

Shoreline kinematics in Libreville (Gabon) derived from very high spatial resolution (VHR) imagery using machine and deep learning techniques

Nina Manomba-Mbadinga^{a,*}, Simona Niculescu^{a,b}

^a University of Brest, CNRS, LETG Brest UMR 6554 CNRS, Technopôle Brest-Iroise, Dumont d'Urville, Plouzané, 29280, France

^b Institut Universitaire de France (IUF), Paris, 75000, France

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ABSTRACT

Artificial Intelligence (AI), remote Sensing (RS) and observations and field data offer a number of advantages for detection and automatic extraction of coastline evolution. However, for many countries in the intertropical zone, such as Gabon, accurate and up-to-date mapping systems and spatial statistics are lacking or incomplete. In this context, RS using Very High Spatial (VHR) resolution satellite imagery and algorithms of AI, Machine Learning (ML) and Deep Learning (DL) associated with field data represents a major asset. The primary objective on this work is to contribute to the understanding of the shoreline dynamics of Libreville, the political and administrative capital of Gabon, through a diachronic analysis covering the period from 2003 to 2024. To this end, a panchromatic aerial image from 2003, two Pleiades images (a stereo image from 2022 and tri-stereo image for 2024), as well, *in situ* shoreline surveys conducted simultaneously with the Pleiades image acquisition, were utilized. Several AI models have been implemented: ML (Pixel-Based Image Analysis (PBIA) and Object-Based Image Analysis (OBIA) with Random Forest (RF) and Support Vector Machine (SVM) algorithms) and DL (Convolutional Neural Network (CNN) processing by pixel-based approach and combined with OBIA). The RF-PBIA and CNN-OBIA approaches yielded the best classification performances (over 80%), enabling the extraction of shorelines from 2022 (Pleiades stereo) and 2024 (Pleiades tri-stereo). The analysis of the End Point Rate index revealed that between 2003 and 2022, the coastline exhibited a general trend of accretion (0.87 m/year). In contrast, the period from 2022 to 2024 recorded an average annual rate of −0.32 m/year.

1. Introduction

Access to the sea or ocean is a significant advantage for many countries due to the multifaceted opportunities it offers, particularly in the economic sector. However, in recent years, a growing threat has emerged for these countries: coastal erosion. This natural phenomenon, characterized by the retreat of the shoreline, poses a serious risk to coastal areas (Boussetta et al., 2022). According to “Climate Change Post” (ClimateChangePost), sandy beaches, which present more than a third of the world's coastline, are the most affected by coastal erosion. Given that half of the world's population lives in coastal areas (Darwish, 2024), obtaining quantitative information about shoreline position is crucial for anticipating future damage (Puissant et al., 2010). Like many coastal countries, Gabon has shown renewed interest in coastal dynamics, given that these processes can influence the behaviour of fluvial systems (Souza et al., 2024). Studies have highlighted coastal erosion in several cities, including Port-Gentil, Mayumba, Cocobeach, and Libreville

(Rabenkogo, 2007), (Mombo), (Mounganga), (Rapport Final These Zephirin), (Mouyalou, 2017).

The shoreline is a complex concept, both in its definition and in its nature. The methods used to analyze it depend largely on the type of coast, the available data, and the data processing tools employed (Valentini et al., 2020), (Maspataud et al.), (Zhao et al., 2023), (Maltese et al., 2023). To date, a variety of shoreline definitions exist (Boak et al., 2005), (Limite terre-mer), (Thior, 2021). Defined as a coastal strip, the shoreline helps to identify the diversity of coastal environments, such as rocky coasts, sandy beaches, estuaries, and others, as well as the associated challenges. However, it is essential to retain the concept of the shoreline as the boundary between land and sea to establish an indicator for monitoring coastal evolution and harmonizing monitoring methods.

Moreover, acquiring data for coastal environmental monitoring is often a laborious task when using traditional land-based survey methods (Bengoufa et al., 2021). These methods include *in situ* photogrammetry, topographic field surveys, field survey sheets, and the use of shoreline

* Corresponding author.

E-mail addresses: mbadinganina@gmail.com (N. Manomba-Mbadinga), simona.niculescu@univ-brest.fr (S. Niculescu).

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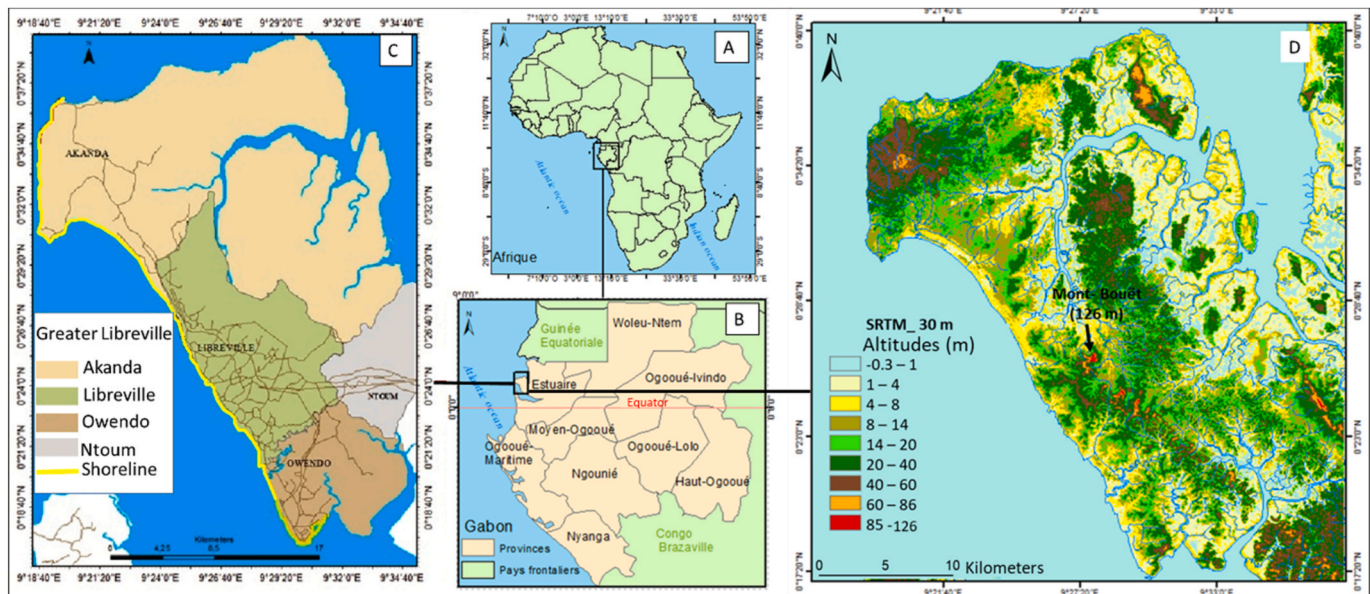


Fig. 1. Geographic location of the study area at different spatial scales (African, Gabonese, and local)

This Figure shows the location of Gabon (b) within Africa (a), and the geographical sitting of Greater Libreville and its shoreline in the national context (c). Panel (d) presents the general elevation of the study area.

benchmarks, which are reference markers employed to monitor shoreline position changes and commonly materialized by wooden stakes, concrete markers, or surveyor's nails. Although these methods provide high precision, the results giving from Very High Resolution (VHR) optical satellite images demonstrate the ability of remote sensing techniques in providing information where techniques using traditional methods present some limitations, especially due to their inability to map hard-to-reach areas and very dynamic near shoreline waters (Randazzo et al., 2020). The advent of high and VHR optical sensors has significantly improved the precision and quality of geospatial analyses, enabling more detailed observations and better-informed decision-making in various fields for coastal monitoring (Dai et al., 2019), (Gagliardi et al., 2023), maritime security (Goudemant et al., 2022), Land Use and Land Cover mapping (Cuyper et al., 2023), (Xia et al., 2024), (Morin et al., 2023). Unfortunately, VHR optical satellite images sufficiently relevant for assessing coastal dynamics through RS are rare or difficult to exploit in many intertropical developing countries, due, on the one hand, to economic constraints related to acquisition costs and, on the other hand, to atmospheric conditions, particularly cloud cover, which can limit the availability of terrestrial information.

In the field of (semi-)automatic coastline detection and extraction, Boussetta et al. (2022), conducted the automatic detection of shoreline features (Djerba Island) using supervised classification, based on an Object-Based Image Analysis (OBIA) approach combined with a Machine Learning (ML) algorithm of the Random Forest (RF) type (RF_Object), thereby demonstrating the relevance of ML techniques for coastal image analysis. Furthermore, Bengoufa and al. (Bengoufa et al., 2023), highlighted the effectiveness of Convolutional Neural Network (CNN) for detecting hydrodynamic and biological indicators along the shoreline of western Algeria.

ML and Deep Learning (DL) are well-documented for supervised classification of Land Use and Land Cover (LULC) in the coastal areas using satellite images of various resolutions (Rogan et al., 2008), (Su et al., 2016), (Niculescu et al., 2018), (Meraner et al., 2020), (Gonzalez-Perez et al., 2022), (Xie et al., 2021), (Zhao et al., 2023), (Carine et al.), (Irfan et al., 2025).

In the past decades, integrating Artificial Intelligence (AI) methods with RS has shown strong potential to enhance data analysis in environmental sciences, especially for land cover studies (McAllister et al.,

2022), leading to the development of automated approaches. This would not only reduce data acquisition costs but also minimize the subjectivity associated with traditional methods for monitoring shoreline position changes, thereby enabling more reliable and informed decision-making. Unfortunately, aerial images sufficiently relevant for assessing coastal dynamics through RS are rare or difficult to exploit in many developing countries.

Most studies assessing coastal dynamics in Gabon rely on traditional photo-interpretation techniques, making extensive use of Landsat satellite imagery, historical aerial photographs, Google Earth images, and field surveys (Pottier et al., 2016). The inherently subjective nature of manual shoreline digitization, combined with the limitations of low-resolution imagery, raises concerns about the overall accuracy, efficiency, and reliability of these approaches. This methodological approach may help explain the limited number of studies focused on shoreline dynamics along the Libreville coastline, despite its status as the main urban hub of Gabon and its location in a coastal zone. To date, the existing literature on shoreline evolution has been more concentrated on the municipality of Libreville. It is worth noting that in recent years, Libreville's coastline has experienced increased human pressure, particularly through the development of port infrastructure and other coastal modifications.

This study first aims to compare the performance of algorithms and approaches specific to AI (ML and DL) using very high spatial resolution satellite images (Pleiades stereo 2022 and Pleiade tri-stereo 2024) and an aerial photograph (2003) for a coastal area of Gabon (Libreville). The objective is to adapt and optimize these algorithms for (semi-)automatic detection and extraction of shoreline conducting a kinematic analysis of in the coastal area in Libreville (Gabon). Initially, RF and Support Vector Machine (SVM) are trained using Pixel-Based Image Analysis (PBIA) and OBIA approaches, and the performance of a pixel-based CNN as well as a CNN combined with the OBIA approach will be tested. From a thematic/applicable perspective, a diachronic analysis with thematic (geomorphological) interpretations is conducted to assess the coastline dynamics of Libreville municipality between 2003 and 2024, identifying the most vulnerable sectors threatened by coastal erosion using spatial statistics calculation.

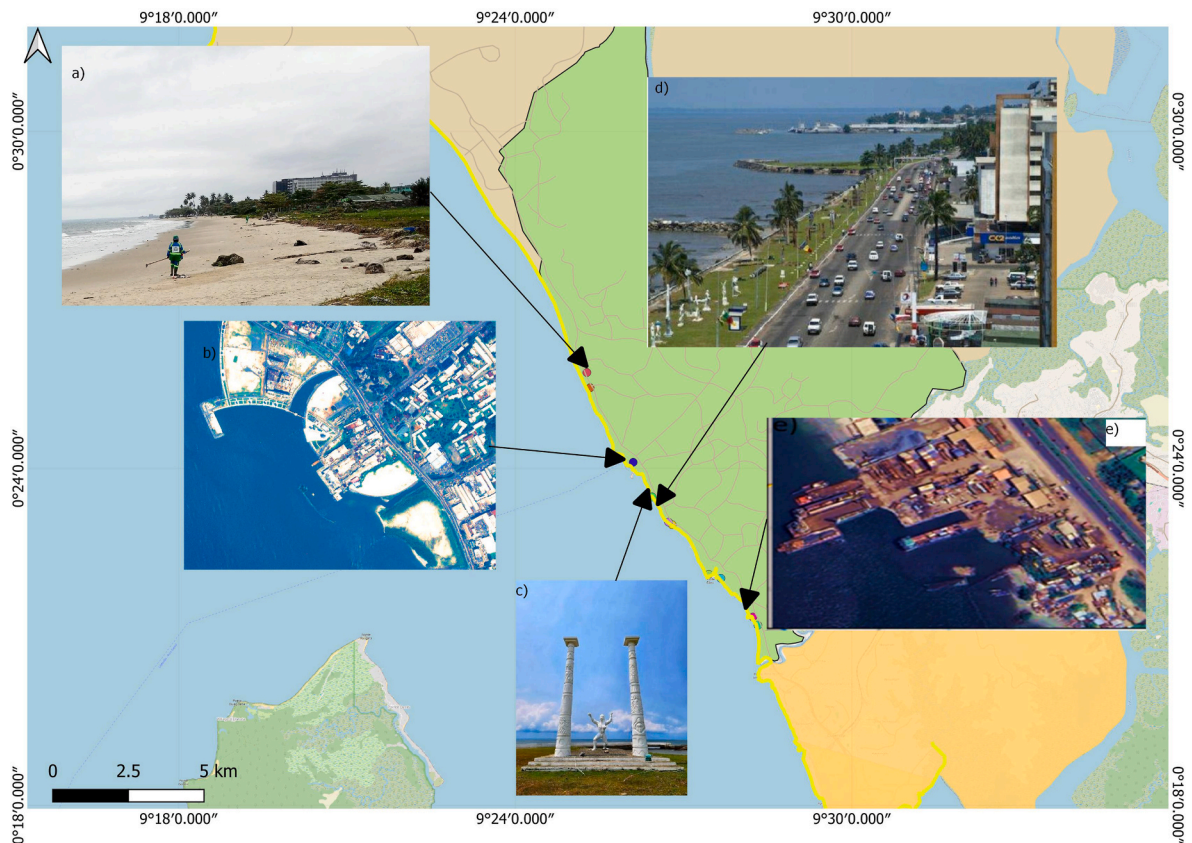


Fig. 2. Overview of coast of Libreville

- a) Beach of Lycée Léon Mba: The Sandy beach;
- b) La Baie des rois: Started in 2015, it's a real estate project that provides for the construction of an eco-business district, housing, leisure establishments, various shops and green spaces, etc.;
- c) The Stele of Liberty: Emblematic monument of the Gabonese Republic. It commemorates the end of the slave trade in 1848. Following the declaration of Schoelcher, 272 slave men, women and children were freed on the coast. These founded the city of Libreville in 1849. Work designed by Me Minko Minzé (painter and sculptor);
- d) Boulevard of the Seafront: it is the only road that allows you to quickly connect the city center from the Léon-Mba international airport located north of Libreville;
- e) The ACAE port: located on the right bank of the Komo and extends over 675 m of perimeter and covering an area.

2. Materials and methods

2.1. Study area

Gabon, located in Central Africa (Fig. 1) within the Gulf of Guinea region, covers a total area of 267667 km² and has an estimated population of 2253716 inhabitants (DGEPP, 2022). It is bordered by: Cameroon and Equatorial Guinea to the north, the Republic of the Congo to the south and east and the Atlantic Ocean to the west. Grand Libreville, the political and administrative capital of Gabon, is situated in the Estuaire Province. Its First municipality, of "Libreville" is demarcated by: Akanda to the north, Owendo to the south, and Ntoun to the east.

