

Article

Multi-Decadal Shoreline Variability Along the Cap Ferret Sand Spit (SW France) Derived from Satellite Images

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Abstract: Building shoreline position databases able to capture event- to centennial-scale coastal changes is critical for scientists to improve knowledge of past coastal dynamics and predict future changes. Thanks to the commissioning of several satellites acquiring recurrent high-resolution optical images over coastal areas, coastal scientists have developed methods for detecting the shoreline position from satellite images in most parts of the world. These methods use image band analyses to delineate the waterline and require post-processing to produce time-consistent satellite-derived shorelines. However, the detection accuracy generally decreases with increasing tidal range. This work investigates an alternative approach for meso- and macrotidal coasts, which relies on the delineation of the boundary between dry and wet sand surfaces. The method was applied to the high-energy meso-macrotidal km-scale Cap Ferret sand spit, SW France, which has undergone large and contrasted shoreline changes over the last decades. Comparisons with topographic surveys conducted at Cap Ferret between 2014 and 2020 have shown that the raw satellite-derived wet/dry line reproduces well the mean high water shoreline, with an overall bias of 1.7 m, RMSE of 20.2 m, and R² of 0.86. Building on this, the shoreline variability at Cap Ferret was investigated over the 1984–2021 period. Results have evidenced an alongshore gradient in the dominant modes of variability in the last 2 km of the sand spit. Near the tip, the shoreline has chronically retreated on the decadal scale at about 8.4 m/year and has been strongly affected on the interannual scale by the onset and migration of shoreline undulations having a wavelength of 500–1200 m and a cross-shore amplitude of 100–200 m. Some 3 km away from the sand spit extremity, the shoreline has been relatively stable in the long term, with a dominance of seasonal and interannual variability. This work brings new arguments for using the wet/dry line to monitor shoreline changes from spatial imagery at meso- and macrotidal sandy coasts.

Keywords: sandy coast; sand spit; sand wave; mesotidal; macrotidal; satellite-derived shoreline (SDS); wet/dry line



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1. Introduction

Worldwide, coastlines are constantly evolving in response to environmental forcings such as sediment inputs and sinks, varying water levels, currents, and waves [1]. This is particularly visible along open sandy coasts where dramatic changes occur on both short and long timescales (e.g., [2–7]), potentially threatening human infrastructures and economical activities along urbanized coasts. Frequent and continuous measurements of coastal descriptors are crucial for scientists to improve the knowledge of past changes (e.g., [5,8–10]) and to predict future changes (e.g., [11–15]), thus addressing the expectations of coastal stakeholders.

The shoreline is commonly used to depict sandy coast dynamics. According to the desired application, the environmental settings, and the type of observation available, different definitions of the shoreline are possible [16]. For instance, the dune foot shoreline proxy can be used to study interannual and decadal dynamics of sandy beaches backed by prominent foredunes (e.g., [9,10]). A shoreline defined as the intersection between a specific tidal datum and the beach topography is widely used as it allows investigating coastal dynamics also occurring on shorter timescales (e.g., [4,17,18]). In microtidal environments, the mean sea level (MSL) is generally used (e.g., [3,19]), while in meso- and macrotidal environments a high tide level, such as the mean high water (MHW) level, is preferred (e.g., [11,14,20]).

Shoreline measurements along sandy coasts are possible thanks to a myriad of approaches (e.g., GNSS survey, lidar, cameras), all with their own advantages and drawbacks [21]. Coastal monitoring programs are usually composed of several approaches to compensate for the limitations of some with the advantages of others [7]. In recent years, the United States Geological Survey (USGS), with support of the National Aeronautics and Space Administration (NASA), and the European Space Agency (ESA) have expanded the satellite constellations providing free and frequent high-resolution imagery with the deployment of Landsat 8/9 and Sentinel-2A/2B, respectively. This has boosted the development of various tools able to derive waterline-based shorelines from satellite imagery (e.g., [22–27]). These tools enable the efficient computation of satellite-derived shorelines (SDS) with image-resolution-dependent cross-shore accuracy (generally up to approximately 5–10 m). Theoretically, it is now possible to investigate the shoreline variability on timescales from at least one year to decades along sandy coasts in most parts of the world from 1984 onwards, with the commissioning of Landsat 5. Monitoring shoreline changes on shorter timescales, such as the seasonal scale, has also progressively become possible thanks to the commissioning of additional satellites such as Landsat 7 in 1999, Landsat 8 in 2013, and Sentinel-2A in 2015 (e.g., [28]). This represents an inescapable opportunity to densify and extend backward existing observation datasets or to build new ones at sites where coastal dynamics still need further investigations (e.g., [29]) or to produce analyses of coastal changes at a global scale (e.g., [23,27,30]).

One difficulty encountered when using waterline-based SDS is that the cross-shore position of the waterline can fluctuate on an hourly scale due to local sea level variations over a non-vertical beach slope, mainly driven by the tide, atmospheric pressure, wave setup, and runup [31–33]. To compensate for variations in sea level from one satellite image to another and compute consistent SDS over time, two different approaches have been investigated. The first approach consists in creating composite waterlines (e.g., taking a specific quantile) from numerous satellite images acquired over a rolling period that is long enough to cancel sea level variation effects (e.g., [23,27,34]). However, this requires the rolling period to be quite long, such as a year, which prevents the investigation of shoreline changes occurring on the seasonal scale and shorter timescales. In contrast, the second approach aims at deriving one datum-based shoreline, such as the MHW shoreline, from each satellite-derived instantaneous waterline (e.g., [21]). To achieve this, a tidal correction is applied to each instantaneous waterline, which is computed as the ratio between the tide level difference relative to the desired datum elevation at the time of image acquisition and the beach slope. Applying this tidal correction significantly improves the SDS accuracy in microtidal environments. However, it brings only minor improvements at meso- to macrotidal environments [28,35] unless satellite images acquired at tide levels below mid-tide are excluded [21,28]. This drastically reduces the potential of using SDS to monitor coastal changes on short timescales. Some studies have shown that the use of a more complete sea level correction, including, for instance, the wave setup (e.g., [36])

or the wave runup (e.g., [28]), was necessary to ensure the computation of reliable SDS at specific sites. However, there are still no generalized formulas for estimating wave setup and runup compatible with all types of sandy coasts. Further investigations on these sea-level corrections are still needed to improve the accuracy of waterline-based SDS [35].

As suggested by [35], extraction of alternative image features should be explored to face this limitation for meso- and macrotidal sites. This includes the interface between the wet and dry sand, hereafter referred to as the wet/dry line, usually visible on the upper part of the beach profile [16]. When the intertidal zone is uncovered, a thin layer of water or simply moisture persists on the sand, making this so-called wet sand area easily distinguishable from the dry sand area by satellite sensors measuring infrared bands [37]. In addition, field observations have generally shown that the cross-shore position of the wet/dry line seems to vary only slightly over a falling and rising tidal cycle and to remain close to the high water line of the previous high tide [38,39]. This makes the wet/dry line potentially useful for approximating high-tide datum-based shorelines. This shoreline proxy has been used since the 1950s to identify shoreline position from aerial photography [38–40]. More recently, a few studies have been devoted to extracting the wet/dry line from other remote sensing techniques, such as video imagery [40], unmanned aerial system imagery [41], airborne hyperspectral imagery [37], and satellite multispectral imagery [42–44].

