Almonacid-Caballer, J., Sánchez-García, E., Pardo-Pascual, J.E., Balaguer-Beser, A.A.,
709 Palomar-Vázquez, J., 2016. Evaluation of annual mean shoreline position deduced from
710 Landsat imagery as a mid-term coastal evolution indicator. *Mar. Geol.* 372, 79–88.
711 <https://doi.org/10.1016/j.margeo.2015.12.015>
- 712 Belgiu, M., Drăguț, L., 2014. Comparing supervised and unsupervised multiresolution
713 segmentation approaches for extracting buildings from very high resolution imagery.
714 *ISPRS J. Photogramm. Remote Sens.* 96, 67–75.
715 <https://doi.org/10.1016/j.isprsjprs.2014.07.002>
- 716 Belgiu, M., Drăguț, L., Strobl, J., 2014. Quantitative evaluation of variations in rule-based
717 classifications of land cover in urban neighbourhoods using WorldView-2 imagery.
718 *ISPRS J. Photogramm. Remote Sens.* 87, 205–215.
719 <https://doi.org/10.1016/j.isprsjprs.2013.11.007>

- 720 Bengoufa, S., Niculescu, S., Mihoubi, M.K., Belkessa, R., Abbad, K., 2023. Automatic
721 Detection of Hydrodynamical and Biological Indicators of the Shoreline Using a
722 Convolutional Neural Network, in: Niculescu, S. (Ed.), *European Spatial Data for
723 Coastal and Marine Remote Sensing*. Springer International Publishing, Cham, pp. 191–
724 205. https://doi.org/10.1007/978-3-031-16213-8_11
- 725 Bengoufa, S., Niculescu, S., Mihoubi, M.K., Belkessa, R., Abbad, K., 2021. ROCKY
726 SHORELINE EXTRACTION USING A DEEP LEARNING MODEL AND OBJECT-
727 BASED IMAGE ANALYSIS. *Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci.*
728 XLIII-B3-2021, 23–29. <https://doi.org/10.5194/isprs-archives-XLIII-B3-2021-23-2021>
- 729 Bengoufa, Soumia, Niculescu, S., Mihoubi, M.K., Belkessa, R., Rami, A., Rabehi, W., Abbad,
730 K., 2021. Machine learning and shoreline monitoring using optical satellite images: case
731 study of the Mostaganem shoreline, Algeria. *J. Appl. Remote Sens.* 15.
732 <https://doi.org/10.1117/1.JRS.15.026509>
- 733 Benz, U.C., Hofmann, P., Willhauck, G., Lingenfelder, I., Heynen, M., 2004. Multi-resolution,
734 object-oriented fuzzy analysis of remote sensing data for GIS-ready information. *ISPRS
735 J. Photogramm. Remote Sens., Integration of Geodata and Imagery for Automated
736 Refinement and Update of Spatial Databases* 58, 239–258.
737 <https://doi.org/10.1016/j.isprsjprs.2003.10.002>
- 738 Boak, E.H., Turner, I.L., 2005. Shoreline Definition and Detection: A Review. *J. Coast. Res.*
739 214, 688–703. <https://doi.org/10.2112/03-0071.1>
- 740 Boussetta, A., Niculescu, S., Bengoufa, S., Mejri, H., Zagrarni, M.F., 2022b. Assessment of
741 Coastal Vulnerability to Erosion Risk Using Geospatial and Remote Sensing Methods
742 (Case of Jerba Island, Tunisia), in: Niculescu, S. (Ed.), *European Spatial Data for
743 Coastal and Marine Remote Sensing*. Springer International Publishing, Cham, pp. 113–
744 132. https://doi.org/10.1007/978-3-031-16213-8_7
- 745 Boussetta, A., Niculescu, S., Bengoufa, S., Zagrarni, M.F., 09/2022a. Spatio-temporal analysis
746 of shoreline changes and erosion risk assessment along Jerba island (Tunisia) based on
747 remote-sensing data and geospatial tools. *Reg. Stud. Mar. Sci.* 55, 102564.
748 <https://doi.org/10.1016/j.rsma.2022.102564>
- 749 Cham, D.D., Son, N.T., Minh, N.Q., Thanh, N.T., Dung, T.T., 2020. An Analysis of Shoreline
750 Changes Using Combined Multitemporal Remote Sensing and Digital Evaluation
751 Model. *Civ. Eng. J.* 6, 1–10. <https://doi.org/10.28991/cej-2020-03091448>
- 752 Cohen, J., 1960. A Coefficient of Agreement for Nominal Scales. *Educ. Psychol. Meas.* 20, 37–
753 46. <https://doi.org/10.1177/001316446002000104>
- 754 Cui, B.-L., Li, X.-Y., 2011. Coastline change of the Yellow River estuary and its response to
755 the sediment and runoff (1976–2005). *Geomorphology* 127, 32–40.