The municipality of Libreville, the historical center from which Grand Libreville expanded («*Okanga*»), serves as the starting point of the study area. Founded in 1849 by freed slaves, hence its name. It concentrates the majority of the country's administrative structures: business centers, port activities, fishing hubs, as well as residential and mixed-use districts. Libreville is experiencing significant anthropogenic pressure (land reclamation, construction of restaurants, hotels, etc.), and the majority of administrative institutions are located there. The Libreville's shoreline is increasingly facing coastal erosion. This is evidenced by the destruction of roads, the weakening of coastal erosion protection structures, and the subsidence of beaches.

2.2. Coastal landscape and climate in Libreville

The coastline of Libreville features sandy beaches (Fig. 2) with occasional rocky outcrops, as well as infrastructure aimed at combating coastal erosion. As one moves inland, the city exhibits a gentle topography characterized by a series of low altitude hills-oriented NNW-SSE, interspersed with shallow valley. Elevations range from less than 10 m to 126 m (Mont-Bouët).

Abundant rainfall characterizes Grand Libreville. The municipality of Akanda receives more precipitation than Libreville and Owendo. The annual rainfall in these municipalities is 3000 mm and 2400 mm, respectively. Rainfall follows a continuous pattern throughout the year, dictated by the atmospheric circulation specific to these latitudes (Godard et al., 2003), (*Les précipitations au Gabon*). The Saharan and Saint Helena anticyclones, the Intertropical Front (ITF), and the Inter-Oceanic Convergence (IOC) primarily influence this dynamic. These results in a period of heavy rains concentrated in October, November, and up to mid-December. Subsequently, there is a notable decrease in rainfall, known as the pseudo-short dry season, which lasts from mid-December to February. Rainfall resumes in a more spread-out manner from March to mid-June. Finally, the region experiences a long dry season from mid-June to mid-September, which can sometimes extend until the end of September. The occurrence of heavy precipitation and the presence of dense forest cover generate persistent cloud cover, reducing the effectiveness of optical satellite imagery. As a result,

Table 1
Data set: aerial and satellite images.

Types	Source	Date	Bands	Resolution (m)
Areal photography	-	2003	Panchromatic	0,5
Pleiades stereo (2D)	AIRBUS	21/08/2022	Red, Green, Blue, Near Infrared	2
Pleiades tri stereo (3D)	AIRBUS	16/06/2023	Red, Green, Blue, Near Infrared	2
			Panchromatic	0,5

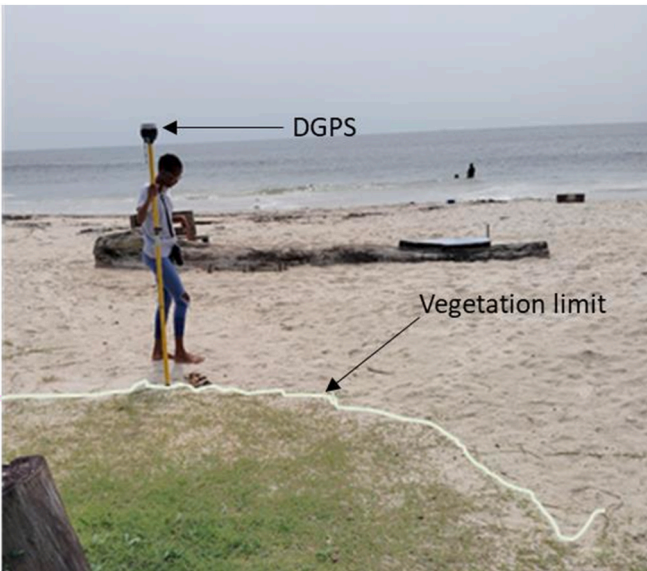


Fig. 3. Topographic survey of the shoreline (Léon Mba High School Beach) with DGPD the 05/02/2024
This photograph shows the in-situ vegetation limit used to determine the shoreline position using DGPS.

viable acquisition windows are limited, often requiring delays of several weeks. In contrast, the dry season provides more favorable atmospheric conditions for optical observations.

2.3. Data acquisition

2.3.1. Aerial images

For the implementation of this study, various types of data were utilized. These data primarily include a panchromatic aerial image, two Pleiades images (stereo and tri-stereo), as well as topographic surveys of the coastline.

The oldest image used in this study dates back to 2003. It is a single-band panchromatic image (black and white) with a resolution of 0.5 m. Additionally, two Pleiades images acquired in stereoscopic and tri-stereoscopic modes were utilized. These datasets are from 2022 to 2024, respectively. These data are of VHR and include four spectral bands in the visible range: Blue (430-550 nm), Green (490-610 nm), Red (600-720 nm), and near-infrared (750-950 nm) (Table 1). It is worth noting that the acquisition of the Pleiades images (August 21, 2022) was specifically scheduled to coincide with the dates of the field surveys done on August 21, 2022.

2.3.2. Field campaign

To evaluate the accuracy of the coastline extracted from the 2022 Pleiades image, an *in situ* field survey of the coastline was conducted on the same day as the satellite overpass (August 21, 2022, starting at 9:56

a.m.) (Fig. 3) using a Differential Global Positioning System (DGPS) georeferenced in the WGS84 datum and UTM coordinate system. The DGPS utilizes a network of fixed reference stations that transmit the discrepancy between the positions indicated by the satellites and their known actual positions, enabling horizontal and vertical positioning with an accuracy often better than 10 cm. DGPS, or Differential GPS, is an enhancement of conventional GPS. The latter is not suitable for creating beach profiles or digital terrain models due to its insufficient accuracy, which is estimated to be within several meters of the actual position.

3. Methodology

3.1. Images pre-processing

A variety of software tools were used to accomplish this work. First, Quantum GIS (QGIS V. 3.36.3) was employed for part of the data pre-processing: assigning projections, georeferencing images using the “Georeferencing” tool, creating samples for image classification, and visualizing data layers. Additionally, the open-source library Orfeo Toolbox (OTB v. 8.1.0) was used to perform PBIA (Pixel-Based Image Analysis) classification and post-processing of the classification results. Furthermore, Trimble eCognition (Version 10.0.0) was utilized for OBIA and CNN-OBIA approaches. This image analysis software is among the most advanced for geospatial applications. Lastly, ArcGIS version 10.8.2, developed by ESRI (a company specializing in geolocation technologies and spatial analysis), was used to assess coastal dynamics through the Dynamic Shoreline Analysis System (DSAS) extension.

3.1.1. Pleiades stereo and tri-stereo images

The Pleiades images from 2022 to 2024 were first projected (EPSG:26632 - M'poraloko/UTM zone 32N). These images then underwent a georeferencing process based on the oldest image (2003) using the “Georeferencing” tool. This was followed by a geometric rectification step to correct geometric distortions. The next step involved enhancing the resolution of the multispectral images using their panchromatic bands through a process called “Pan sharpening” or resampling. This resulted in images with a resolution of 0.5 m each. Additionally, the extraction of the area of interest was performed using the “Clip raster by mask layer” extension. All the aforementioned operations were carried out using QGIS. However, with OTB, the stereo and tri-stereo Pleiades images underwent atmospheric correction (TOA) using the “Optical Calibration” extension. This step aimed to obtain precise measurements of the Earth's surface by removing the effects of atmospheric scattering and absorption. This conversion is defined by the following formula.

• $R(b) = (\pi \cdot L(b) \cdot d \cdot d) / (ESUN(b) \cdot \cos(\theta))$ (no dimension)

(https://www.orfeo-toolbox.org/CookBook/Applications/app_OpticalCalibration.html) where:

- $L(b)$ is the spectral radiance for band b
- π is the famous mathematical constant (3.14159 ...)
- d is the earth-sun distance (in astronomical units) and depends on the acquisition's day and month
- $ESUN(b)$ is the mean TOA solar irradiance (or solar illumination) in $W / m^2 / micrometers$
- θ is the solar zenith angle in degrees.

3.1.2. Data from field survey (Differential GPS)

The topographic surveys conducted provided the in-situ coastline for the 2022 Pleiades image. These topographic data were initially provided in Excel spreadsheet format (.xlsx). The data were then converted into a “semicolon-separated values (CSV)” format. Subsequently, they were imported into ArcMap v. 10.8.2, where they were converted into point

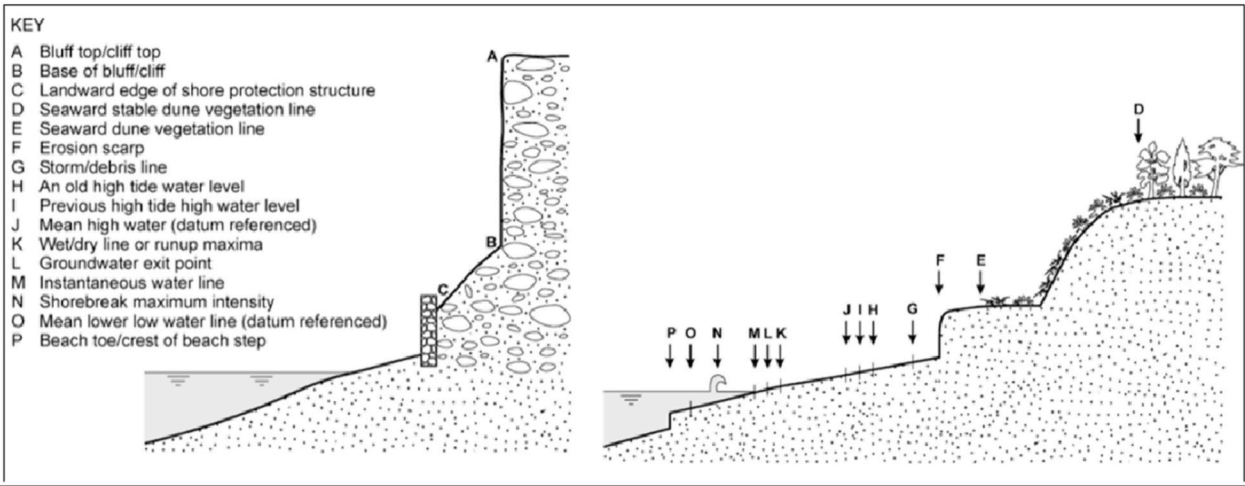


Fig. 4. Most used shoreline indicators adapted according to Boak and Turner (2005). This figure presents the distinct shoreline indicators as classified by Boak and Turner.

Water	     	All types of water bodies combined (mainly sea water)
Sand	     	Wet and dry sand localized on the beach and inside the mainland
Vegetation	     	Herbaceous vegetation (Plants with no persistent branches or shoots above the surface and no apparent solid structure) and Woody plants
Urban	           	Area of land covered with buildings and other man-made features.

Fig. 5. Samples of LULC of our study area This figure displays sample categories of coastal zone objects used for classification purposes.

vectors and then into polyline vectors.

3.1.3. Shoreline reference choice

The choice of the shoreline reference is crucial for the reliability of the results and the relevance of the analyses intended to be conducted on shoreline dynamics. Specific references are recommended depending on the spatial and temporal, temporal, seasonal scales at which coastal dynamic are observed (*Rapport en Français*). Boak and Turner (Boak et al., 2005) are categorized shorelines based on their origin: botanical, hydrodynamic, anthropogenic, or morphological (Fig. 4). Therefore, Mallet and al (« RP) recommend using the “vegetation line” and the “landward edge of shore protection structure” for observations with spatial and temporal scales exceeding 10 km and spanning multiple decades, respectively. We have therefore chosen to follow this approach.

3.2. Images processing

3.2.1. Training and validation samples

In addition to the aforementioned data, other crucial data were utilized, namely training and validation samples. These samples are indicative of LULC characteristics (Fig. 5). They are organized into classes and labeled. Four (4) classes were defined: “water” class (all water bodies combined), “sand” classes (wet and dry), “vegetation” class (herbaceous and woody), “urban” class (all signs of human activity: bare

soil, rooftops, buildings, roads, coastal erosion protection structures, etc.). These classes were created such that the validation samples represent 30% of the training samples.

3.2.2. Approaches and algorithms AI implemented

3.2.2.1. PBIA and OBIA. The PBIA approach involves directly classifying each pixel of an image based on various pixel-specific characteristics, such as spectral values and texture, for example. The application of this approach requires input data such as: an image and training samples. These samples are labeled according to predefined land cover classes. The training samples are used to train the model, while the control samples are used to evaluate its performance. The main phases of image classification (Fig. 6) include: model training, model prediction and the accuracy assessment using indices such as Overall Accuracy (OA), the Kappa index, and the F-score. On the other hand, the OBIA approach groups pixels into meaningful objects based on spatial, spectral, and contextual characteristics before classification. This method is particularly useful for analyzing high-resolution images and capturing complex patterns in the data. Both approaches are complementary and are chosen based on the specific requirements of the study.

3.2.2.1.1. Algorithm RF. RF is an algorithm integrated into the OTB software. RF are a collection of tree predictors, collectively referred to as a forest. The classification process works in such a way that the random

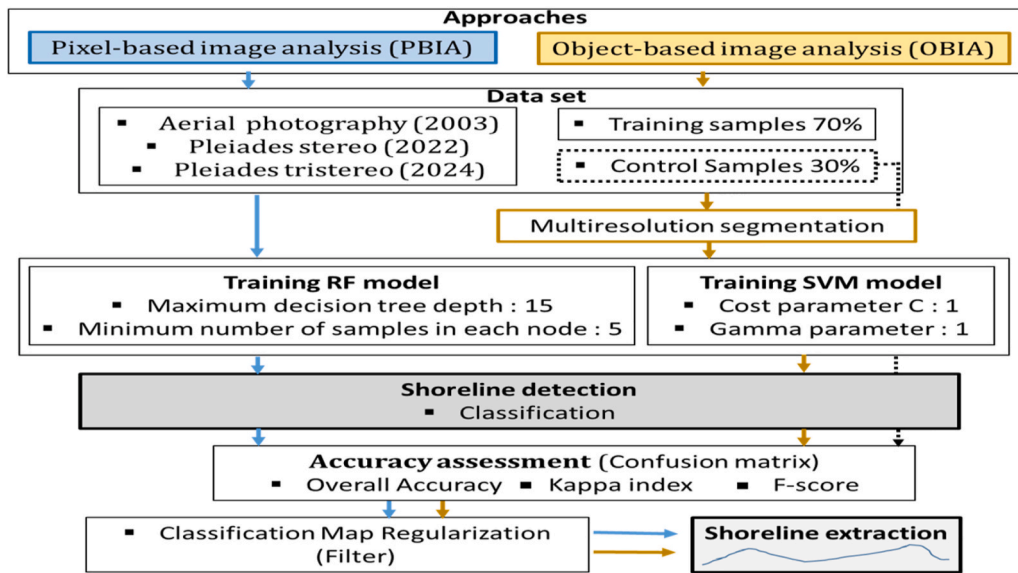


Fig. 6. Workflow of PBIA and OBIA approaches

This figure shows the processing workflows of PBIA and OBIA approaches for automatic shoreline detection and extraction. The blue and brown arrows indicate the workflows of the PBIA and OBIA approaches, respectively.

tree classifier takes the input feature vector, classifies it with each tree in the forest, and outputs the class label that receives the majority of votes. In the case of regression, the classifier's response is the average of the responses from all the trees in the forest. Thus, it generates multiple decision trees from a subset of randomly selected samples and training variables. It is one of the best and most efficient machine learning classifiers. It offers several advantages, such as high-precision output (Rodriguez-Galiano et al., 2012) and better performance than other powerful machine learning models. Despite its robustness, RF has some notable drawbacks, such as the difficulty of visualizing the trees since it uses multiple trees to make predictions (Breiman, 2001). This refers to a bagging technique where the same sample can be continuously drawn at the expense of other samples. These trees are trained with approximately two-thirds of the samples (called bagged samples). The remaining third, called out-of-bag samples, is used for internal cross-validation to evaluate the RF model or estimate the error. In this study, after several rounds of cross-validation, only the value of the "maximum depth of the tree" parameter was modified and set to 15, while the others parameters were kept at their default values.