Sand spits are common features of km-scale inlets interrupting open sandy coasts and can be found in many places worldwide (e.g., [45–48]). The development of sand spits is known to be driven by several forcings, such as waves, water level, currents, wind, and sediment supply and composition [49–54]. However, the physical mechanisms involved appear rather site-specific, and only a limited number of sand spits worldwide have been the subject of in-depth studies based on long-term, high-frequency monitoring. At decadal scales, sand spit shape can easily vary by a hundred meters, due to ongoing elongation (e.g., [45,47]), or alternating phases of elongation and retreat (e.g., [55]), and, eventually, occurrences of beaching along the neck of the spit (e.g., [45,46]). The development of beach sand waves migrating in the direction of the sand spit tip has also been documented and was shown to drive large changes in beach width of at least 50 m on timescales of a few months to several years (e.g., [56–61]). Main sand spit evolutions can, therefore, be monitored using SDS with a high signal-to-noise ratio. The use of satellite imagery has recently demonstrated its ability to provide multi-decadal, continuous monitoring of some regional-scale sand spits (e.g., [62,63]). This opens new perspectives in understanding sand spit dynamics, from seasonal to decadal scales, in a broad range of environmental settings.

In the present study, a method for SDS computation based on the wet/dry line is introduced and applied to the high-energy meso-macrotidal km-scale sand spit of Cap Ferret, SW France, over the 1984–2021 period. The objectives are threefold: (1) to assess the accuracy of wet/dry-line-based SDS at a meso-macrotidal sandy coast; (2) to highlight potential advantages of using the wet/dry line instead of the waterline in SDS computation; and (3) to provide new insights into shoreline variability along the Cap Ferret sand spit.

2. Study Site

The Cap Ferret sand spit is located along the coast of New Aquitaine, SW France, and consists of a 17-km long sandy barrier that semi-encloses the tidal lagoon of Arcachon (Figure 1). This sandy barrier has formed over the past 3000 years from the northern side of the historical fluvial estuary of the Leyre [64,65] and has progressively extended southward due to the prevalence of a net southward longshore sediment transport [55]. The longshore sediment transport along the open coast of Cap Ferret has been estimated at around 650,000 m³/year [66].

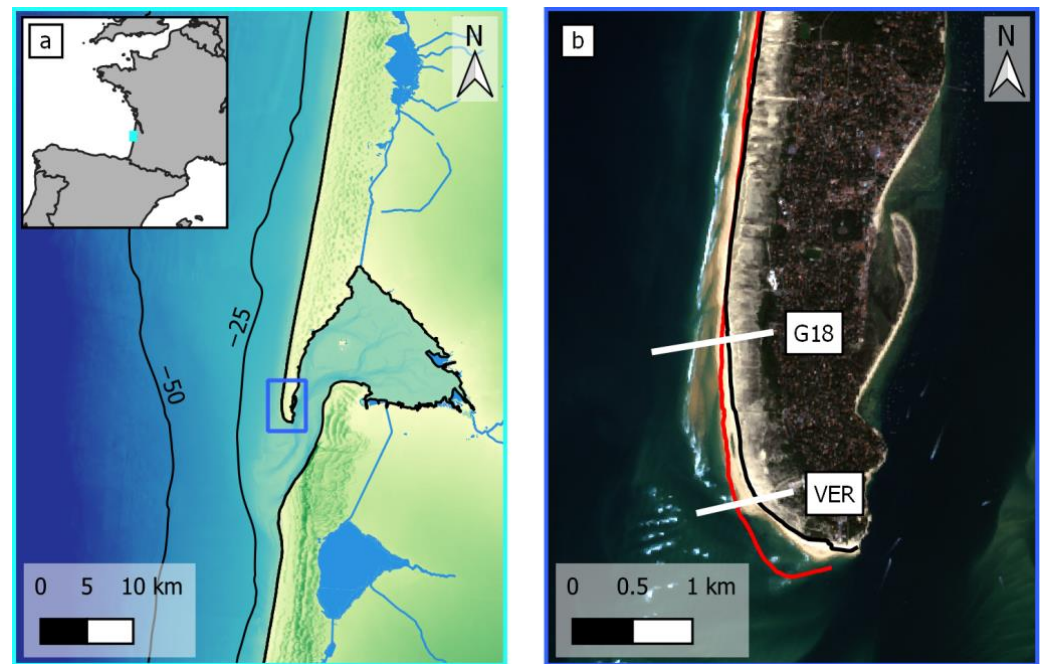


Figure 1. (a) A location map of the Cap Ferret sand spit and the extent of the study area (blue rectangle). (b) Sentinel-2 RGB image acquired on 11 October 2017 zoomed over the study area. In panel (b), red and black lines locate the dune foot position in 1985 and 2021, respectively. The white segments indicate two transects along which beach profiles have been measured by a regional coastal observatory since 2008 and 2011 for the G18 and VER transects, respectively.

The open coast of the Cap Ferret sand spit (W side) is exposed to long and energetic waves generated in the North Atlantic Ocean by eastward tracking extra-tropical cyclones [11,67]. This stretch of coast is also under the influence of shorter waves generated more locally within the Bay of Biscay by wind coming on average from the northwest direction. The local wave climate is seasonally modulated with large waves coming predominantly from the WNW direction during winter and smaller waves coming predominantly from the NW direction during summer [4,68]. Winter-averaged significant wave height (H_s) and peak wave period (T_p) are, respectively, around 2.4 m and 13 s, while summer-averaged H_s and T_p are, respectively, around 1.1 m and 9 s [68]. The tidal regime offshore the Cap Ferret is meso-macrotidal, with mean spring tidal range of 3.8 m [54]. The Cap Ferret sand spit is connected at its southern extremity to the ebb delta of the Arcachon lagoon where strong tidal currents develop, exceeding 2 m/s in the main channels during spring tides [69].

Along the open coast of the sand spit, the sediment consists of medium quartz sand with a median grain size generally ranging between 0.32 and 0.49 mm [70,71]. The beach is backed by prominent foredunes [72] and is characterized by the presence of double rhythmic sandbar systems [73], which migrate southward at a rate of a few meters per day [74]. Away from the tip of the sand spit, the beach profile exhibits a strong seasonality related to variability in incident wave energy. During winter, storm waves lead to offshore migration of the inner bar and erosion of the upper beach, while during the summer, fair wave conditions favor onshore migration of the inner bar, which sometimes welds to the upper beach, and development of berms [20,73]. This leads to higher values of alongshore-averaged intertidal beach slope during summer [20,28]. Alongshore variability of the upper beach generally increases in summer with the formation of accretive beach megacusps, which are enforced by ridge–runnel systems that develop during accretive downstate sequences [20,75–77]. At Truc Vert beach [78], located only 13 km northward

from the tip of the Cap Ferret sand spit and intensively monitored since 2000, the MWH shoreline variability is dominated by seasonal and interannual fluctuations driven by variability in incident wave energy [11,20].

Shoreline and beach changes along the Cap Ferret sand spit have been studied on secular [55,79], multi-decadal [9,28,80,81], and interannual to seasonal timescales [7]. The Cap Ferret sand spit distal end has undergone large-scale oscillations over the last two centuries, partly due to the climate variability over the North Atlantic Ocean and its influence on local wave climate and sea level [55]. Along the last 2–3 km of the open coast of the sand spit, chronic erosion has been observed since 1985, with a rate of dune foot retreat that increases from 2 to 9 m/year toward the tip [7,9,28,80,81]. Some observations along the distal end of the sand spit have also shown the existence of a strong variability of the upper beach width occurring at the scale of several months [71,79]. It is argued that this variability is mostly related to the development of massive intertidal bars, which either lead to steady beach erosion downdrift of their location [82] or to the formation of large beach sand waves when these sandbars weld to the upper beach [71].

In this study, the detection of the shoreline and analysis of spatiotemporal changes cover only the last 5 km of the tip of the Cap Ferret sand spit (Figure 1b) where dramatic and contrasted coastal changes have been observed in recent decades.