756 <https://doi.org/10.1016/j.geomorph.2010.12.001>
- 757 Dang, K.B., Dang, V.B., Ngo, V.L., Vu, K.C., Nguyen, H., Nguyen, D.A., Nguyen, T.D.L.,
758 Pham, T.P.N., Giang, T.L., Nguyen, H.D., Hieu Do, T., 2022. Application of deep
759 learning models to detect coastlines and shorelines. *J. Environ. Manage.* 320, 115732.
760 <https://doi.org/10.1016/j.jenvman.2022.115732>
- 761 Deliry, S.I., Avdan, Z.Y., Avdan, U., 2021. Extracting urban impervious surfaces from
762 Sentinel-2 and Landsat-8 satellite data for urban planning and environmental
763 management. *Environ. Sci. Pollut. Res.* 28, 6572–6586. [https://doi.org/10.1007/s11356-
764 020-11007-4](https://doi.org/10.1007/s11356-020-11007-4)
- 765 Demir, N., Oy, S., Erdem, F., Şeker, D.Z., Bayram, B., 2017. INTEGRATED SHORELINE
766 EXTRACTION APPROACH WITH USE OF RASAT MS AND SENTINEL-1A SAR
767 IMAGES. *ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci.* IV-2/W4, 445–449.
768 <https://doi.org/10.5194/isprs-annals-IV-2-W4-445-2017>

769 Erdem, F., Bayram, B., Bakirman, T., Bayrak, O.C., Akpınar, B., 2021. An ensemble deep
770 learning based shoreline segmentation approach (WaterNet) from Landsat 8 OLI
771 images. *Adv. Space Res.* 67, 964–974. <https://doi.org/10.1016/j.asr.2020.10.043>
772 Fukushima, K., 1988. Neocognitron: A hierarchical neural network capable of visual pattern
773 recognition. *Neural Netw.* 1, 119–130. [https://doi.org/10.1016/0893-6080\(88\)90014-7](https://doi.org/10.1016/0893-6080(88)90014-7)
774 Gomez-de la Pena, E., Coco, G., Whittaker, C., Montano, J., 2023. On the use of Convolutional
775 Deep Learning to predict shoreline change. *EGUsphere* 1–24.
776 <https://doi.org/10.5194/egusphere-2023-958>
777 Gonçalves, G., Andriolo, U., Gonçalves, L., Sobral, P., Bessa, F., 2020. Quantifying Marine
778 Macro Litter Abundance on a Sandy Beach Using Unmanned Aerial Systems and
779 Object-Oriented Machine Learning Methods. *Remote Sens.* 12, 2599.
780 <https://doi.org/10.3390/rs12162599>
781 Görmüş, T., Ayat, B., Aydoğan, B., Tătui, F., 2021. Basin scale spatiotemporal analysis of
782 shoreline change in the Black Sea. *Estuar. Coast. Shelf Sci.* 252, 107247.
783 <https://doi.org/10.1016/j.ecss.2021.107247>
784 Guariglia, A., Buonamassa, A., Losurdo, A., Saladino, R., Trivigno, M.L., Zaccagnino, A.,
785 Colangelo, A., 2006. A multisource approach for coastline mapping and identification
786 of shoreline changes 10.
787 Guo, S., Du, P., Xia, J., Tang, P., Wang, X., Meng, Y., Wang, H., 2021. Spatiotemporal changes
788 of glacier and seasonal snow fluctuations over the Namcha Barwa–Gyala Peri massif
789 using object-based classification from Landsat time series. *ISPRS J. Photogramm.*
790 *Remote Sens.* 177, 21–37. <https://doi.org/10.1016/j.isprsjprs.2021.04.018>
791 Hegde, A.V., Akshaya, B.J., 2015. Shoreline Transformation Study of Karnataka Coast:
792 Geospatial Approach. *Aquat. Procedia*, INTERNATIONAL CONFERENCE ON
793 WATER RESOURCES, COASTAL AND OCEAN ENGINEERING (ICWRCOE'15)
794 4, 151–156. <https://doi.org/10.1016/j.aqpro.2015.02.021>
795 Himmelstoss, E.A., Henderson, R.E., Kratzmann, M.G., Farris, A.S., 2018. Digital Shoreline
796 Analysis System (DSAS) version 5.0 user guide (USGS Numbered Series No. 2018–
797 1179), Digital Shoreline Analysis System (DSAS) version 5.0 user guide, Open-File
798 Report. U.S. Geological Survey, Reston, VA. <https://doi.org/10.3133/ofr20181179>
799 Hossain, M.D., Chen, D., 2019. Segmentation for Object-Based Image Analysis (OBIA): A
800 review of algorithms and challenges from remote sensing perspective. *ISPRS J.*
801 *Photogramm. Remote Sens.* 150, 115–134.