3.2.2.1.2. *Algorithm Support Vector Machine (SVM)*. SVM is a supervised ML algorithm primarily utilized for classification tasks. It

functions as a linear classifier and is widely regarded as one of the most robust algorithms in ML. The core principle of SVM involves transforming a classification or discrimination problem into the identification of a hyperplane within a feature space. This hyperplane optimally separates data points into distinct classes by maximizing the margin the distance between the hyperplane and the nearest data points from each class. SVM models can employ various kernel functions, including linear, polynomial, radial basis function (RBF), and sigmoid kernels. For pixel classification in this study, the one-to-one method was selected using the OTB software. Two critical parameters that significantly influence SVM performance are the kernel parameter (γ) and the error parameter (C). In the context of this study, all SVM tuning parameters were maintained at their default settings, with no modifications applied.

3.2.2.2. *Algorithm CNN*. DP is a specialized subfield of ML, characterized by the use of deep neural networks architectures comprising multiple layers of processing units. These networks are designed to emulate, in a simplified manner, the functioning of the human brain through interconnected units known as artificial neurons, organized in hierarchical layers. Training a CNN model requires input data in the form of images and corresponding training data for the various classes (Fig. 7).

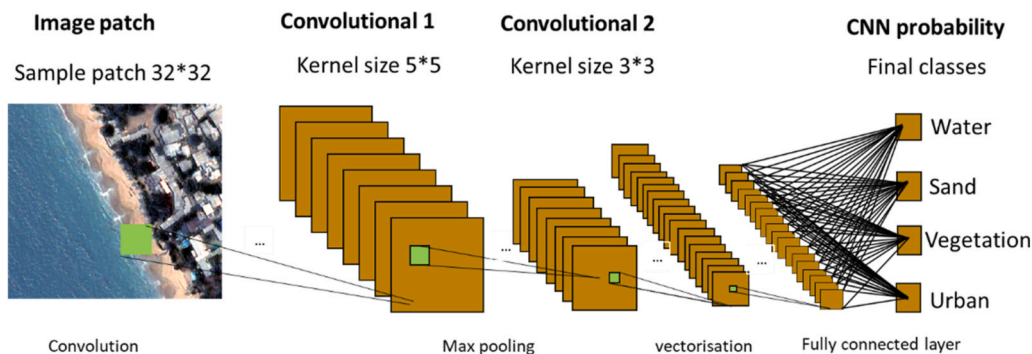


Fig. 7. Architecture of the CNN model implemented (eCognition, 2025)

The figure illustrating the image processing workflow for shoreline detection using a Convolutional Neural Network (CNN). On the left, the satellite image of the coastal area is segmented into patches (square regions). These patches are then successively processed by several convolutional layers (conv1, conv2, conv3), where spatial features are extracted and downsampled/reduced. Finally, the fully connected layers classify each patch based on the presence or absence of the shoreline, enabling accurate detection of the shoreline indicator.

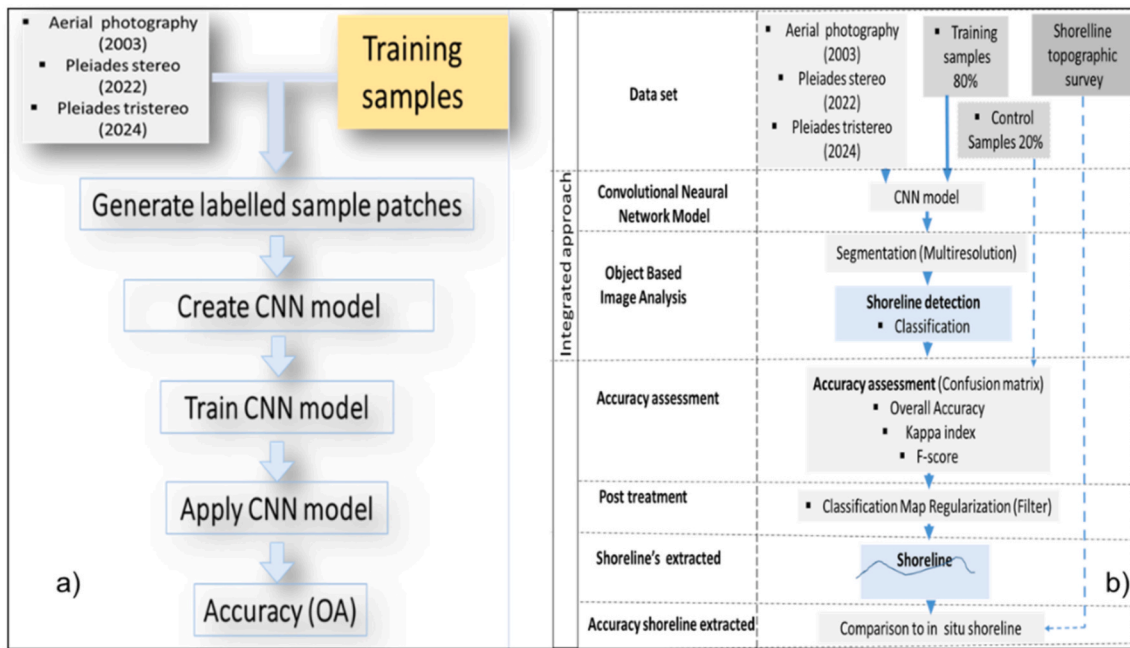


Fig. 8. Workflow of DL approaches; a) Main steps of pixel-based CNN approach; b) Main steps of CNN-OBIA approach.

In this study, the available remote sensing images were processed using a CNN model. CNN are a type of deep learning model inspired by the structure of biological neural networks. They consist of multiple layers, including convolutional layers, pooling layers, and fully connected layers, interconnected by weights and biases. The convolutional layers process image samples as input, extracting features by scanning the entire image. This process involves generating feature maps at each

layer, which are then passed to subsequent layers for further processing.

The first approach of DL tested in this study is the pixel-based CNN (Fig. 8-a). This approach is processing by five main steps: (1) the generating of label sample patches, (2) the creating of CNN model, (3) the training CNN model, (4) the applying CNN mode and the assessment of accuracy (5). With eCognition software, only the Overall Accuracy is calculated for pixel CNN approach. The second approach adopted

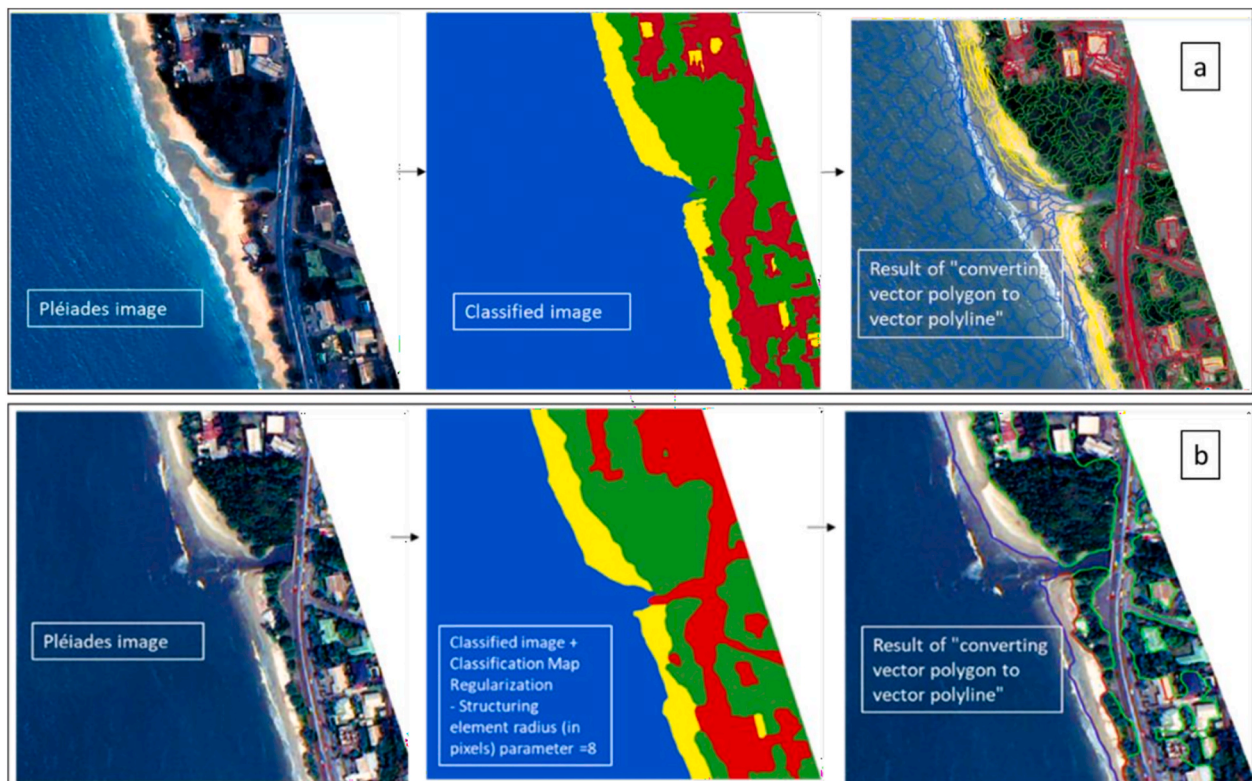


Fig. 9. Preprocessing of classified images

a) Visualization of the raw shoreline; b) Visualization of the preprocessed shoreline using "Classification Map Regularization".

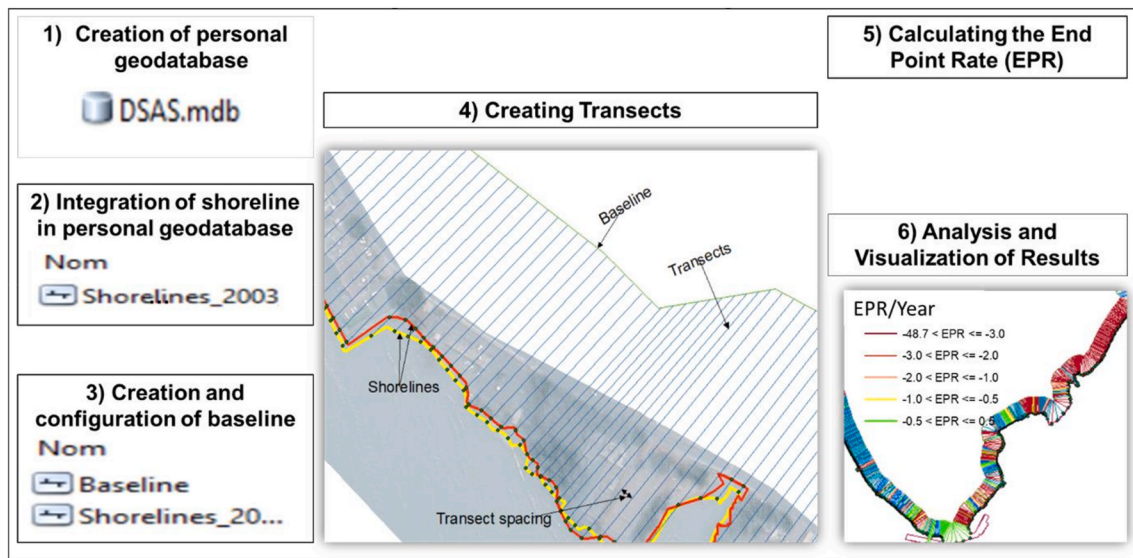


Fig. 10. Workflow for calculating coastal erosion statistics

This figure illustrates the 6-step workflow for analyzing shoreline dynamics. The final step (Step 6) presents the cartographic results, showing shoreline displacement rates calculated using the End Point Rate (EPR) method along transects. Rates are expressed in meters per year.

combines the Object-Based Image Analysis (OBIA) methodology with the CNN model, resulting in a hybrid CNN-OBIA framework. The CNN-OBIA model was designed and trained using Trimble's eCognition 10 software. The model utilized four (4) spectral bands (RGB and Near-Infrared (NIR)) for the Pleiades imagery and one (1) band for the panchromatic image. This integration of OBIA and CNN leverages the strengths of both methods, enabling more accurate and efficient analysis of remote sensing data. The training dataset was used to generate convolution inputs by sampling patches selected from 1204×1204 pixels of the original image. To determine an appropriate sample size, the dimensions of the target classes were taken into consideration. Following a cross-validation process, the designed CNN was configured with a sample size of 32×32 . Given this small size, the number of hidden layers was set to 2, with kernel sizes of 5×5 and 3×3 , respectively. A max-pooling layer with a kernel size of 2×2 was applied after the first convolutional layer. The role of max-pooling is to merge semantically similar features.

Additionally, a patch size of 50 and 5000 training steps enabled achieving good performance. A cross-validation process revealed that the optimal learning rate could be set to 0.0006. When the learning rate is too low, the training process may become excessively long, and the network risks getting stuck in suboptimal solutions. Conversely, if the rate is too high, the training may proceed too quickly, preventing the network from reaching the best solutions. In both cases, this can lead to incorrect weights.

Once the CNN model was created, the integration of OBIA into the CNN followed (Fig. 8-b). For the image segmentation step, values of 20, 0.1, and 0.9 were assigned to the respective parameters: "scale parameter," "shape," and "compactness." After segmentation, classification was performed, followed by the final step of calculating accuracy using a confusion matrix.

3.2.2.2.1. Extraction of the shoreline from Pleiades stereo (2022) and tri-stereo (2024) images. The classified Pleiades images from 2022 to 2024, resulting from the RF-PBIA and CNN-OBIA approaches respectively, were preprocessed to facilitate easier shoreline extraction. Firstly, the "Classification Map Regularization" filter (Fig. 9a-b) was applied using the OTB software. This filter helps reduce errors or eliminate noise in the image. In other words, it transforms "isolated" pixels based on the majority of surrounding pixels. As a result, areas with similar classes become more homogeneous, producing a cleaner and more interpretable image. Additionally, this process also contributes to the continuity of the

shoreline. While this filter offers the ability to adjust several parameters, in this case, configuring the "Structuring element radius (in pixels)" parameter was sufficient. A value of (8) was assigned to it.

3.3. Erosion vulnerability assessment

For the calculation of shoreline evolution trends, the Digital Shoreline Analysis System (DSAS V6.0), an extension of ArcGIS Desktop developed by the United States Geological Survey (USGS), was utilized. The Digital Shoreline Analysis System (DSAS) is a freely available plugin that operates within the Geographic Information System (GIS) software ArcGIS, developed by the Environmental Systems Research Institute (ESRI). It generates statistical rates of change for a time series of vector shoreline data. This tool provides the advantage of delivering both graphical and statistical representations of shoreline evolution. Using a standardized methodology, DSAS performs statistical evolution calculations while analyzing past (Fig. 10), present, and future shoreline changes.

DSAS enables the calculation of several indices to assess shoreline dynamics over time (Himmelstoss et al.). In this study, only the End Point Rate (EPR) was used. This metric quantifies the rate of shoreline change between two specific dates by dividing the distance between two shoreline positions by the time interval between those dates (Thior et al., 2019), (Terres De Lima et al., 2021), (Saad), (Murray et al., 2023). The Net Shoreline Movement was divided by the duration of the intervals, first for the 2003-2022 period, and then for the 2022-2024 period.

Initially, the shorelines (2003, 2022, and 2024) were integrated into a personal geodatabase. This was followed by the creation of baselines. A baseline serves as a reference origin for the transects, which are perpendicular to the various shoreline positions. Transects, on the other hand, are predefined-length segments generated at constant intervals, extending from the baseline toward the digitized shoreline vectors. Once the transects were generated, the final step of the method involved running statistical calculations to measure the deviations or distances between the digitized shorelines. These calculations are automatically generated and recorded in an attribute table containing information about each transect.