3. Materials and Methods

3.1. Satellite Images

The satellite image database was composed of cloud-free images acquired by Landsat 5/7/8 (NASA, USGS), by Sentinel-2A/2B (ESA), and by SPOT 1/2/4/5 (Centre National des Etudes Spatiales, CNES). The annual number of images used in this study per type of satellite is shown in Figure 2. Because Sentinel-2A and Sentinel-2B sensors share very close characteristics, Sentinel-2A and Sentinel-2B satellites were here regarded as a single satellite, simply named Sentinel-2. Following a device failure on Landsat 7 that occurred on 31 May 2003, the images acquired by this satellite after this date include pixel strips where surface reflectance is not available. These corrupted images were disregarded from the present study although they could still bring valuable information. Landsat and Sentinel images over the study area were obtained using the downloading module of the Python toolkit CoastSat (version of 1 February 2023) [24], which relies on the Google Earth engine (version of 1 February 2023) [83]. SPOT images were downloaded from the former web platform of the CNES Kalideos program (<http://www.kalideos.fr/>, accessed on 2 September 2020) [84] and were cropped to the spatial extent of the study area. Among the various spectral bands available in the satellite images, only some were considered in this work. The selected bands and their respective pixel size are listed per satellite in Table 1. Using bilinear interpolation, 30 m bands of Landsat 5/7/8 images were upsampled to 15 m and 20 m bands of SPOT 1/2/4 images and Sentinel-2 images were upsampled to 10 m. The panchromatic band available within Landsat 7/8 images enabled the application of pansharpening to some specific bands instead of bilinear interpolation. For Landsat 7 images, pansharpening was applied to the green, red, and near-infrared bands. For Landsat 8 images, pansharpening was applied to the blue, green, and red. The pansharpening algorithm implemented in CoastSat [24], which is based on principal component analysis, was used for that purpose. For several SPOT 4 images, the panchromatic band was also available, and pansharpening was applied to the green, red, and near-infrared bands directly by the image provider.

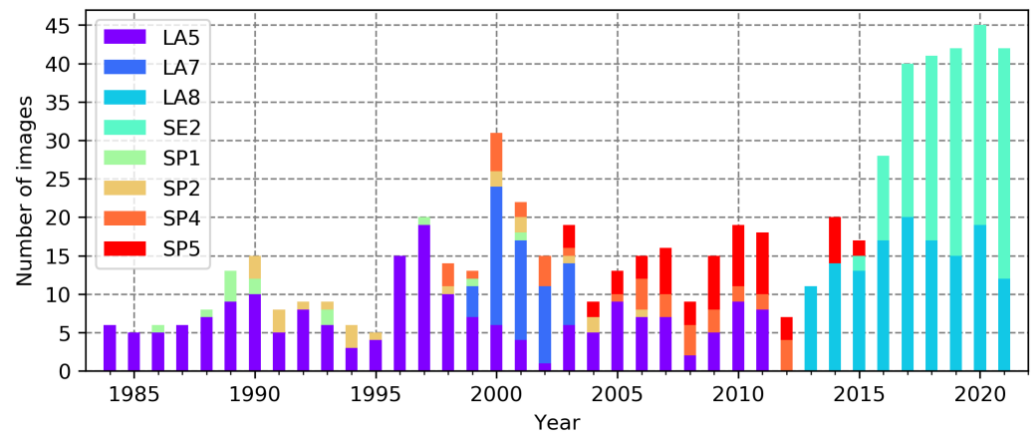


Figure 2. The number of usable satellite images per year and per satellite. The abbreviations LA, SE, and SP used in the legend mean Landsat, Sentinel, and SPOT, respectively.

Table 1. The original pixel size in meters and the name of the image bands considered in this work for each satellite.

	Blue	Green	Red	Near-Infrared	Short Wave Infrared	Panchromatic
Landsat 5	30—band 1	30—band 2	30—band 3	30—band 4	30—band 5	-
Landsat 7	30—band 1	30—band 2	30—band 3	30—band 4	30—band 5	15—band 8
Landsat 8	30—band 2	30—band 3	30—band 4	30—band 5	30—band 6	15—band 8
Sentinel-2	10—band 2	10—band 3	10—band 4	10—band 8	20—band 11	-
SPOT 1/2	-	20—band 1	20—band 2	20—band 3	-	-
SPOT 4	-	20—band 1	20—band 2	20—band 3	20—band 4	10—band 5 *
SPOT 5	-	10—band 1	10—band 2	10—band 3	20—band 4	-

* The panchromatic band was not available for some SPOT 4 images.

A visual check of all collected images was carried out to remove images with clearly poor radiometric quality. Images affected by clouds and cloud shadows within the study area were also removed. Classification of those images would inevitably lead to systematic errors in the association of image pixels with the different surface classes used in this work (see description in Section 3.3). This check was performed by a single operator using Red–Green–Blue (RGB) figures that were generated for all satellite images with the same stretching of the band surface reflectance (between 0 and 0.4). This manual task represents about one working day. In the end, 652 usable images were available over the 1984–2021 period, with 4–14 images per year between 1984 and 1995, 8–31 images per year between 1996 and 2015 (except in 2012 with only 6 images), and more than 33 images per year since 2016 (Figure 2).

3.2. Topographic Surveys and Shorelines

A regional coastal observatory (Observatoire de la côte de Nouvelle-Aquitaine) has carried out beach profiles since 2008 at several cross-shore transects distributed all along the coast of Aquitaine [7]. The surveys were conducted annually in spring at low tide with a centimetric-precision Global Navigation Satellite System (GNSS). Only the beach profiles acquired along the two transects included in the study area were used, namely, transects G18 and VER (Figure 1b). Measurements at transect VER only began in 2011.

This coastal observatory has also ordered acquisitions of topographic lidar over the entire Aquitaine coastline in autumn since 2014 on an almost annual basis. No lidar

acquisition was made in 2015 and the acquisition of autumn 2019 was postponed to January 2020. As for the beach profiles, the lidar acquisitions were conducted at low tide. Lidar point clouds were processed to build 1-m-gridded digital terrain models (DTMs). A comparison with thousands of salient fixed ground control points has shown vertical errors under 0.15 m [85].

Lidar DTMs were used to compute lidar-based beach profiles along the above-mentioned transects. Combining those profiles with the GNSS-based profiles allows for exploring the seasonal beach changes since 2014 [7].

Shorelines were extracted from lidar DTMs and beach profiles using the MHW contour, which is a relevant shoreline proxy for the nearby Truc Vert beach [28]. A mean high water elevation of 1.9 m NGF IGN69 (official French vertical datum) was used in this study. This corresponds to an elevation of about 1.5 m above MSL. Two shoreline datasets were then used here for validation purposes: (i) full MHW shorelines with seasonal frequency since 2014 and (ii) cross-shore positions of the MHW shoreline along transects G18 and VER with annual frequency since 2008 and 2011, respectively, and with seasonal frequency since 2014.

3.3. Supervised Classification

The satellite images were classified (Figure 3a,b) using a supervised classification algorithm based on a multi-layer perceptron neural network. Although the classification method is the same as in CoastSat [24], new classifiers were set up from scratch with different parameters to include additional surface classes. The four surface classes (sand, water, white waters, and others) originally used in CoastSat [21,24] were updated and extended to eight classes, which are listed in Table 2. Classifiers were trained and applied separately for every image group (i.e., every satellite) as image characteristics are very specific to each satellite imaging sensor. In the end, eight distinct trained classifiers were set up. The MLPClassifier class implemented in the scikit-learn Python library [86] was used with two hidden layers made of 10 neurons with the Adam solver. The default values for the max_iter and alpha parameters were changed to 500 and 0.001, respectively.