802 <https://doi.org/10.1016/j.isprsjprs.2019.02.009>
803 Incekara, A.H., Seker, D.Z., Bayram, B., 2018. Qualifying the LIDAR-Derived Intensity Image
804 as an Infrared Band in NDWI-Based Shoreline Extraction. *IEEE J. Sel. Top. Appl. Earth*
805 *Obs. Remote Sens.* 11, 5053–5062. <https://doi.org/10.1109/JSTARS.2018.2875792>
806 Islam, Md.S., Uddin, Md.A., Hossain, M.A., 2021. Assessing the dynamics of land cover and
807 shoreline changes of Nijhum Dwip (Island) of Bangladesh using remote sensing and
808 GIS techniques. *Reg. Stud. Mar. Sci.* 41, 101578.
809 <https://doi.org/10.1016/j.rsma.2020.101578>
810 Jhonnerie, R., Siregar, V.P., Nababan, B., Prasetyo, L.B., Wouthuyzen, S., 2015. Random
811 Forest Classification for Mangrove Land Cover Mapping Using Landsat 5 TM and Alos
812 Palsar Imageries. *Procedia Environ. Sci.* 24, 215–221.
813 <https://doi.org/10.1016/j.proenv.2015.03.028>
814 Luijendijk, A., Hagenaars, G., Ranasinghe, R., Baart, F., Donchyts, G., Aarninkhof, S., 2018.
815 The State of the World's Beaches. *Sci. Rep.* 8, 6641. <https://doi.org/10.1038/s41598-018-24630-6>
816

- 817 Matin, N., Hasan, G.M.J., 2021. A quantitative analysis of shoreline changes along the coast of
818 Bangladesh using remote sensing and GIS techniques. *CATENA* 201, 105185.
819 <https://doi.org/10.1016/j.catena.2021.105185>
- 820 McAllister, E., Payo, A., Novellino, A., Dolphin, T., Medina-Lopez, E., 2022. Multispectral
821 satellite imagery and machine learning for the extraction of shoreline indicators. *Coast.*
822 *Eng.* 174, 104102. <https://doi.org/10.1016/j.coastaleng.2022.104102>
- 823 Merchant, M.A., 2020. Classifying open water features using optical satellite imagery and an
824 object-oriented convolutional neural network. *Remote Sens. Lett.* 11, 1127–1136.
825 <https://doi.org/10.1080/2150704X.2020.1825869>
- 826 Millard, K., Richardson, M., 2015. On the Importance of Training Data Sample Selection in
827 Random Forest Image Classification: A Case Study in Peatland Ecosystem Mapping.
828 *Remote Sens.* 7, 8489–8515. <https://doi.org/10.3390/rs70708489>
- 829 Mollick, T., Azam, M.G., Karim, S., 2023. Geospatial-based machine learning techniques for
830 land use and land cover mapping using a high-resolution unmanned aerial vehicle
831 image. *Remote Sens. Appl. Soc. Environ.* 29, 100859.
832 <https://doi.org/10.1016/j.rsase.2022.100859>
- 833 Niculescu, S., Billey, A., Jr, H.T.-O.-A., 2018. Random forest classification using Sentinel-1
834 and Sentinel-2 series for vegetation monitoring in the Pays de Brest (France), in: *Remote*
835 *Sensing for Agriculture, Ecosystems, and Hydrology XX*. Presented at the *Remote*
836 *Sensing for Agriculture, Ecosystems, and Hydrology XX*, SPIE, p. 1078305.
837 <https://doi.org/10.1117/12.2325546>
- 838 Paskoff, R., 1984. Rapport III. 7 Erosion et protection des plages : une nouvelle approche 1–7.
- 839 Puissant, A., Rougier, S., Stumpf, A., 2014. Object-oriented mapping of urban trees using
840 Random Forest classifiers. *Int. J. Appl. Earth Obs. Geoinformation* 26, 235–245.
841 <https://doi.org/10.1016/j.jag.2013.07.002>
- 842 Ramesh, V., Singh, D., 2020. Monitoring Shorelines via High-Resolution Satellite Imagery and
843 Deep Learning.
- 844 Rodriguez-Galiano, V.F., Ghimire, B., Rogan, J., Chica-Olmo, M., Rigol-Sanchez, J.P., 2012.