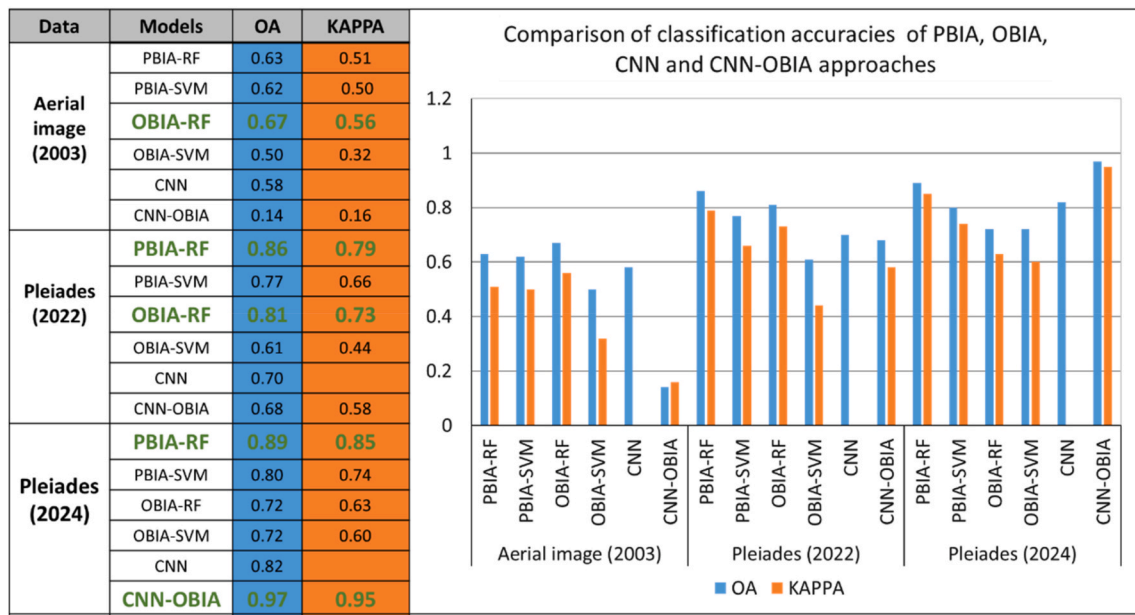


Fig. 11. Classification accuracy of PBIA, OBIA, CNN and CNN-OBIA approaches and methods

This figure is composed one table on the left and on graph on the right. The objective is to compare the classification analysis performance by approaches on each image. The first column shows the areal data (aerial/satellite input data), the second, the classification approaches (PBIA, OBIA, CNN, VNN-OBIA), the third Overall Accuracy (OA) in blue and Kappa coefficient in orange. The best per-image results highlighted (green). The graph shows the same result but in a different form.

3.4. Accuracy assessment: Image classification and automatic extraction shoreline

The statistical accuracy evaluation was carried out for two reasons. First, to compare the performance of RF and SVM methods using PBIA (pixel-based image analysis) and OBIA (object-based image analysis) approaches. The results of the pixel-based CNN and CNN-OBIA approach were also compared with those of the previous approaches to determine which methods achieved the highest classification scores for the automatic extraction of shoreline features. Classification performance was evaluated in terms of overall accuracy (OA) and the kappa coefficient, based on the final output (classified image) of the classification process as well as validation samples.

For each image, a confusion matrix was generated. The Overall Accuracy (OA) represents the percentage of ground objects correctly classified. The kappa index, on the other hand, measures the agreement between the model's classifications and the true labels. The confusion matrix and the Kappa index are among the most widely discussed methods for assessing image classification accuracy in the remote sensing (RS) literature (Rosenfield and Fitzpatrick-Lins, 1986), (Cohen, 1960), (Koukoulas et al., 2001), (Foody, 2002), (Congalton et al., 2008). These two elements form the basis for evaluating classifications. First, the classification performance results of different models are presented. Then, the models with the highest classification scores are retained for shoreline extraction and coastal dynamics assessment.

3.5. Extracted shoreline accuracy

The accuracy of the extracted shoreline using the approaches that achieved the highest classification scores on the Pleiades stereo image (2022) and tri-stereo image (2024) was assessed using *in situ* measurements (field survey) conducted currently with the satellite overpass on August 21, 2022. It is worth noting that the Pleiades stereo satellite are equipped with two sensors, 1A and 1B, providing a spatial resolution of 0.5 m in PAN and 2 m in MS, with the ground swath width of 20 km. The distances between the extracted shorelines and the *in situ* collected shoreline were automatically calculated using the DSAS.

4. Results

The results of this work focus on three major insights: the automatic detection of the Libreville shoreline on three specific years (2003, 2022, and 2024), its automatic extraction, and the diachronic analysis of shoreline evolution over a period of approximately 21 years (from 2003 to June 16, 2024).

4.1. Shoreline detection using PBIA, OBIA, pixel-based CNN and CNN-OBIA approaches and methods

The figure presents the performance results of various image approaches tested (PBIA-OBIA, CNN and CNN-OBIA) on an aerial image (2003) and two Pleiades images stereo (2022) and tri-stereo (2024). The performances are evaluated using Overall Accuracy (OA) and Kappa index (Fig. 11).

The results obtained for the classifications of the 2003 image, the accuracies of the approaches are generally not satisfactory. However, the OBIA approach achieves the best performance with an OA of 0.67 and a Kappa index of 0.56 using RF. In contrast, the CNN-OBIA approach shows poor performance (OA = 0.14, Kappa = 0.16).

Regarding the results obtained from the Pleiades Stereo image (2022), the PBIA-RF approach (OA: 0.86; Kappa: 0.79) records the highest accuracy scores, followed by the OBIA-RF approach (OA: 0.81; Kappa: 0.73), while the CNN-OBIA approach (OA: 0.68; Kappa: 0.58) proves to be the least robust. Both PBIA and OBIA approaches demonstrate strong potential when combined with the RF algorithm for the classification of the Pleiades Stereo image. Compared to RF, the SVM algorithm remains less effective, achieving a maximum accuracy of 0.77 for OA and 0.68 for the Kappa index when integrated with the PBIA approach.

The RF-PBIA approach, having obtained the best classification results, was used to extract the 2022 shoreline. The figure below provides a spatial visualization of the classification results along with its confusion matrices, which illustrate the performance of each classification model across four classes: water, sand, vegetation, and urban. Each cell represents the number of predicted instances for a given class compared to the actual class (Fig. 12).

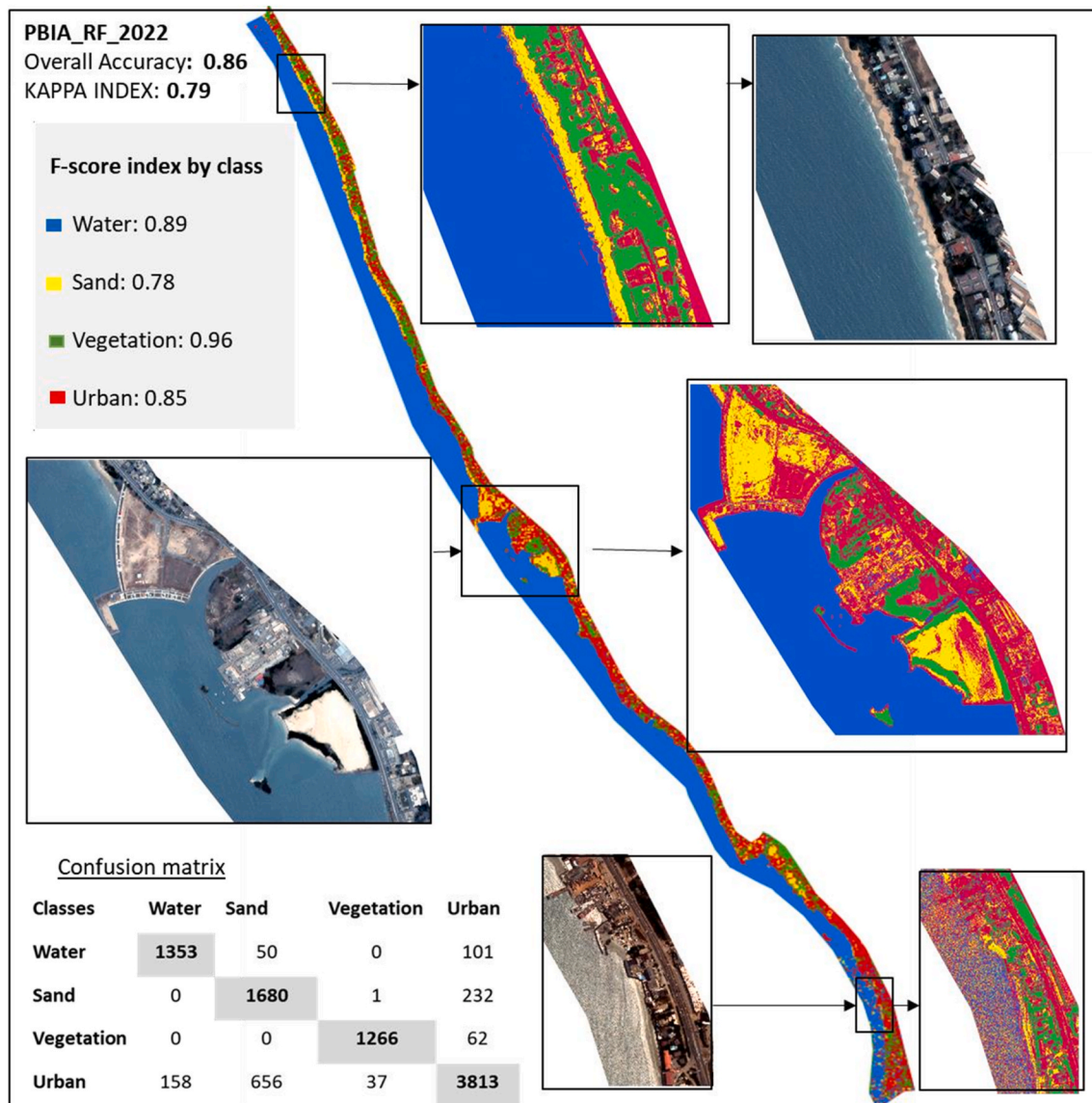


Fig. 12. Automatic Detection of shoreline Pleiades stereo 2022 via RF-PBIA

This figure shows the results of the classification of the study area. The classification enables the identification of different land use classes. Four classes were identified: water (blue), sand (yellow), vegetation (green), and urban areas (red). The Overall Accuracy (OA), Kappa index, and class-wise F-score are also presented. The accompanying table displays the confusion matrix. In a confusion matrix, the columns represent the predicted values for each class, while the rows correspond to the actual values (i.e., ground truth) per class. This grid-based structure provides a practical tool for visualizing model classification accuracy, as it displays the number of correct and incorrect predictions for each class.

The classification prediction of the 2022 Pleiades Stereo image using the PBIA-RF approach proves to be the most relevant for shoreline detection, as the class-specific prediction rates are generally above 0.8. This approach enabled the identification of the “Water” class with 89% accuracy, the “Sand” class with 78%, the “Vegetation” class with 96%, and the “Urban” class with 85%. It appears that the PBIA-RF approach is particularly sensitive to the detection of objects related to urban areas, water bodies, and vegetation.

Although the overall classification is satisfactory, some class confusions persist. The confusion matrix reveals that each class contains misclassified pixels, with the most significant confusion occurring between the “Urban” and “Sand” classes. It appears that 656 pixels belonging to the “Urban” class were misclassified as “Sand.” This confusion can be attributed to the spectral reflectance similarity between bare soil often present in urban areas and dry or wet sand typically found on beaches.

Regarding shoreline detection from the 2024 Pleiades Tri-stereo

image, the CNN-OBIA and RF-PBIA approaches demonstrate satisfactory accuracies. However, the CNN-OBIA approach exhibits significantly higher performance, with an overall accuracy of 0.97 and a Kappa index of 0.95, clearly outperforming the PBIA-RF approach (OA: 0.89; Kappa: 0.85). The confusion matrix reveals an almost perfect classification of the land cover classes (Fig. 13).

The F-score indices, which represent the classification precision for each class, are all above 0.90. The “Water” and “Vegetation” classes are the most accurately classified, with respective precision rates of 1 and 0.98. Minor confusions are observed between the “Urban” class and other land cover classes.

While the CNN-OBIA approach proved to be the most robust for shoreline detection from the 2024 Pleiades Tri-stereo image, it is important to highlight that, overall, the PBIA-RF approach achieved satisfactory classification results across most of the spatio-temporal series analyzed. In contrast, the OBIA-RF and OBIA-SVM approaches showed the weakest performance, both with an overall accuracy of 0.72,

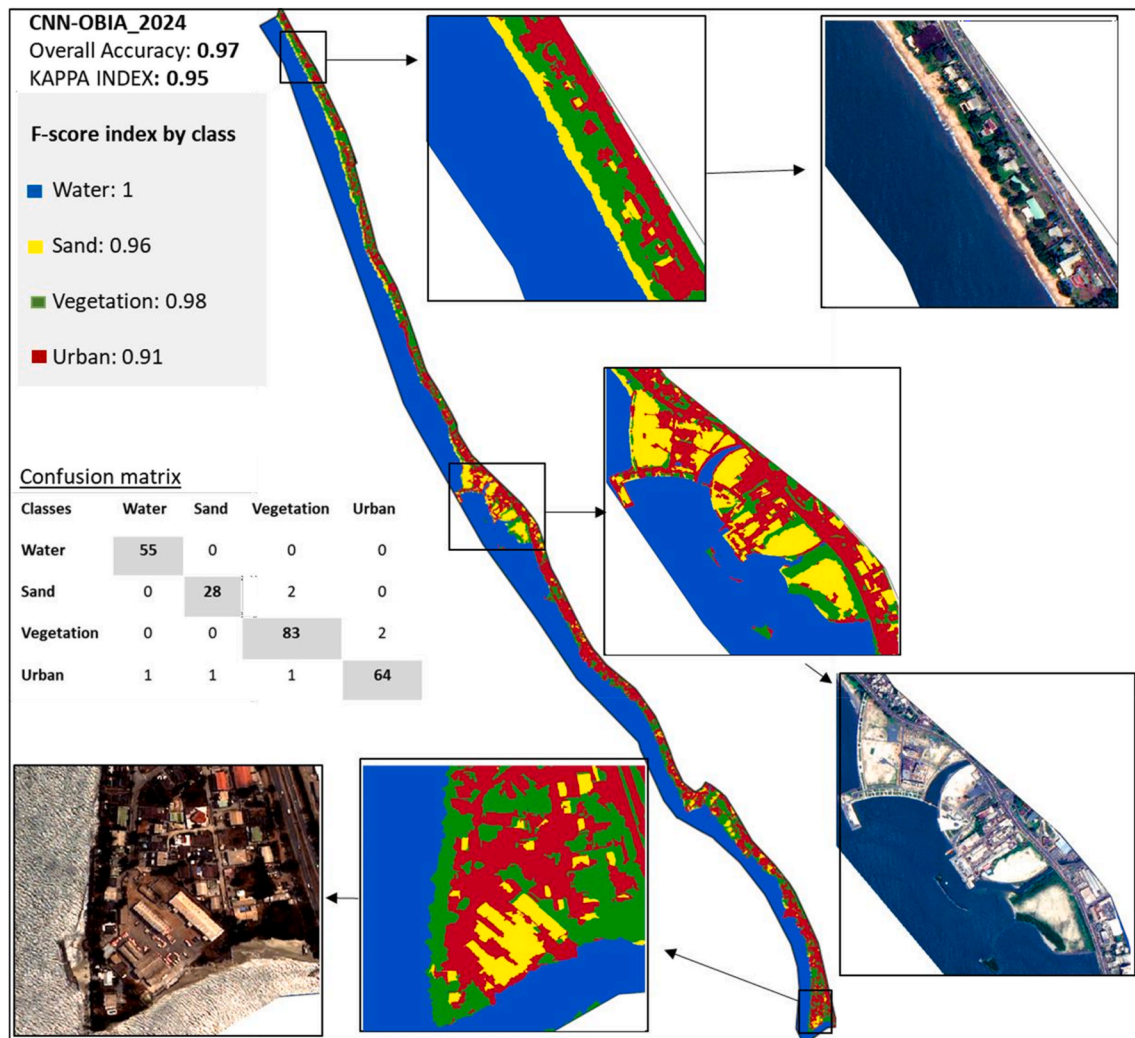


Fig. 13. Automatic Detection of shoreline of Pleiades images tri-stereo 2024 via CNN-OBIA

This figure shows the results of the classification of the study area. The classification enables the identification of different land use classes. Four classes were identified: water (blue), sand (yellow), vegetation (green), and urban areas (red). The Overall Accuracy (OA), Kappa index, and class-wise F-score are also presented. The accompanying table displays the confusion matrix. In a confusion matrix, the columns represent the predicted values for each class, while the rows correspond to the actual values (i.e., ground truth) per class. This grid-based structure provides a practical tool for visualizing model classification accuracy, as it displays the number of correct and incorrect predictions for each class.

but with Kappa indices of 0.63 and 0.60, respectively.