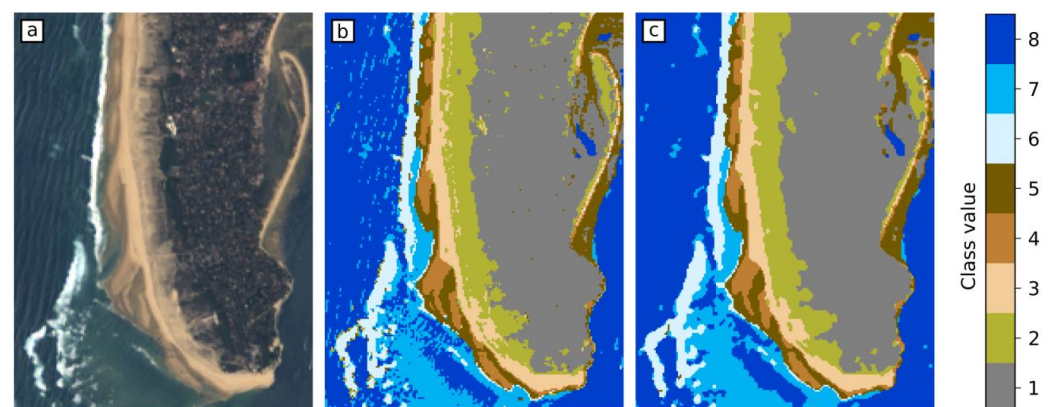


Figure 3. An illustration of image classification and filtering. (a) Landsat 8 RGB image of 10 June 2017. (b) A raw classified image. (c) A classified image after application of the filtering. Class values and names are provided in Table 2.

Table 2. The name and numerical value of the surface classes used to classify satellite images.

Name	Urbanized Area and Dense Vegetation	Vegetated Dune	Dry Sand	Slightly Wet Sand	Very Wet Sand	Breaking Waves and Foam	Shallow Water	Deep Water
Value	1	2	3	4	5	6	7	8

Among all the bands available in the raw satellite images, only those listed in Table 1 were used for image classification. However, additional composite bands were added to each image to improve the classification performance. This includes the following radiometric indices: (i) the normalized difference vegetation index; (ii) the normalized difference water index [87]; (iii) the modified normalized difference water index [88]; and (iv) a normalized difference index based on the green and red bands. Other bands made of the local standard deviation of individual and composite bands computed over a 3-by-3-pixel kernel were also added to the images to be classified.

For every image group, the training sample database was made of hundreds to thousands of pixels belonging to the different surface classes that were digitized and extracted from several images. These training images were chosen to encompass a large range of environmental conditions observed within all images. For each of the Landsat 5/8 and Sentinel-2 groups, 12 images were used, while for each of the SPOT 1/2/4/5 and Landsat 7 groups, only 9 images were used due to the reduced number of images available and to limit over-fitting. QGIS software (version 3.22) was employed to visualize the training images and to digitize a large number of polygons that surround image pixels belonging to the eight surface classes. Then, a Python code was implemented to extract the digital numbers of the selected pixels. Digitizing the polygons meticulously for all image groups took around five working days.

Tenfold cross-validations were performed to estimate the accuracy of the trained classifiers. Cross-validation consisted in using 70% of the training samples to train the classifier and using the remaining 30% to assess the prediction accuracy. This operation was repeated 10 times with random training and validation pools of samples. For every image group, the mean percentage of pixels that were associated with the correct class ranged between 95 and 97%.

Although the classification skills were high, post-processing of classified images was also performed to slightly improve the aspect of the classified images and to reduce the noise sometimes visible along inter-class boundaries (Figure 3b,c). Pixel-scale noise was removed by applying a median filter that used a 3-by-3-pixel kernel. Then, small patches of pixels isolated in wide areas of different classes were removed using image opening and closing.

3.4. Wet/Dry Line Detection

A set of time-invariant cross-shore transects (Figure 4) was implemented to perform the alongshore extraction and processing of the boundary between dry surfaces (classes 1 to 3) and marine-wet surfaces (classes 4 to 8). These transects were distributed along the last 5.5 km of the tip of the Cap Ferret sand spit with an alongshore transect spacing of 10 m (Figure 4). Transect origins were positioned along a baseline that follows the local coastline orientation during the entire study period (green curve in Figure 4). The baseline was manually drawn using QGIS software.

Multiple boundaries between dry classes and marine-wet classes were sometimes found along the same transect. This was caused by intertidal sandbars that occasionally emerged above the water surface at low tide for a period of time long enough to let the sand dry out at the surface (e.g., between transects nos. 50 and 100 in Figure 5a,b). In this situation, it was chosen to keep the most offshore wet/dry boundary, excluding potential boundaries located on sandbars visually detached from the upper dry beach. To do so, the most offshore wet/dry boundary among those not located seaward of any pixels belonging to the very wet sand and marine classes was kept (e.g., near transect no. 100 in Figure 5a,b). This choice has given more consistency to the extracted wet/dry boundary from one transect to another and from one date to another. Finally, the wet/dry line was derived for every satellite image by applying an alongshore concatenation of the cross-shore position of the wet/dry boundary (e.g., the black curve in Figure 5) extracted along each transect.

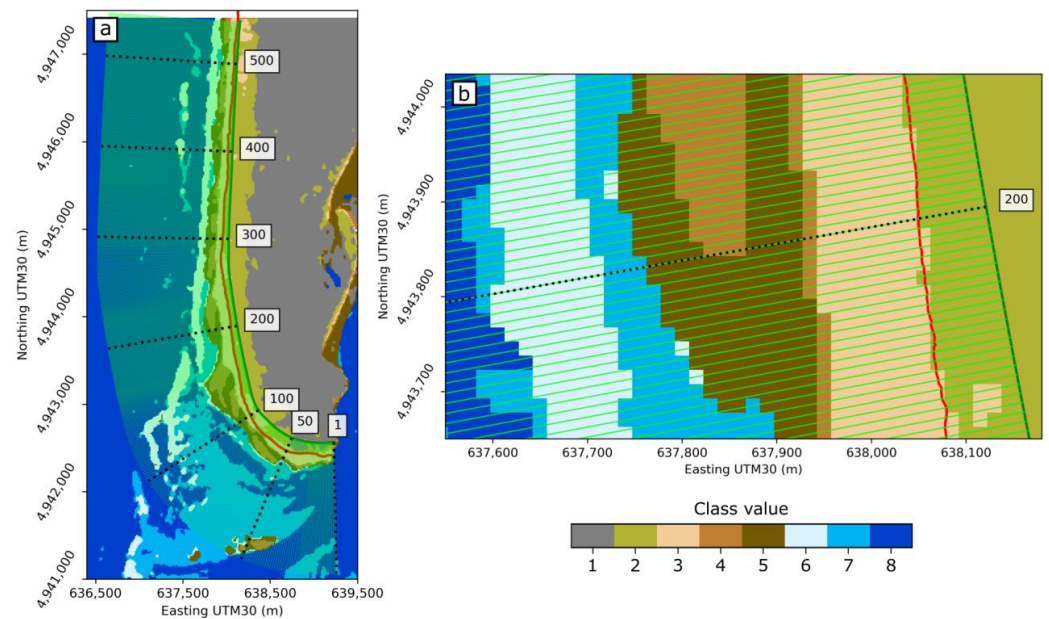


Figure 4. (a) An illustration of the cross-shore transects (light green lines) used to discretize the tip of the Cap Ferret sand spit and to extract the boundary between dry classes and marine-wet classes. To ease the reading, specific transects are highlighted by dotted black lines, while their numbering is indicated in adjacent white boxes. The classified image is derived from a Landsat 8 image of 10 June 2017. The red and dark green curves indicate the dune foot line derived from the lidar of autumn 2017 and the baseline defining the transect origin, respectively. (b) Zoom around the transect no. 200. Class values and names are provided in Table 2.