845 An assessment of the effectiveness of a random forest classifier for land-cover
846 classification. *ISPRS J. Photogramm. Remote Sens.* 67, 93–104.
847 <https://doi.org/10.1016/j.isprsjprs.2011.11.002>
- 848 Roy, S., Mahapatra, M., Chakraborty, A., 2018. Shoreline change detection along the coast of
849 Odisha, India using digital shoreline analysis system. *Spat. Inf. Res.* 26, 563–571.
850 <https://doi.org/10.1007/s41324-018-0199-6>
- 851 Sabat-Tomala, A., Raczko, E., Zagajewski, B., 2020. Comparison of Support Vector Machine
852 and Random Forest Algorithms for Invasive and Expansive Species Classification
853 Using Airborne Hyperspectral Data. *Remote Sens.* 12, 516.
854 <https://doi.org/10.3390/rs12030516>
- 855 Sanlaville, P., 2001. Roland Paskoff - L'élévation du niveau de la mer et les espaces côtiers. *Le*
856 *mythe et la réalité* 3.
- 857 Seale, C., Redfern, T., Chatfield, P., Luo, C., Dempsey, K., 2022. Coastline detection in satellite
858 imagery: A deep learning approach on new benchmark data. *Remote Sens. Environ.*
859 278, 113044. <https://doi.org/10.1016/j.rse.2022.113044>
- 860 Serbaji, M.M., Bouaziz, M., Weslati, O., 2023. Soil Water Erosion Modeling in Tunisia Using
861 RUSLE and GIS Integrated Approaches and Geospatial Data. *Land* 12, 548.
862 <https://doi.org/10.3390/land12030548>
- 863 Sertel, E., Ekim, B., Etehad Osgouei, P., Kabadayi, M.E., 2022. Land Use and Land Cover
864 Mapping Using Deep Learning Based Segmentation Approaches and VHR Worldview-
865 3 Images. *Remote Sens.* 14, 4558. <https://doi.org/10.3390/rs14184558>

- 866 Shayeganpour, S., Tangestani, M.H., Homayouni, S., Vincent, R.K., 2021. Evaluating pixel-
867 based vs. object-based image analysis approaches for lithological discrimination using
868 VNIR data of WorldView-3. *Front. Earth Sci.* 15, 38–53.
869 <https://doi.org/10.1007/s11707-020-0848-7>
- 870 Šiljeg, A., Panđa, L., Domazetović, F., 2022. Comparative Assessment of Pixel and Object-
871 Based Approaches for Mapping of Olive Tree Crowns Based on UAV Multispectral
872 Imagery.
- 873 Souto-Ceccon, P., Simarro, G., Ciavola, P., Taramelli, A., Armaroli, C., 2023. Shoreline
874 Detection from PRISMA Hyperspectral Remotely-Sensed Images. *Remote Sens.* 15,
875 2117. <https://doi.org/10.3390/rs15082117>
- 876 Sreekesh, S., Kaur, N., Sreerama Naik, S.R., 2020. An OBIA and Rule Algorithm for Coastline
877 Extraction from High- and Medium-Resolution Multispectral Remote Sensing Images.
878 *Remote Sens. Earth Syst. Sci.* 3, 24–34. <https://doi.org/10.1007/s41976-020-00032-z>
- 879 Sunder, S., Ramsankaran, R., Ramakrishnan, B., 2017. Inter-comparison of remote sensing
880 sensing-based shoreline mapping techniques at different coastal stretches of India.
881 *Environ. Monit. Assess.* 189, 290. <https://doi.org/10.1007/s10661-017-5996-1>
- 882 Toure, S., Diop, O., Kpalma, K., Maiga, A., 2019. Shoreline Detection using Optical Remote
883 Sensing: A Review. *ISPRS Int. J. Geo-Inf.* 8, 75. <https://doi.org/10.3390/ijgi8020075>
- 884 Tsiakos, C.-A.D., Chalkias, C., 2023. Use of Machine Learning and Remote Sensing
885 Techniques for Shoreline Monitoring: A Review of Recent Literature. *Appl. Sci.* 13,
886 3268. <https://doi.org/10.3390/app13053268>
- 887 Valderrama-Landeros, L., Flores-de-Santiago, F., 2019. Assessing coastal erosion and
888 accretion trends along two contrasting subtropical rivers based on remote sensing data.
889 *Ocean Coast. Manag.* 169, 58–67. <https://doi.org/10.1016/j.ocecoaman.2018.12.006>
- 890 Varo-Martínez, M.Á., Navarro-Cerrillo, R.M., 2021. Stand Delineation of *Pinus sylvestris* L.