The various approaches presented were generally effective for detecting shorelines in our satellite data, with the exception of the panchromatic aerial image from 2003. This image did not yield satisfactory results in predicting the different classes. Therefore, the automatic shoreline extraction was performed based on the prediction results from the RF-PBIA approach on Pleiades stereo image (2022) and the CNN-OBIA approach to Pleiades tri-stereo image (2024).

4.2. Extraction of shoreline features (2003, 2022 and 2024)

Due to the low classification accuracy rates of the 2003 aerial image, the extraction of the shoreline was not feasible. As a result, manual digitization of the shoreline was required. This task was performed using the software QGIS 3.37.7.

4.2.1. Automatic extraction of shoreline by using AI algorithms (ML and DL) from Pleiades images stereo (2022) and tri-stereo (2024)

The extracted shorelines each extend approximately 25 km (Figs. 14 and 15). After extraction, it was observed that they exhibited discontinuities. Therefore, manual digitization was necessary for the shoreline

segments that could not be automatically extracted. Consequently, the 2022 shoreline was automatically extracted for 61% of its length, while the remaining 39% required manual digitization. In contrast, the 2024 shoreline was extracted almost entirely, with only 13% of its length requiring manual digitization.

After extracting the shorelines using the PBIA-RF approach for the year 2022 and the CNN-OBIA approach for the year 2024, a classification step was carried out. This step aimed to identify the nature of shorelines indicators and to assess their representativeness (Figs. 16 and 18) within the overall extracted shoreline extent.

It was observed that the 2022 shoreline is composed of the three reference features mentioned earlier. The “vegetation line” accounts for 52% of the shoreline, followed by the “landward edge of shore protection structure” at 46%, and the “instantaneous water line” at 2% (Fig. 16). A similar distribution is observed for the 2024 shoreline, where the “vegetation line” and the “landward edge of shore protection structure” are equally represented, each accounting for 49%, while the “instantaneous water line” also constitutes 2% of the total length (Fig. 17).



Fig. 14. Classification of Libreville shoreline in 2022 based on non-automatic and automatic extraction

This figure presents an image of the shoreline extracted by Pleiades image 2022. Automatically extracted sectors are shown in green, while non-automatically extracted sectors are shown in red. The accompanying graph and table display the percentage of shoreline extracted automatically versus manually.

4.2.1.1. Accuracy of automatic coastline extraction (distance calculation) in 2022. The comparison between the automatically extracted shoreline and the *in situ* shoreline is presented in Table 2. The first row on this figure represents the position of the *in situ* shoreline. The second line corresponds to the position of a segment of the shoreline automatically in relation to the *in situ* shoreline.

Using the DSAS (processed in ArcGIS software), the accuracy of the shoreline generated from the PBIA-RF method (based on the 2022 Pleiades image) was assessed in relation to the *in situ* shoreline.

The approach involved selecting a segment of the automatically extracted shoreline and comparing it to the position of the shoreline collected simultaneously *in situ* for the same area. Both shorelines

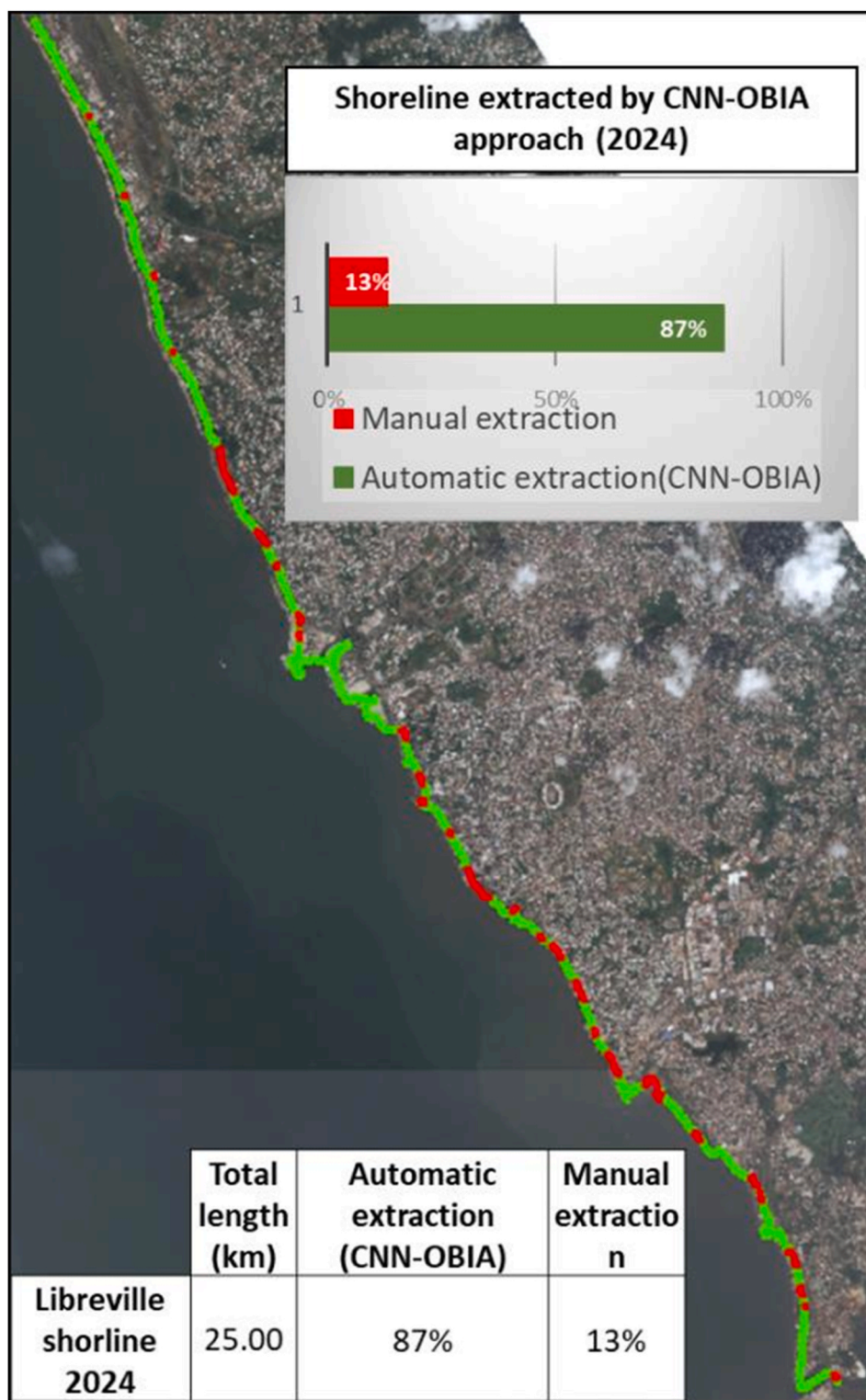


Fig. 15. Classification of Libreville shoreline in 2024 based on non-automatic and automatic extraction

This figure presents an image of the shoreline extracted by Pleiades image 2024. Automatically extracted sectors are shown in green, while non-automatically extracted sectors are shown in red. The accompanying graph and table display the percentage of shoreline extracted automatically versus manually.

correspond to the vegetation line. It is observed that the distances between the *in situ* shoreline and the shoreline derived from the RF-PBIA approach are reasonable, demonstrating the relevance of the method. The overall accuracy of this approach is 1,88 m.

4.3. Dynamics of the Libreville shoreline (2003-2024)

After conducting a performance comparison of classification approaches, including PBIA (Random Forest and SVM), OBIA (RF and SVM), and CNN-OBIA, on two Pleiades images (stereo and tri-stereo) of our study area from 2022 to 2024, two shorelines were detected and

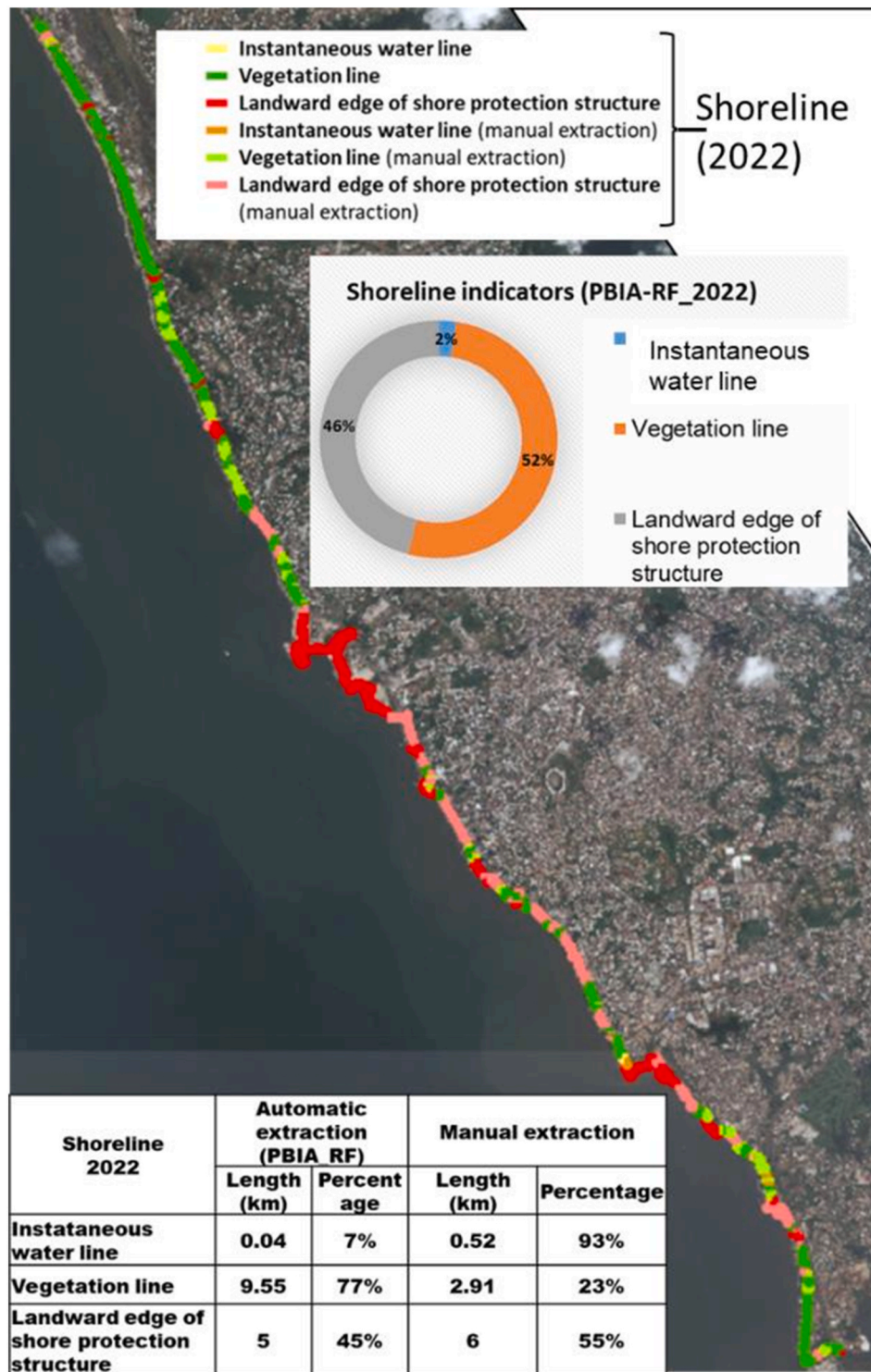


Fig. 16. Classification of the Libreville shoreline indicators in 2022

This figure presents an image illustrating the indicators used to extract the 2022 shoreline. The accompanying graph and table show the percentage distribution of these shoreline indicators.

semi-automatically extracted for diachronic analysis. This diachronic study was analyzed using the End Point Rate (EPR) index over a global period from 2003 to 2024, which was further divided into two sub-periods (2003-2022 and 2022-2024). Particular emphasis was placed on analyzing trends based on erosion and accretion rates.

4.3.1. Key trends for the period 2003-2022

The spatial dynamics of the Libreville shoreline over the period

2003-2022 are illustrated in Fig. 18-a, along with a graph providing an overview of shoreline evolution based on transects (Fig. 18-b).

Three thousand one hundred fifty-seven (3137) transects, spaced 5 m apart, were generated for the statistical analysis of shoreline evolution. The results revealed that the shoreline exhibits an erosional trend at 53%, compared to 47% accretion. However, the average shoreline evolution rate is 0.87 m/year. Erosion rates range from -0.01 m/year to -2.86 m/year, while accretion rates range from 0.01 m/year to

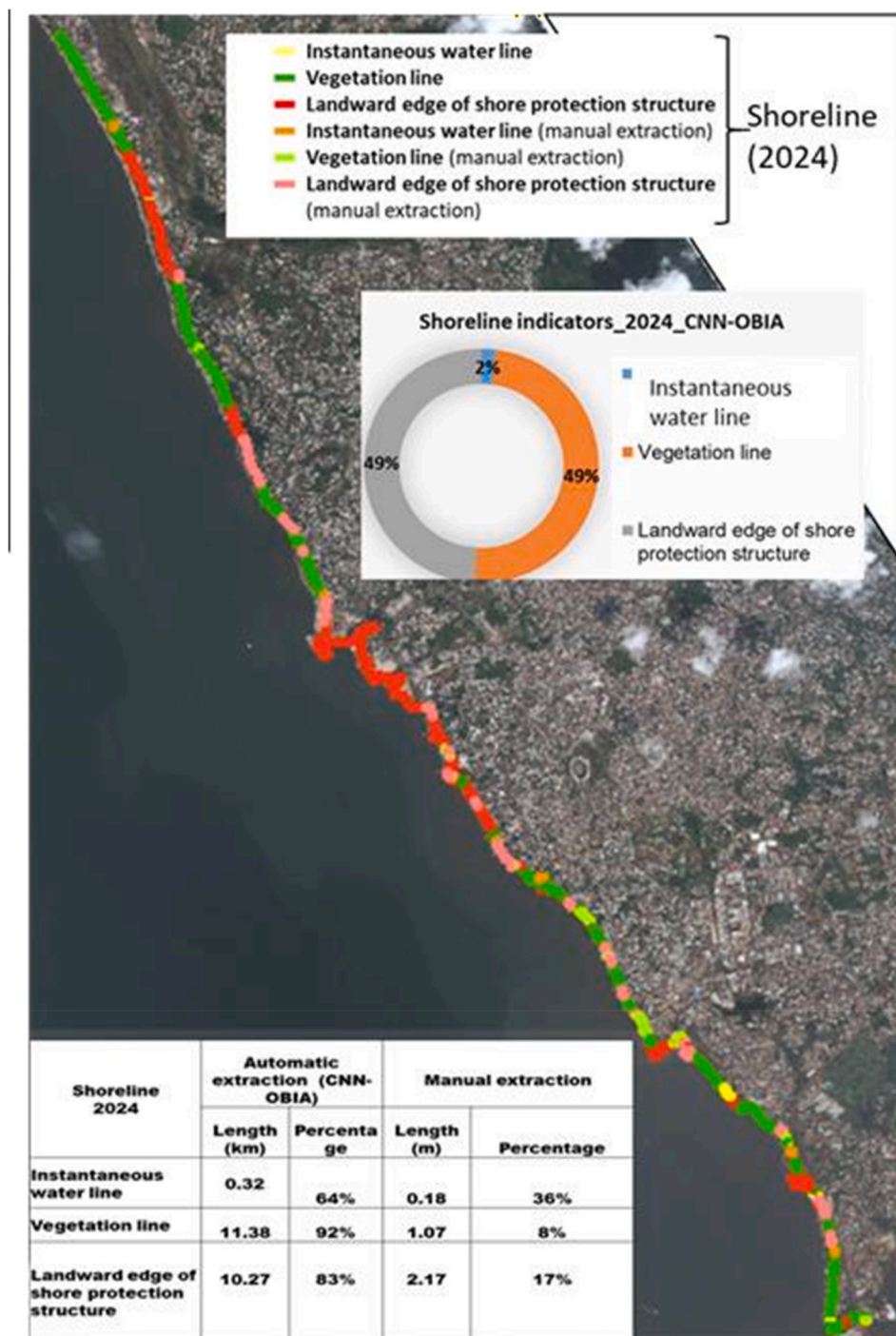


Fig. 17. Classification of the Libreville shoreline indicators in 2024

This figure presents an image illustrating the indicators used to extract the 2024 shoreline. The accompanying graph and table show the percentage distribution of these shoreline indicators.