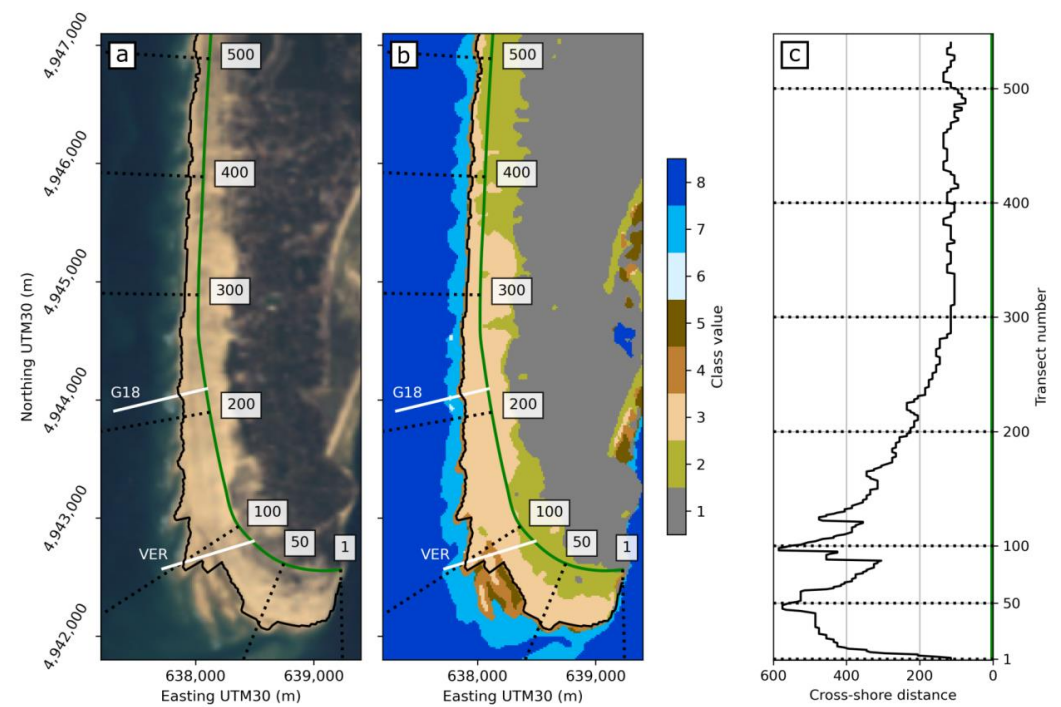


Figure 5. An illustration of the wet/dry line (black curve) computation along the tip of the Cap Ferret sand spit from a satellite image. (a) Landsat 5 RGB image of 26 July 1984. (b) Classified and filtered image. Class values and names are provided in Table 2. (c) Cross-shore distance of the wet/dry line extracted from classified and filtered image and where a zero value corresponds to the transect origin. In panels (a–c), the green curve indicates the baseline defining the transect origin and the dotted black lines indicate specific transects, whose numbers are given in the adjacent white boxes in panels (a,b). In panels (a,b), the white segments indicate the location of the G18 and VER transects.

3.5. Comparison with Measurements

The first comparison consisted in assessing the skill of the satellite-derived wet/dry lines to reproduce the alongshore spatial variability of the MHW shoreline. To do so, the satellite-derived wet/dry lines computed at dates very close to lidar acquisitions within a ± 7 -days window were identified. Then, each of these wet/dry lines was compared to the MHW shoreline derived from the corresponding lidar DTM.

A second comparison consisted in assessing the skill of the satellite-derived wet/dry lines to reproduce the temporal variability of the MHW shoreline at transects G18 and VER where more observation dates were available. First, intersections between all wet/dry lines and transects G18 and VER were computed. Then, the cross-shore position of these intersections along these transects was compared to the cross-shore position of the MHW shoreline derived from the measured beach profiles. Transects G18 and VER correspond approximately to transects nos. 210 and 90 in Figure 5, respectively.

3.6. Wet/Dry Line Post-Processing

The cross-shore position of satellite-derived wet/dry lines computed along the transects was concatenated together along the time axis to generate a spatiotemporal diagram, usually called timestack, with a regular time step of 5 days (see Section 4.2). Wet/dry lines located temporally within the same 5-day interval were averaged together. The second processing consisted in detrending this raw timestack from spatial and temporal trends. The aim was (i) to remove potential cross-shore position offset caused by the relatively arbitrary choice in defining the baseline position and (ii) to highlight the wet/dry line dynamics on the short-term up to the interannual scale (see Section 4.3). A timestack containing the spatial and temporal trends to be removed was first computed by applying a moving average to the raw timestack. A temporal window width of 5 years was used to separate changes occurring at decadal scale, such as the long-term erosion trend observed along the tip of the Cap Ferret sand spit, from changes occurring at temporal scales shorter than a few years. A spatial window width of 11 transects, which corresponds to an alongshore distance of 100 m at transect origin, was used to slightly smooth out the alongshore variation of the temporal trends while preserving the existence of distinct temporal trends alongshore at the scale of hundreds of meters. Then, the result of this spatiotemporal moving average was subtracted from the raw timestack.

4. Results

4.1. Relation Between Wet/Dry Line and MHW Shoreline

By applying a temporal tolerance of ± 7 days, the lidar-derived MWH shorelines could be compared to wet/dry lines derived from five Landsat 8 images (Figure 6) and six Sentinel-2 images (Figure 7). No comparison was possible for the other types of satellite images used in this study. Comparisons made in Figures 6 and 7 show that the use of the wet/dry line enables the reproduction of the overall alongshore variability of the shoreline. The overall skill when using Landsat 8 images (Figure 8a) appears slightly lower than the one obtained using Sentinel-2 images (Figure 8b). By combining these two lidar-based comparison datasets, the global root-mean-square error (RMSE) and bias are 20.2 m and 1.7 m, respectively (Figure 8c). These skills can be considered relatively high considering that the wet/dry boundary extraction was made at pixel scale (as opposed to subpixel approaches, e.g., [21,24]) with a pixel width of 10 m for Sentinel-2 images and 15 m for the upsampled Landsat 8 images.

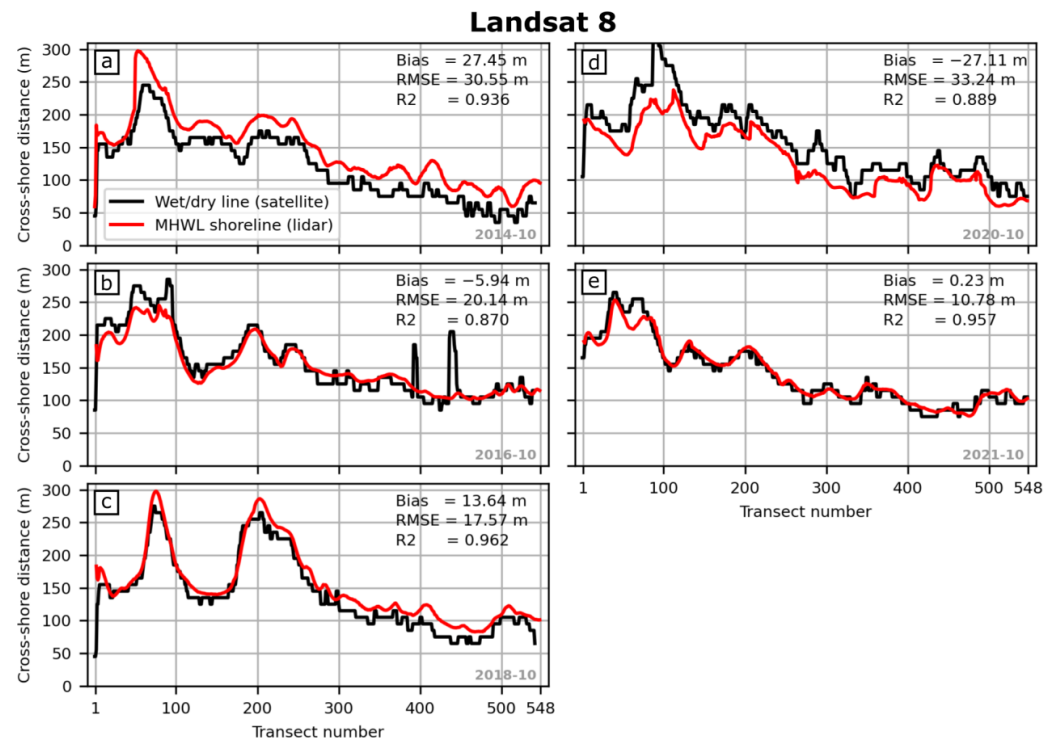


Figure 6. A comparison between cross-shore positions of the lidar-derived MHW shoreline (red curve) and the wet/dry line derived from a Landsat 8 image (black curve) for five matchups. (a) Lidar of 23 October 2014 with an image of 17 October 2014. (b) Lidar of 29 October 2016 with an image of 29 October 2016. (c) Lidar of 23 October 2018 with an image of 19 October 2018. (d) Lidar of 17 October 2020 with an image of 17 October 2020. (e) Lidar of 7 October 2021 with an image of 11 October 2021. A positive (negative) bias denotes an overall landward (seaward) offset of the wet/dry line.