891 Plantations Suffering Decline Processes Based on Biophysical Tree Crown Variables:
892 A Necessary Tool for Adaptive Silviculture. *Remote Sens.* 13, 436.
893 <https://doi.org/10.3390/rs13030436>
- 894 Wang, J., Wang, L., Feng, S., Peng, B., Huang, L., Fatholahi, S.N., Tang, L., Li, J., 2023. An
895 Overview of Shoreline Mapping by Using Airborne LiDAR. *Remote Sens.* 15, 253.
896 <https://doi.org/10.3390/rs15010253>
- 897 Wang, Z., Liu, J., Li, J., Zhang, D., 2018. Multi-Spectral Water Index (MuWI): A Native 10-m
898 Multi-Spectral Water Index for Accurate Water Mapping on Sentinel-2. *Remote Sens.*
899 10, 1643. <https://doi.org/10.3390/rs10101643>
- 900 Wicaksono, A., Wicaksono, P., 2019. Geometric Accuracy Assessment for Shoreline Derived
901 from NDWI, MNDWI, and AWEI Transformation on Various Coastal Physical
902 Typology in Jepara Regency using Landsat 8 OLI Imagery in 2018. *Geoplanning J.*
903 *Geomat. Plan.* 6, 55. <https://doi.org/10.14710/geoplanning.6.1.55-72>
- 904 Yan, D., Yao, X., Li, J., Qi, L., Luan, Z., 2021. Shoreline Change Detection and Forecast along
905 the Yancheng Coast Using a Digital Shoreline Analysis System. *Wetlands* 41, 47.
906 <https://doi.org/10.1007/s13157-021-01444-3>
- 907 Yan, Y., 2023. Inversion et assimilation de données de télédétection: Estimation des paramètres
908 géophysiques. ISTE Group.
- 909 Yang, M., Zou, L., Cai, H., Qiang, Y., Lin, B., Zhou, B., Abedin, J., Mandal, D., 2022. Spatial–
910 Temporal Land Loss Modeling and Simulation in a Vulnerable Coast: A Case Study in
911 Coastal Louisiana. *Remote Sens.* 14, 896. <https://doi.org/10.3390/rs14040896>
- 912 Yang, X., Qin, Q., Yésou, H., Ledauphin, T., Koehl, M., Grussenmeyer, P., Zhu, Z., 2020.
913 Monthly estimation of the surface water extent in France at a 10-m resolution using
914 Sentinel-2 data. *Remote Sens. Environ.* 244, 111803.
915 <https://doi.org/10.1016/j.rse.2020.111803>

- 916 Zaabar, N., Niculescu, S., Kamel, M.M., 2022. Application of Convolutional Neural Networks
917 With Object-Based Image Analysis for Land Cover and Land Use Mapping in Coastal
918 Areas: A Case Study in Ain Témouchent, Algeria. *IEEE J. Sel. Top. Appl. Earth Obs.*
919 *Remote Sens.* 15, 5177–5189. <https://doi.org/10.1109/JSTARS.2022.3185185>
- 920 Zagórski, P., Jarosz, K., Superson, J., 2020. Integrated Assessment of Shoreline Change along
921 the Calypsostranda (Svalbard) from Remote Sensing, Field Survey and GIS. *Mar. Geod.*
922 43, 433–471. <https://doi.org/10.1080/01490419.2020.1715516>
- 923 Zhang, Liangpei, Zhang, Lefei, Du, B., 2016. Deep Learning for Remote Sensing Data: A
924 Technical Tutorial on the State of the Art. *IEEE Geosci. Remote Sens. Mag.* 4, 22–40.
925 <https://doi.org/10.1109/MGRS.2016.2540798>
- 926 Zhao, B., Liu, Yongxue, Wang, L., Liu, Yongchao, Sun, C., Fagherazzi, S., 2022. Stability
927 evaluation of tidal flats based on time-series satellite images: A case study of the Jiangsu
928 central coast, China. *Estuar. Coast. Shelf Sci.* 264, 107697.
929 <https://doi.org/10.1016/j.ecss.2021.107697>
- 930 Zhu, X.X., Tuia, D., Mou, L., Xia, G.-S., Zhang, L., Xu, F., Fraundorfer, F., 2017. Deep
931 Learning in Remote Sensing: A Comprehensive Review and List of Resources. *IEEE*
932 *Geosci. Remote Sens. Mag.* 5, 8–36. <https://doi.org/10.1109/MGRS.2017.2762307>
- 933