21.66 m/year. Additionally, it was observed that 4.72% of all transects exhibit statistically significant erosion. These are predominantly located in the southern part of Libreville, particularly on the right bank of the outlet of the “Lowé” River. On the other hand, a significant proportion of transects show statistically significant accretion, accounting for 17%. Some areas experience dramatic advancement, reaching up to 21,66 m/yr. These areas primarily include a segment of the Lycée Léon Mba beach, the “Baie des Rois” area, the Michel Marine marina zone, and another sector in the southern part of Libreville, which is a port area (Port d’ACAE).

4.3.1.1. Significant erosion sectors for the period 2003–2022. The erosion phenomenon is noticeable along nearly the entire coastal stretch. However, three specific areas stand out with particularly high erosion rates, significantly exceeding the observed average.

The first sector is located a few hundred meters south of «CAPAL», with erosion rates ranging from -2.12 m/yr to -2.27 m/yr. The presence of rock armoring at the site since 2003 highlights the intense erosion activity affecting this coastal sector (Figs. 19–1). Further south of this sector, another area is characterized by high erosion rates: the coastline of the Port of ACAE (Figs. 19–2). Erosion rates vary from

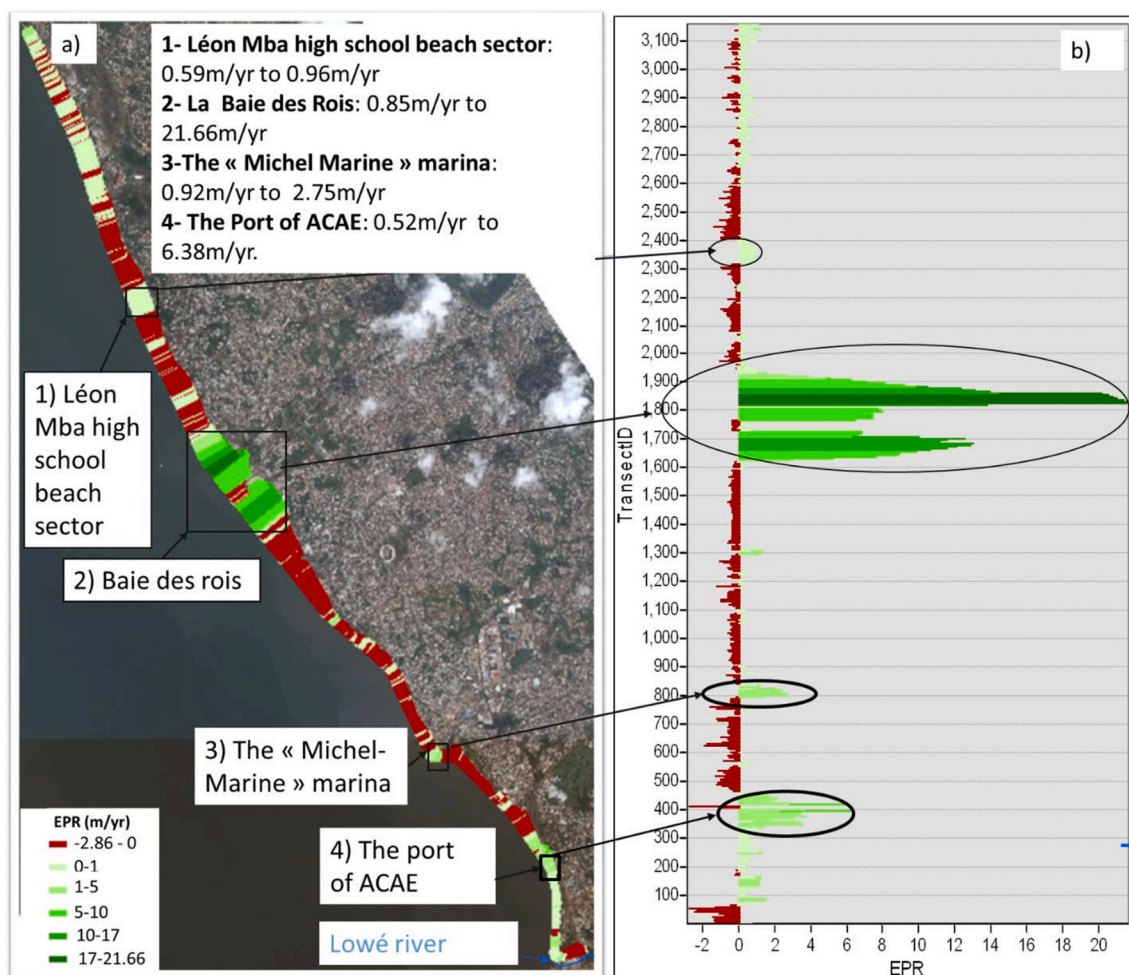


Fig. 18. Trends of Coastal dynamics (Accretion and Erosion) of Libreville between 2003 and 2022; a) Map evolution of the Libreville shoreline between 2003 and 2022; b) Graph of the End Point Rate (EPR) for Libreville shoreline between 2003 and 2022.

Table 2

Extract of calculated distances between *in situ* shoreline and automatically extracted shoreline (PBIA-RF, 2022).

In situ shoreline	P1	P2	P3	P4	P5	P6	P7	P8
Shoreline automatically extracted	1.74	1.41	1.29	1.6	1.83	2.98	2.54	1.86

P1 ... P8: Each bold point in the first row of the table represents an *in situ* measured shoreline position *in situ*. The values in the second row correspond to the distances between these *in situ* reference points and the shoreline automatically extracted from the Pleiades image.

−1.63 m/yr to −1.85 m/yr. These rates were recorded in a dock area. In fact, these rates can be explained by the fact that the digitization of the shoreline on the 2003 image was partially based on a landing infrastructure. However, by 2022, this infrastructure (pontoons or ships) had been relocated, hence the negative evolution. In reality, this does not represent actual land erosion but rather the displacement of an infrastructure. This raises questions about the inclusion of port infrastructure in the definition of the shoreline.

Additionally, the area located at the mouth of the Lowé River, on its right bank, records erosion rates peaking at −2.86 m/year (Figs. 19–3). The most significant erosional dynamics are concentrated in a zone corresponding to a former landing structure, which has since disappeared. Two main factors may account for this disappearance:

anthropogenic activity and fluvial erosion.

From an anthropogenic perspective, it appears that in 2003, the area in question belonged to a maritime transit and stevedoring company. It is therefore likely that the structures identified in the 2003 imagery and used for shoreline digitization were floating pontoons. Their temporary and mobile nature could explain their absence in the 2022 imagery.

Furthermore, natural erosion processes may have also contributed to the retreat of the shoreline in this sector. Indeed, the meandering channel of the Lowé River locally intensifies erosion, particularly along concave banks. It is well established that fluvial erosion is generally more pronounced near river mouths. In a meander, the current erodes the concave bank while depositing sediments on the convex bank, a process that may explain the current shoreline dynamics in this area, which corresponds to a convex bank.

4.3.1.2. Significant accretion sectors for the period 2003–2022. During the 2003–2022 period, several coastal sectors experienced accretion. However, only the four sectors with the highest accretion rates will be presented below. These include: the sector located along Lycée Léon Mba Beach (22; 1), the Baie des Rois sector (22; 2), the Michel Marine marina sector (22; 3), and (22; 4) the ACAE port sector.

The accretion sector located along Lycée Léon Mba Beach is between the 2323rd and 2373rd transects, the accretion rates range from 0.59 m/yr to 0.96 m/yr. It appears that this shoreline morphology primarily to anthropogenic activities. In 1970s, a groin made of lateritic rock blocks was built which is the immediate cause of the modification of the

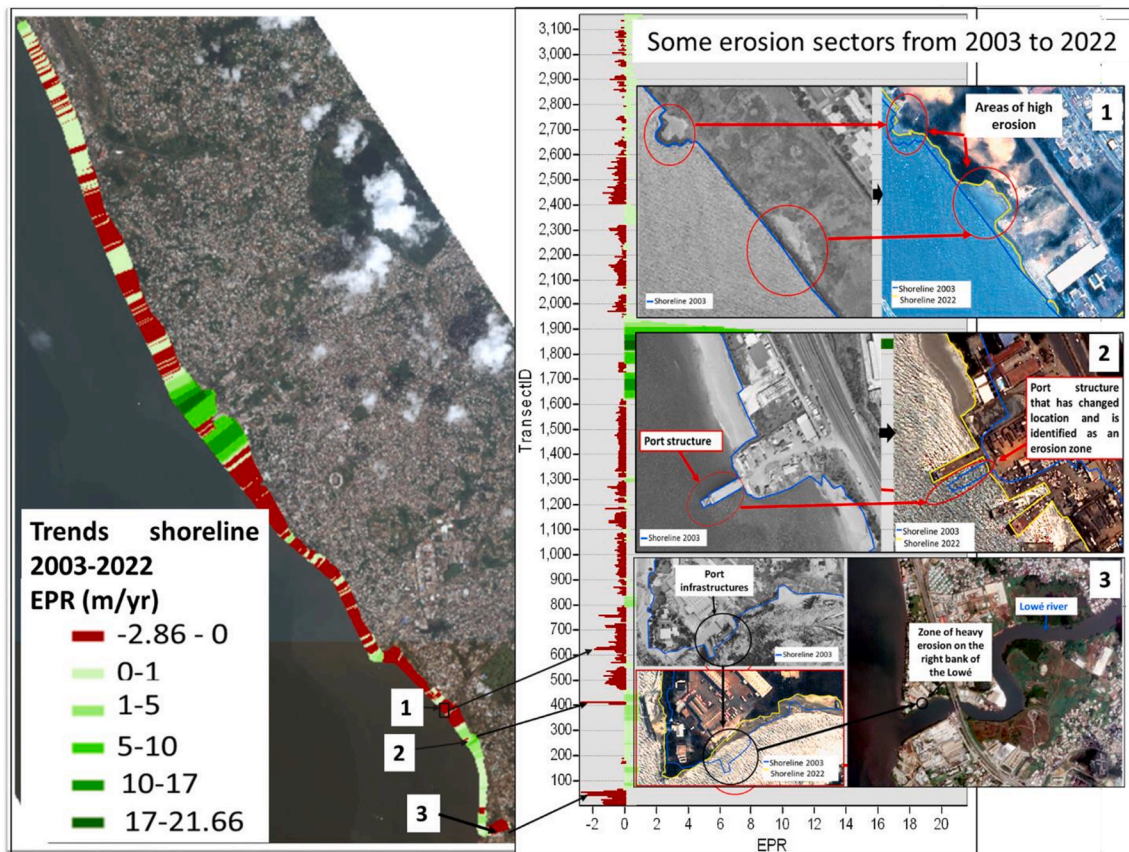


Fig. 19. Significant erosion sectors for the period 2003–2022

1) The sector between the 625th and 632nd transects; 2) the ACAE Port; 3) The sector between the 5th and 63rd transects.

morpho-sedimentary landscape. Indeed, the groin interrupts sediment transport along the intertidal beach, to the detriment of the downstream area, where the disappearance of sandy beaches has given way to the rocky foreshore of the Sibang formation dating from the Turonian period. This phenomenon has also been highlighted by Moyalou (Mouyalou, 2017). Additionally, it could be hypothesized that the demolition works of the hotel complex may have led to backfilling activities, which could have contributed to gaining a few meters of land. In addition, other coastal sectors, such as the Baie des Rois, exhibiting similar accretion patterns have also been identified further south of this area.

The Baie des Rois sector is bounded by the 1625th and 1945th transects, with rates ranging from 0.85 m/yr to 21.66 m/yr. Similarly, the rapid advancement of land towards the sea in the Baie des Rois area is attributed to sea filling or poldering activities. These activities are part of a project initiated by the Gabonese government, with the primary objective of creating a business and leisure center. The project was launched in 2013 under the name “Champ Triomphal Port-Môle” and was later revised on September 18, 2017, under the new name “Baie des Rois”. Further south, the Michel Marine marina sector also stands out for its significant accretion rates.

The marina Michel Marine sector Located between the 800th and 840th transects show rates varying from 0.92 m/yr to 2.75 m/yr. The accretion in the “Michel Marine” sector (the marina) results from backfilling works aimed at expanding the activity zone (boat parking). This sector serves as a marina for pleasure boats.

Finally, the ACAE's port sector, located between the 327th and 453rd transects, with rates ranging from 0.52 m/yr to 6.38 m/yr. The Acaé port area in the south has also undergone poldering activities to expand the port zone. Several structures have emerged in this sector, including the Hotel Boulevard d'ACEA.

Ultimately, the average rate for the period 2003–2022, which is positive (0.87 m/year), suggests a generalized trend of accretion along the Libreville shoreline. However, this is not entirely accurate when considering the shoreline dynamics mapping in (Fig. 20) the statistical calculations. The mapping shows a spatial distribution that is quite representative of erosion (from the north to the south of Libreville), while the areas of strong accretion correspond to zones with port activities (Michel Marine and the Port of Acaé) or leisure and business centers (Baie des Rois). The shoreline is 52% marked by erosion, with 4.72% experiencing severe erosion reaching up to -2.86 m/year (outlet of the Lowé River). Several construction projects were carried out along the shoreline between 2003 and 2022, significantly altering the morphology of the shoreline in central Libreville.