Individual comparisons (Figures 6 and 7) reveal a strong spatial correlation between the satellite-derived wet/dry lines and lidar-derived MHW shorelines with determination coefficients (R^2) higher than 0.93, except for the two matchups of October 2016 and the matchup of October 2020 based on a Landsat 8 image. For the two matchups of October 2016, R^2 is lowered to 0.87 (Landsat 8 matchup) and 0.80 (Sentinel-2 matchup), essentially due to the large and suspicious variations in cross-shore position of the wet/dry line between transects nos. 380 and 548 (Figures 6b and 7a), which are not consistent with the observations. The reasons for these shoreline detection errors are addressed later in the Discussion section. Apart from these rare and easy-to-detect inconsistencies, the location and longshore extent of planview MHW shoreline oscillations extending over more than a few tens of transects (approximately a few hundred meters) are well captured by the satellite-derived wet/dry lines. For the matchup of October 2020 based on a Landsat 8 image, R^2 is lowered to 0.89, probably due to significant differences in alongshore variability and phasing around transects nos. 100 and 300 (Figure 6d).

Individual comparisons also show that the deviations in the cross-shore position of the wet/dry line can sometimes be locally as large as the cross-shore extension of small MHW shoreline oscillations (Figures 6a,b and 7a,b). Indeed, the RMSE ranges from 10.78 to 33.24 m and the bias ranges from -27.11 to 27.45 m, while the cross-shore extension of the small MHW shoreline oscillations located in the northern sector of the study site was sometimes lower than 25 m. This means that changes in the cross-shore position of the satellite-derived wet/dry line occurring on the scale of a few tens of meters from one image to a subsequent one could be related, in some cases, to detection errors rather than actual changes in beach morphology. These deviations are likely related to a number of environmental factors, which are examined later in the Discussion section.

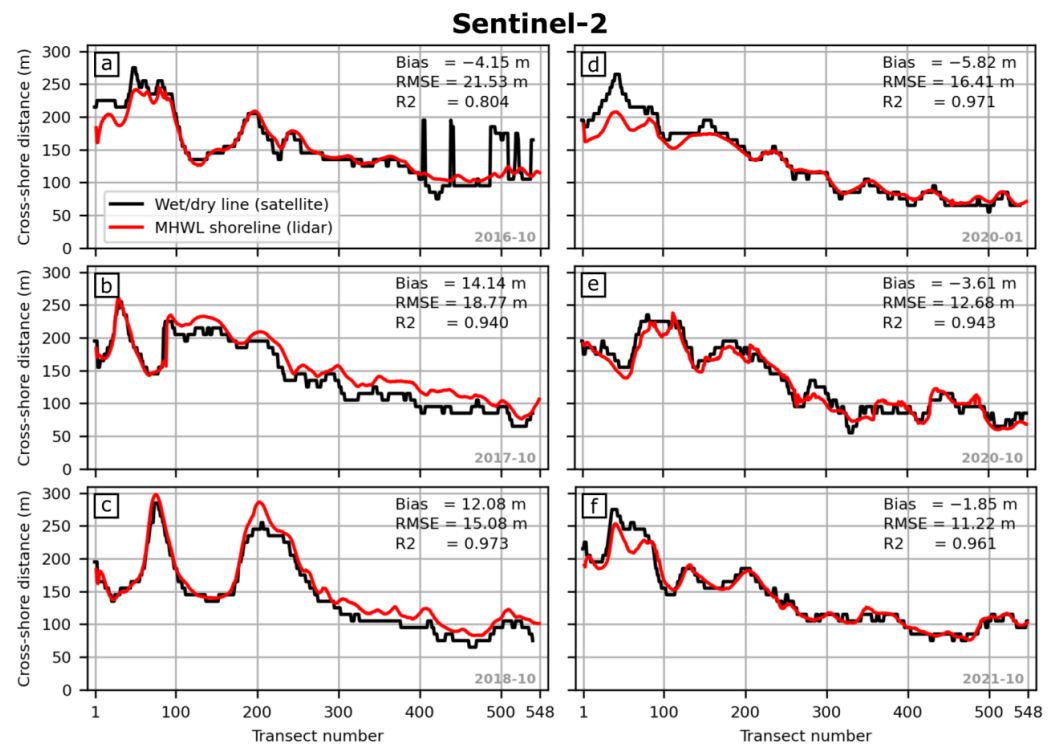


Figure 7. A comparison between cross-shore positions of the lidar-derived MHW shoreline and the wet/dry line derived from a Sentinel-2 image for six matchups. (a) Lidar of 29 October 2016 with an image of 31 October 2016. (b) Lidar of 4 October 2017 with an image of 11 October 2017. (c) Lidar of 23 October 2018 with an image of 16 October 2018. (d) Lidar of 11 January 2020 with an image of 9 January 2020. (e) Lidar of 17 October 2020 with an image of 10 October 2020. (f) Lidar of 7 October 2021 with an image of 10 October 2021. A positive (negative) bias denotes an overall landward (seaward) offset of the wet/dry line.

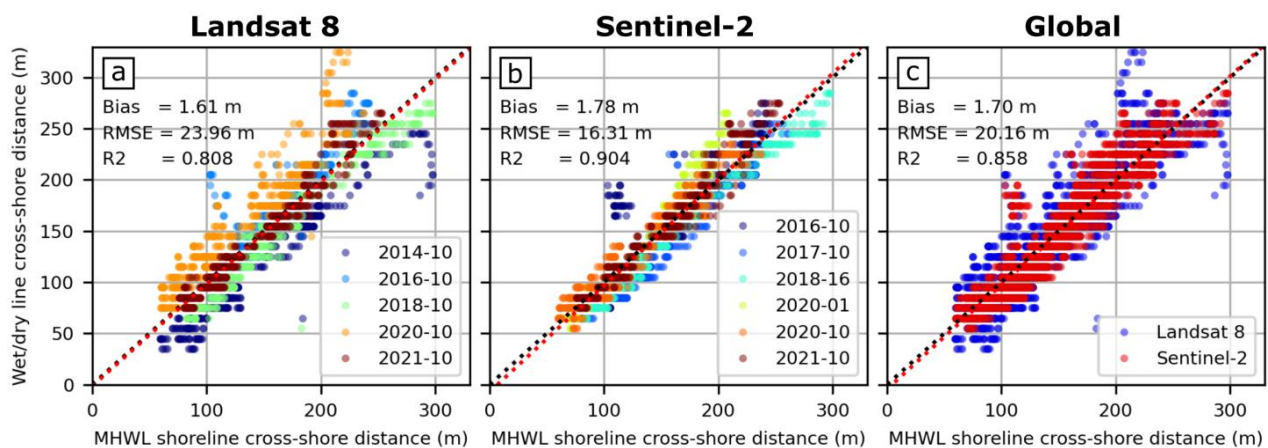


Figure 8. Scatter plots for Landsat 8 matchups shown in Figure 6 (a), Sentinel-2 matchups shown in Figure 7 (b), and all matchups (c). For these comparisons, only lidar-derived MHW shorelines were used. A positive (negative) bias denotes an overall landward (seaward) offset of the wet/dry line.

Temporal comparisons between satellite-derived wet/dry lines and profile-derived MHW shorelines extracted along transects G18 and VER are shown in Figure 9. Changes in wet/dry line cross-shore position (black dots in Figure 9) sometimes appear quite noisy at short timescales (from days to a few months). Nonetheless, the seasonal and interannual changes in the cross-shore position of the observed MHW shorelines (red squares in Figure 9) are relatively well reproduced. To highlight this, the 3-month moving average of the wet/dry line cross-shore position was computed at both transects and added to Figure 9 (grey lines).

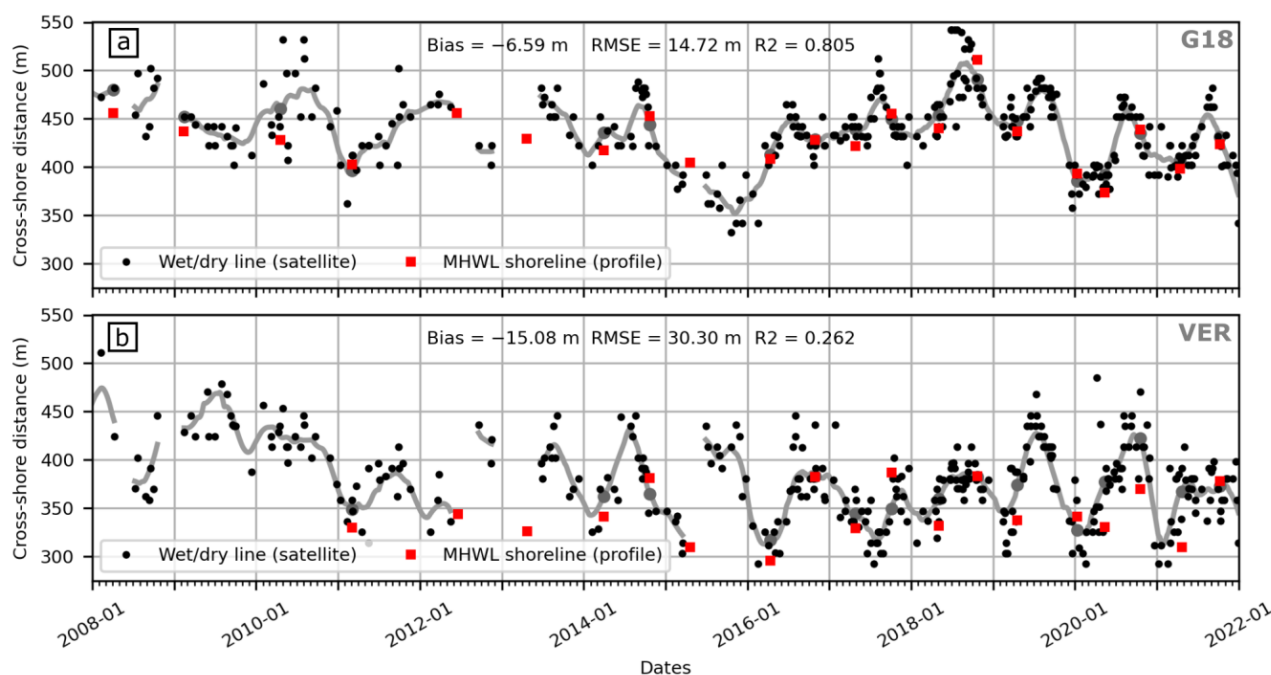


Figure 9. Time series of the cross-shore position of satellite-derived wet/dry line (black dots) and profile-derived MHW shoreline (red squares) extracted at transects G18 (a) and VER (b). The skills shown in both panels are computed using the cross-shore position of the profile-derived MHW shoreline and the concurrent cross-shore positions (grey dots) of the wet/dry line 3-month moving average (grey curves). Profile-derived MHW shoreline cross-shore positions that are ± 2 weeks away from an image acquisition were not used in skill computation. Values of the 3-month moving average computed within 3-month image-free periods were disregarded and masked in panels (a,b).

Visual inspection of Figure 9a shows that the wet/dry line reproduces well the large erosion that occurred at transect G18 between autumn 2014 and spring 2015 and between spring 2019 and spring 2020, and captures the slight accretion trend between spring 2016 and spring 2019. Comparing the observations with the concurrent wet/dry line moving average values (grey dots in Figure 9a) gives a good ability at this transect with a bias of -6.6 m (the wet/dry line is located most seaward on average), an RMSE of 14.7 m and an R^2 of 0.81 .

At transect VER, the match between the wet/dry line and the MHW shoreline is lower (Figure 9b), with an overall seaward offset that is occasionally important, such as in autumn 2020 and spring 2021. Skill assessment between the observations and the concurrent wet/dry line moving average values (grey dots in Figure 9b) shows a bias of -15.1 m, an RMSE of 30.3 m, and no significant correlation at the 0.05 confidence level. Even if there is no correlation and non-negligible offsets between the two time series, seasonal changes of the MHW shoreline observed since spring 2014 are still in phase with those of the wet/dry line. The slight interannual changes of the MHW shoreline are also well captured by the wet/dry line such as the 2-year-long erosion trend observed between spring 2014 and spring 2016 and the 3-year-long accretion trend that followed until spring 2019.

The results obtained from these spatial and temporal comparisons (Figures 6–9) support the use of the satellite-derived wet/dry line as a proxy of the MHW shoreline as long as the temporal and longshore changes in observed shoreline cross-shore position are greater than 20 – 30 m. Observations shown here (red lines in Figures 6 and 7, red squares in Figure 9) confirm that this condition is met along the tip of the Cap Ferret sand spit when studying shoreline changes on timescales greater than the season. Therefore, the satellite-derived wet/dry line was used in the following to explore the spatiotemporal dynamics of the MHW shoreline along the tip of the Cap Ferret sand spit between 1984 and 2021.

4.2. Spatiotemporal Evolution of Shoreline

The timestack of the satellite-derived wet/dry line was implemented to provide a complete overview of the shoreline changes that have occurred along the tip of the Cap Ferret sand spit over the 1984–2021 period (Figure 10). Although this raw timestack is not always continuous in time on a 5-day time step basis and appears slightly noisy, it shows that dramatic shoreline changes regularly occurred south of transect no. 300. The dominant pattern of change was undoubtedly the erosion trend located between transects nos. 1 and 100, which has led to a retreat of the shoreline of at least 300 m from 1984 to 2021 (Figure 10). Large temporal fluctuations of the shoreline position, of at least 50–100 m, have also occurred on seasonal and interannual scales south of transect no. 300 where the shoreline orientation of the sand spit begins to change. In this area, Figure 10 shows that these temporal fluctuations were not alongshore uniform, and they were often related to the southward migration of shoreline undulations. This component of the shoreline variability is further analyzed in Section 4.3. North of transect no. 300, the shoreline variability is not affected by any significant trend at decadal scales. On seasonal and interannual scales, small-scale changes are visible, but they cannot be interpreted on the basis of Figure 10 only.