4.3.2. Main temporal trends observed over the 2022-2024

The figure below primarily illustrates the spatio-temporal evolution trends of the Libreville shoreline during the period 2022-2024 (Fig. 21, a) and a graph (Fig. 21, b) that provides an overview of the shoreline evolution based on transects. It is observed that 58% (1802 transects) of the transects exhibited erosion rates, while 42% (1309 transects) exhibit accretion rates. The average rate of shoreline evolution in Libreville from 2022 to 2024 is -0.32 m/yr, compared to 0.87 m/yr for the period 2003-2022. This suggests a regressive trend of the shoreline overall. The transects show erosion rates ranging from -0.01 m/yr to -51.27 m/yr, while those with accretion vary from 0.01 m/yr to 52.35 m/yr. The areas experiencing erosion are retreating at an average rate of -1.83 m/yr, which is significantly higher than during the previous period (-0.36 m/yr from 2003 to 2022). Only 1.83% of the transects show statistically significant erosion, suggesting that erosion is more intense in certain areas or sectors. However, the shoreline as a whole is experiencing moderate erosion. The areas most affected by erosion are located in the

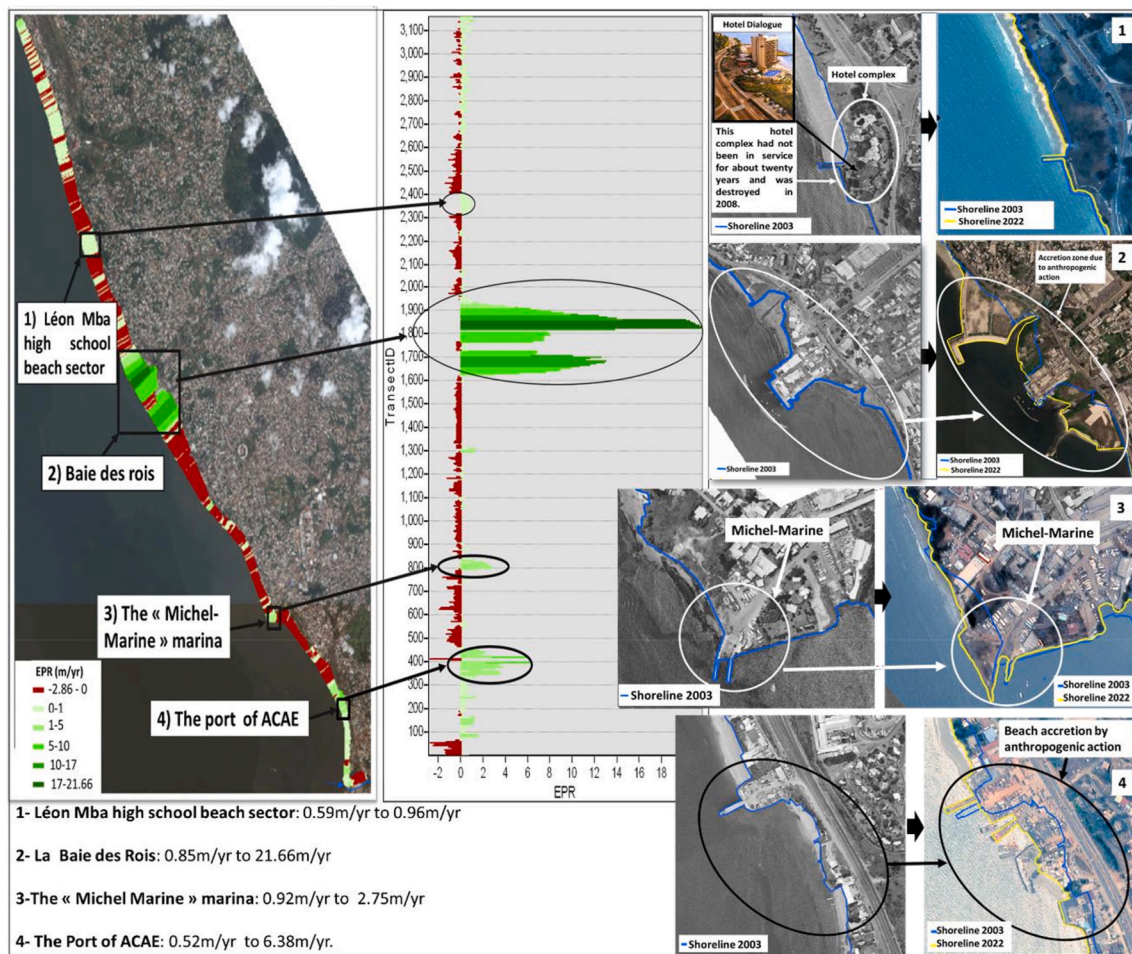


Fig. 20. Significant accretion sectors for the period 2003–2022

1) Accretion sector on the beach of Lycée Léon Mba during the period 2003 to 2022; 2) Accretion in the current Baie des Rois: Poldering of the coastline between 2003 and 2022; 3) Marine backfilling and rock armouring work was carried out along the Michel Marine marina shoreline between 2003 and 2022; 4) Sea filling of and development of the ACAE port area.

Baie des Rois (Polder) area and south of Libreville (port area). Additionally, a small proportion of transects (1.19%) exhibit significant accretion rates. Overall, transects with accretion show an evolutionary trend of 1.99 m/year.

4.3.20.1. Significant erosion sectors for the period 2022–2024. While erosion zones occur sporadically along the general shoreline, two specific areas show significantly more pronounced erosion compared to others.

The Baie des Rois's sector the affected sector spans transects 1661 to 1705 (with erosion rates ranging from -6.19 m/yr to -15.78 m/yr). This zone comprises an artificial beach segment where the installed rock armor has proven ineffective in mitigating marine erosion (Figs. 22–1).

The other sector also touched by intensive erosion is located on ACAE's port. This port zone includes sectors subjected to exceptionally high coastal erosion rates, with substantial variability observed across the studied transects. The most severely affected stretch extends from transect 10 to transect 445, where erosion rates range from 7.82 m/year to 51.27 m/year. A particularly critical zone is located between transects 396 and 397, with extreme erosion rates of -50.91 m/year and -51.27 m/year, respectively. In this sector, shoreline delineation was based on the « landward edge of shoreline protection structures », particularly mobile port infrastructure such as piers or vessels that were periodically relocated over time (Figs. 22–2).

4.3.20.2. Significant accretion sectors for the period 2022–2024. Between 2022 and 2024, multiple sectors experienced significant accretion. Among these, four areas exhibiting the highest accretion rates will be highlighted: the Baie des Rois shoreline (Figs. 23–1), the Michel Marine sector and its vicinity (Figs. 23–2), the CAPAL coastline sector (Figs. 23–3), and a sector along the Port of ACAE coastline (Figs. 23–4).

This first zone, the Baie des Rois is shoreline marked by both areas of strong accretion and erosion. Regarding accretion, three zones were identified. The first zone is delimited by the 1781th and 1784th transects (with rates ranging from 6.5 m/year to 8.96 m/year). This accretion is due to the development of walking paths. In the 2022 image, it is evident that a portion of land had already been eroded by coastal erosion (due to weather-marine agents) in the absence of solid infrastructure. A few dozen meters further south, the second zone, a port area (Port Môle), is experiencing strong accretion. This sector is delimited by transects 1763 and 1765, which show rates of 18.3 m/year and 19 m/year, respectively. This evolution is explained by the port nature of the site and the element considered during the digitization of the shoreline. Specifically, the shoreline was extracted based on a dock or a ship. Finally, the third zone, located further south of the previous one (defined between the 1607th and 1615th transects), has rates ranging from 4.73 m/year to 8.96 m/year. This area features an artificial beach (polder).

The second sector, the Michel Marine shoreline is marked by an accretion rate of 12.62 m/yr (Figs. 23–3). This significant accretion is explained by the extension of a rocky groin. This structure reduces erosion by dissipating wave energy, promoting sediment accumulation

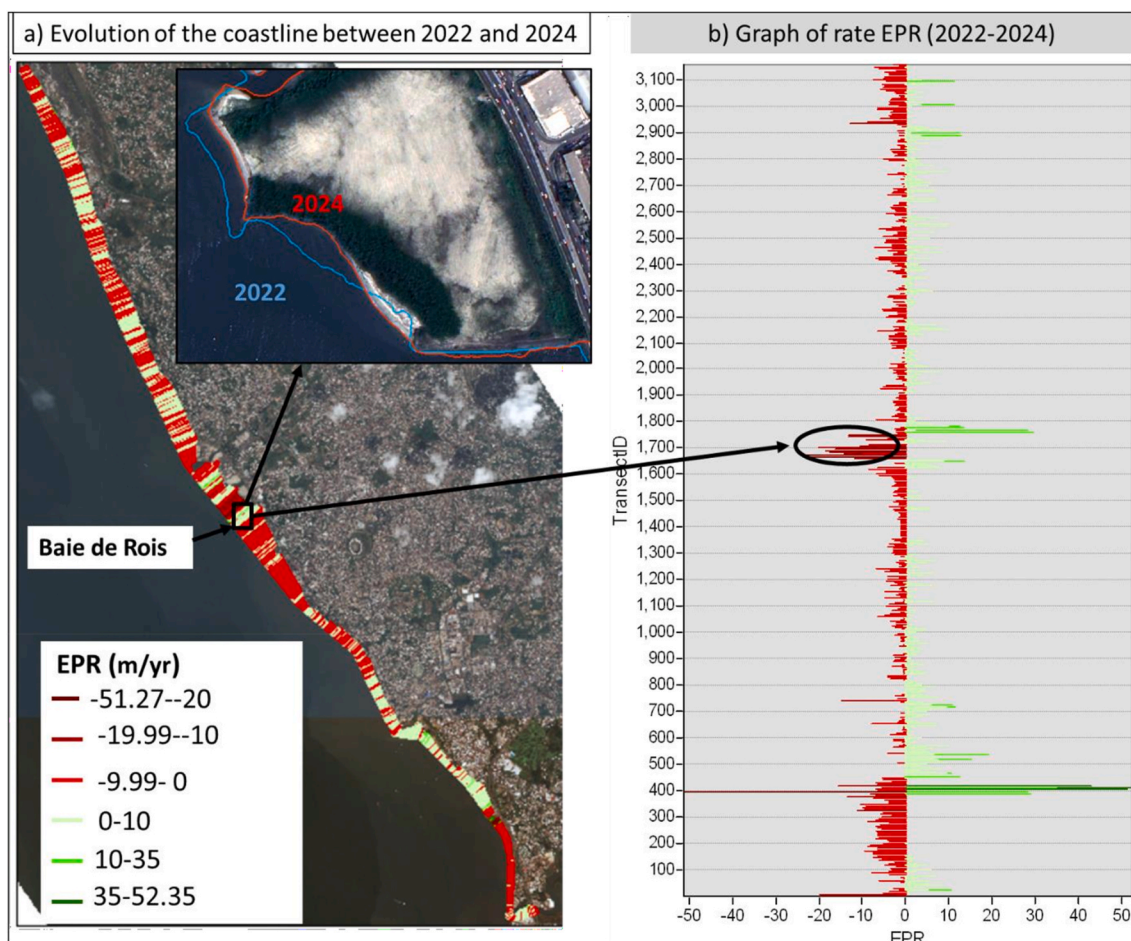


Fig. 21. Shoreline dynamics of Libreville from 2022 to 2024

a) Evolution of the shoreline of Libreville between 2022 and 2024; b) Graph of the EPR (End Point Rate) of Libreville between 2022 and 2024.

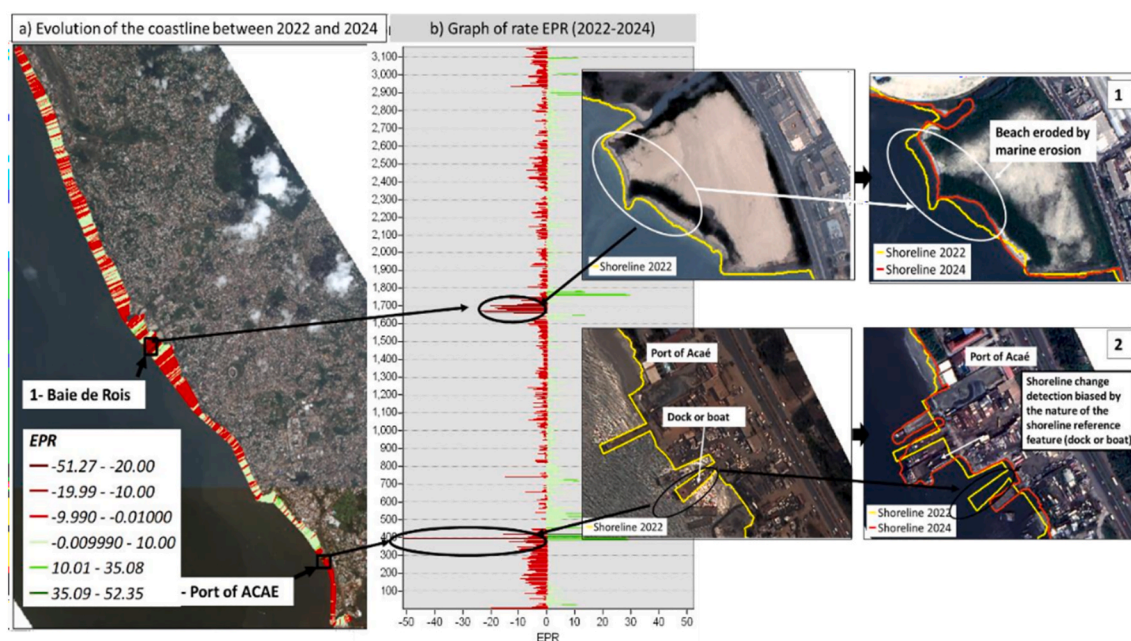


Fig. 22. Intensive erosion of a coastal beach in Baie des Rois between 2022 and 2024.

on the beach upstream of the groin. However, it can also lead to increased erosion downstream.

The third sector is located a few tens of meters from Michel Marine (between the 701th and 714th transects). This sector corresponds to the

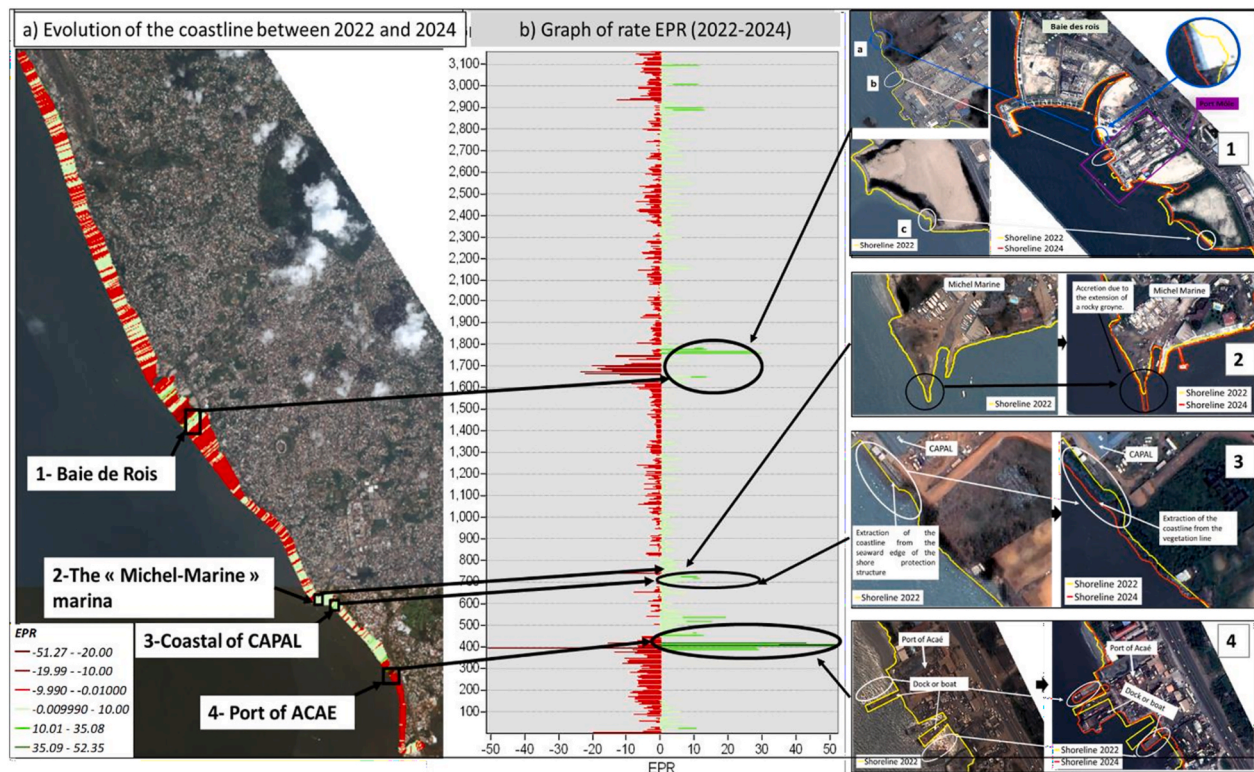


Fig. 23. Intensive accretion of coastal beach in Baie des Rois between 2022 and 2024

1) Intensive erosion of a coastal beach in Baie des Rois between 2022 and 2024; 1-a and 1-c) Accretion resulting to sea filling between 2022 and 2024; 1-b) Bias in accretion detection caused by errors in the reference shoreline; 2) Bias in erosion detection caused by errors in the reference shoreline; 2 and 4) Accretion due from the construction of a coastal erosion protection structure; 3) Bias in accretion detection due to variation in the reference shoreline between 2022 and 2024.

shoreline of the Centre d'Appui de la Pêche Artisanale de Libreville (CAPAL) (Support Center for Artisanal Fishing in Libreville). The measured accretion rates range between 5.49 m/year and 7.35 m/year. The shoreline extraction from the 2022 Pleiades imagery was performed using the "landward edge of shore protection structure" indicator. However, on the 2024 Pleiades imagery, the emergence of vegetation upstream of the infrastructure necessitated a change in indicator, leading to the use of the "vegetation line" for this year. In reality, the shoreline position has not undergone any change. Indeed, the apparent variation primarily results from the change in the shoreline indicator over the same area between two different dates. This observation underscores the importance of standardizing indicator selection in coastal dynamics analysis.

The last sector is located on the ACAE port shoreline. The areas marked by accretion are defined by transects 392 to 394 (with rates ranging from 18.83 m/yr to 19.51 m/yr), transects 409 to 414 (with rates varying between 26.41 m/yr and 35.51 m/yr), and finally, transects 420 and 421, which show respective rates of 28.93 m/yr and 28.8 m/yr.

In all cases, the positive evolution of these sectors is explained by land use (presence of port infrastructure) and the nature of the selected indicator (landward edge of shore protection). Since this is a port area, the extracted shorelines (2022 and 2024) accounted for mobile infrastructure, leading to highly significant positional changes. Thus, the shoreline dynamics were biased by the inclusion of port infrastructure (pontoons or ships) as shoreline indicator objects, rather than reflecting natural geomorphological processes.

5. Discussion

5.1. The shoreline detection analysis

This study initially explores the potential of very high-resolution (VHR) satellite imagery for the automated detection of the Libreville's shoreline, using ML and DL methods, respectively.

The proposed methodology applied PBIA, OBIA, pixel-based CNN and CNN-OBIA approaches, first on a 2003 panchromatic aerial photograph, then on two Pleiades images (stereo and tri-stereo) from 2022 to 2024, respectively, for automatic shoreline detection.

To this end, the robustness of the ML approaches (PBIA-RF, OBIA-RF, OBIA-SVM) was tested and compared, alongside the DL based on pixel-based CNN model and CNN-OBIA approach. The land cover classes targeted in this classification included: "water", "sand", "vegetation", and "urban". The objective was to determine the most effective classification approach for each image in order to use it for shoreline extraction and subsequently analyze shoreline dynamics. Validation of the extracted shorelines was carried out using an *insitu* shoreline collected on the same day as the Pleiades image acquisition (August 21, 2022), using a DGPS.

Finally, a diachronic analysis of the shoreline from 2003 to 2024 was conducted based on the three extracted shorelines. This period was divided into two sub-periods: 2003-2022 and 2022-2024.

The classification results from the 2003 panchromatic aerial image were generally inconclusive for shoreline detection. However, the PBIA-RF approach emerged as the most relevant among all tested methods, with overall accuracy (OA) and Kappa index scores of 63% and 51%, respectively.

Moreover, for the LULC classification of the 2022 Pleiades stereo image, the PBIA-RF method again delivered the highest accuracy, achieving 86% OA and a Kappa index of 79%, consistent with ground

truth data. These results contradict Boussetta and al. (Boussetta et al., 2023), who argued that the OBIA-RF approach offers a better recognition of terrestrial objects compared to PBIA-RF.

However, results for the classification of the same image also showed that OBIA-RF was more robust (81% OA; 73% Kappa) than CNN-OBIA (68% OA; 58% Kappa), aligning with Boussetta et al. (2023), who concluded that OBIA-RF outperforms CNN-OBIA and achieves higher classification accuracy coastal areas in the Mediterranean environment.

On the other hand, for the classification of the 2024 Pleiades tri-stereo image, the CNN-OBIA approach proved to be the most effective for shoreline detection, achieving a land cover classification accuracy of 97% (OA). This result is consistent with the study by Zaabar et al. (2021), which demonstrated that CNN combined with OBIA, applied to Sentinel-2 spectral data, is the most efficient method for detecting various land-use classes, outperforming OBIA-RF in terms of OA in the context of semi-arid areas in the Mediterranean environment.

The PBIA-RF approach also achieved satisfactory classification scores, though still trailing CNN-OBIA by less than 10%. Considering the classification scores of each approach for each image (particularly the Pleiades images), PBIA-RF achieved the highest Land Cover classification accuracy: 86% (Pleiades stereo, 2022) and 89% (Pleiades tri-stereo, 2024). The OBIA approach followed, with 81% accuracy for the 2022 Pleiades image and 80% for the 2024 image both trailing behind PBIA-RF and CNN-OBIA.

Lastly, CNN-OBIA demonstrated superior land cover classification performance compared to all ML-based approaches when applied to the 2024 Pleiades tri-stereo image, achieving 97% OA compared to 68% for the 2022 image.

Based on these classification performance results from the various ML and DL approaches, it can be concluded that: ML-based approaches (PBIA-RF, OBIA-RF) are more suitable for detecting and classifying LULC in VHR multispectral Pleiades stereo imagery; CNN-OBIA is the most appropriate method for classifying LULC classes in Pleiades tri-stereo imagery, with a classification accuracy of 97%. Given these differences in performance, it was logical to extract shorelines using the classification results from the highest-performing methods: PBIA-RF for the 2022 Pleiades stereo image and CNN-OBIA for the 2024 Pleiades tri-stereo image.

Furthermore, considering the less conclusive classification results from both ML and DL approaches on the 2003 aerial image, it can be inferred that shoreline detection and extraction techniques vary according to the characteristics and quality of the image being processed. Each data type requires an appropriate methodological approach.

5.2. Automatic shoreline extraction

Automatic shoreline extraction involves more image processing steps than the traditional manual digitization approach (photo-interpretation). Although the manual method requires fewer steps, classification-based detection remains faster (Aleman et al., 2019).

Following the classification stage of our Pleiades stereo and tri-stereo imagery, the next step was to extract the shorelines for the years 2022 and 2024. Given that our study area is mainly characterized by low-elevation sandy beaches, highly urbanized zones, and a consistently representative vegetative cover along the coastline, it was appropriate to classify the satellite imagery into the following land cover classes: *water*, *sand*, *vegetation*, and *urban*. From these classes, we derived specific shoreline indicators: the *instantaneous water line* for the *water* class, the *vegetation line* for the *vegetation* class, and the *landward edge of shore protection structures* for the *urban* class.

These indicators are among those described by McAllister et al. (2022) in Section 2 of their study as visually discernible features that can be detected using conventional photography and multispectral imagery.

The effectiveness of automatic shoreline extracted depends on the accuracy of satellite image classification. For example, in the 2022

Pleiades stereo image, with an overall classification accuracy of 86% (PBIA-RF), the shoreline was extracted 61% automatically and 39% manually. In contrast, the 2024 Pleiades tri-stereo image, with an overall classification accuracy of 97% (CNN-OBIA), allowed for 87% of the shoreline to be extracted automatically, with only 13% requiring manual digitization. Since the shoreline features occasionally suffered from discontinuities due to classification errors, manual digitization was necessary to obtain a continuous delineation.

Furthermore, the accuracy of the shoreline extracted from the 2022 image was assessed at 1.88 m when compared to field data. The section evaluated on this shoreline corresponds to the indicator *landward edge of shore protection structures*, which was extracted automatically.

5.3. Diachronic analysis of the shoreline of Libreville from 2022 to 2024

The analysis of shoreline dynamics in Libreville is based on shoreline positions from 2003 (manually extracted), and 2022 and 2024 (semi-automatically extracted). To enable a more detailed assessment, the analysis was structured into two periods: 2003–2022 and 2022–2024. Quantitative evaluation was carried out by calculating the distances between the shoreline positions for each period using the DSAS (Thieler et al., 2009). The results presented in Figs. 18 and 21 are derived from the EPR, which expresses shoreline change trends in meters per year (m/year).

It was observed that the shoreline of Libreville showed a positive trend of +0.87 m/year during the period 2003–2022, whereas a trend reversal was recorded during the 2022–2024 period, with an average retreat of −0.32 m/year. Mentaschi and al (Mentaschi et al., 2018) shown that several anthropogenic factors are prominent drivers of global coastal morphological changes.

In effect, between 2003 and 2022, Libreville's shoreline underwent significant transformations, marked by the demolition of Hôtel Dialogue (in 2008), the construction of “Baie des Rois”, the installation of a groin structure to protect the Michel Marine marina from coastal erosion, and the development of the ACAE port whom are consistency change the profil's coastal.

Despite widespread erosion along the coastline during this period, the EPR results indicate a positive average rate, suggesting an overall trend of accretion. However, this interpretation requires nuance, as 52.68% of the shoreline was actually affected by erosion. Moreover, the apparent positive trend is mainly due to the previously mentioned coastal developments, particularly significant land reclamation activities following the demolition of Hôtel Dialogue, the creation of artificial landmasses (e.g., Baie des Rois), and the construction of coastal protection structures (groins and revetments), which resulted in localized artificial accretion zones that heavily influenced shoreline evolution trends.

This anthropogenic forcing introduces a significant bias in interpreting shoreline changes if based solely on average EPR values. Indeed, high accretion rates in developed areas tend to mask the broader erosional trend, highlighting the limitations of relying exclusively on mean shoreline change rates for coastal change assessment.

In contrast, during the second period (2022–2024), although relatively short, shoreline position changes were still appreciable due to the VHR quality of Pleiades imagery, which enables detection of changes at centimetric to metric scales. No major development projects were recorded during this period. It was found that 58% of the shoreline was affected by coastal erosion, representing a 5% increase compared to the previous period. The city center and southern coastal sectors were the most impacted.

In the central area (Baie des Rois), significant sediment loss was observed on a portion of the artificial beach, likely caused by marine erosion, possibly exacerbated downstream by existing coastal protection structures (riprap and groins). Similarly, in the southern area (Acaé beach), severe erosion may also be attributed to indirect effects of installed protection works. In both cases, anthropogenic activity appears

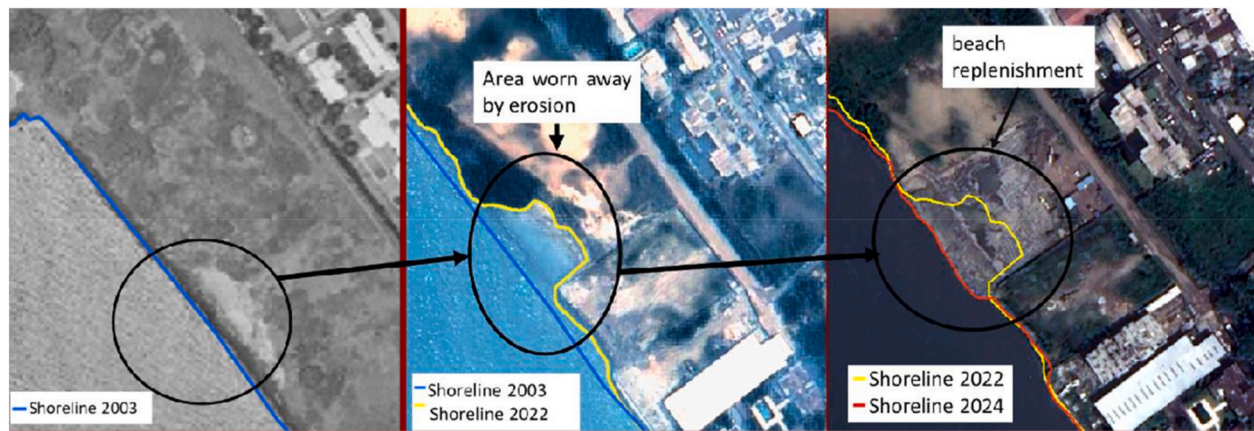


Fig. 24. Erosion mitigation strategies involving sea filling.

This figure illustrates anthropogenic actions implemented to combat coastal erosion. The photograph on the left shows the position of the shoreline (blue line) in Greater Libreville in 2003. The central image highlights the shoreline retreat between 2003 and 2022 (yellow line). Finally, the image on the right shows a seaward shift of the shoreline (accretion) in 2024 (red line), following land reclamation works.

to have indirectly intensified coastal erosion. These observations corroborate the results of Issala (*Gestion des risques littoraux*), who highlighted that shoreline of Libreville is undergoing erosion, particularly along is southern sector.

It is important to note that between 2003 and 2024, most developments along the coastline were primarily aimed at establishing economic infrastructure, often without implementing erosion control measures. However, some observations indicate the local implementation of erosion mitigation measures in the most severely affected areas (Fig. 24; 2). This situation highlights the absence of a comprehensive coastal management plan or an adaptive strategy to address ongoing coastal erosion in Libreville. Coastal development projects, when poorly planned, can worsen erosion. Therefore, an integrated coastal zone management plan urgently needed (Martínez et al., 2018).

6. Conclusion

The shoreline kinematics at Libreville between 2003 and 2024 indicate the influence of a natural processes and anthropogenic activities. The results of this work show that RS techniques and specific AI algorithms (RF, SVM and CNN) and approaches (PBIA, OBIA, pixel-based CNN and CNN-OBIA) of have produced very satisfactory results to detect, and (semi)-automatic extraction of the shoreline evolution (2003-2024) used VHR images, with levels of automation and complexity varying according to the definition of the shoreline and the indicators selected for shoreline mapping.

RF and CNN-OBIA demonstrated the best performance, particularly when trained with the PBIA approach for RF (2022 Pleiades stereo image) and CNN-OBIA for the 2024 Pleiades tri-stereo image. The shorelines were extracted semi-automatically, with 61% of the 2022 shoreline and 87% of the 2024 shoreline extracted automatically. The trends in shoreline evolution between 2003-2022 and 2022-2024 revealed two main patterns: erosion and accretion. The areas most affected by erosion are primarily located in the city center (Baie des Rois) and the southern sector, specifically the Acaé Port area. Erosion was moderate during both periods, though the latter period (2022-2024) experienced more intense erosion compared to the previous one.

This study highlighted the erosive nature of the current shoreline. While the classification and extraction results were largely satisfactory, field surveys remain crucial to cross-validate the diachronic analysis results with on-ground realities. This would not only confirm the recorded erosion/accretion trends but also ensure a higher degree of reliability for the methodology employed. Furthermore, such data integration would enhance the understanding of coastal evolution

processes and enable a more detailed analysis of the causes and effects of this shoreline dynamics.

CRediT authorship contribution statement

Nina Manomba-Mbadinga: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Conceptualization, Data curation, Formal analysis, Visualization. **Simona Niculescu:** Writing – review & editing, Validation, Supervision, Project administration, Conceptualization, Formal analysis, Funding acquisition, Investigation.

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Declaration of competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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