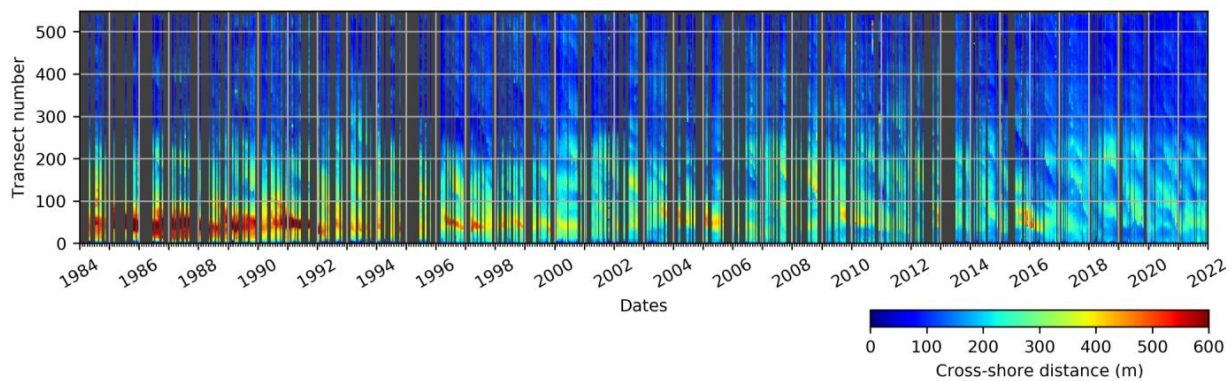


Figure 10. A raw timestack of satellite-derived wet/dry line, which shows the changes in wet/dry line cross-shore position along the cross-shore transects discretizing the southern end of the Cap Ferret sand spit over the 1984–2021 period with a 5-day time step. Dark grey areas denote periods during which wet/dry line extraction from satellite images was not possible. The cross-shore distance is defined as positive seaward.

Time series of satellite-derived wet/dry line cross-shore position computed at transects nos. 50, 150, 250, 350, and 450 are shown in Figure 11 (black dots). Figure 11 enables a more in-depth analysis of the shift in the temporal variability of the shoreline along the tip of the Cap Ferret sand spit. In the north of the study area (transects nos. 350 and 450), the shoreline variability was dominated by both seasonal and interannual changes with amplitudes of about 50 m. In contrast, near the extremity of the sand spit (transect no. 50), the shoreline variability was dominated by a strong erosion trend that was estimated to be -8.71 m/year over the 1984–2021 period. This erosion trend is superimposed on a strong interannual variability that includes changes up to 150–200 m at the scale of a few years. Shoreline changes at the scale of seasons have still occurred occasionally in this area, but their contribution to the overall shoreline variability was much smaller. In between, there was a gradual evolution between these two distinct shoreline dynamics. At transect no. 250, there was a dominance of 100-meter-amplitude interannual changes with no obvious trend, while at transect no. 150, there was a dominance of 150-meter-amplitude interannual changes combined with a 2.19 -m/year erosion trend. Seasonal changes occurred at both transects nos. 150 and 250, with amplitudes of change that were sometimes greater than the

maximum seasonal amplitudes observed in the northern sector. Finally, Figure 11 shows that seasonal and interannual changes in cross-shore shoreline position at transects nos. 450 and 350 were rather in phase. In contrast, the seasonal and interannual changes at the other three transects (nos. 250, 150, and 50) were no longer in phase with those observed at transects nos. 450 and 350, nor with each other. For instance, at transects nos. 350 and 450, the shoreline has typically experienced an advance during summer and a retreat during winter, while at transects nos. 50, 150, and 250, maximum shoreline advances related to seasonal-scale changes sometimes occurred during winter and early spring.

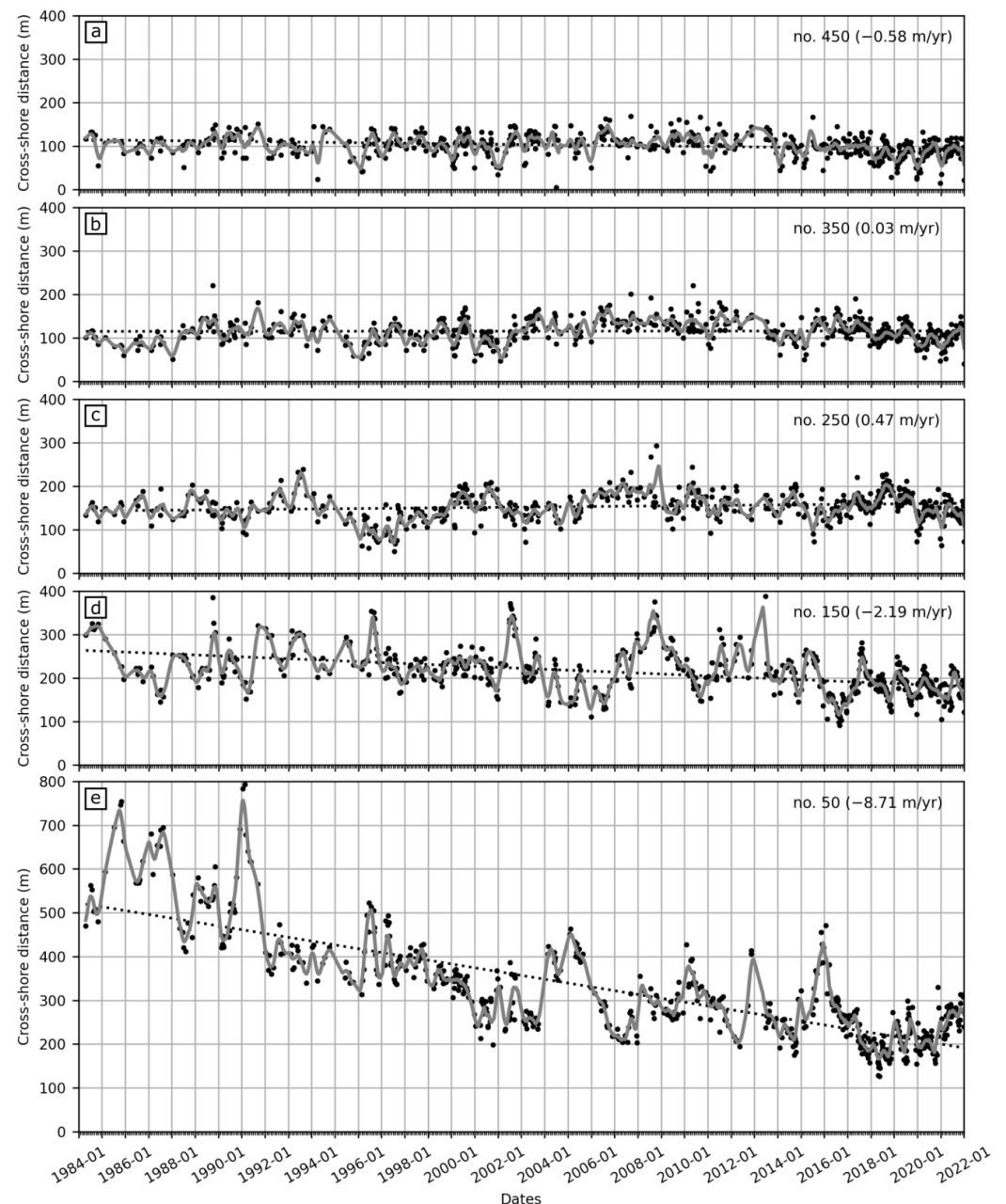


Figure 11. Time series of satellite-derived wet/dry line cross-shore position (black dots) along transects nos. 450 (a), 350 (b), 250 (c), 150 (d), and 50 (e). The thick grey line indicates the local moving average computed with a 3-month and 11-transect window. The dotted black line indicates the linear trend whose slope coefficient is provided in brackets next to the transect number.

4.3. Migrating Shoreline Undulations

The alongshore variation of the shoreline dynamics along the tip of the Cap Ferret sand spit shown previously is further highlighted in Figure 12, which allows for visualizing separately the shoreline variability occurring on timescales roughly above and below 5 years (Figure 12a,b).

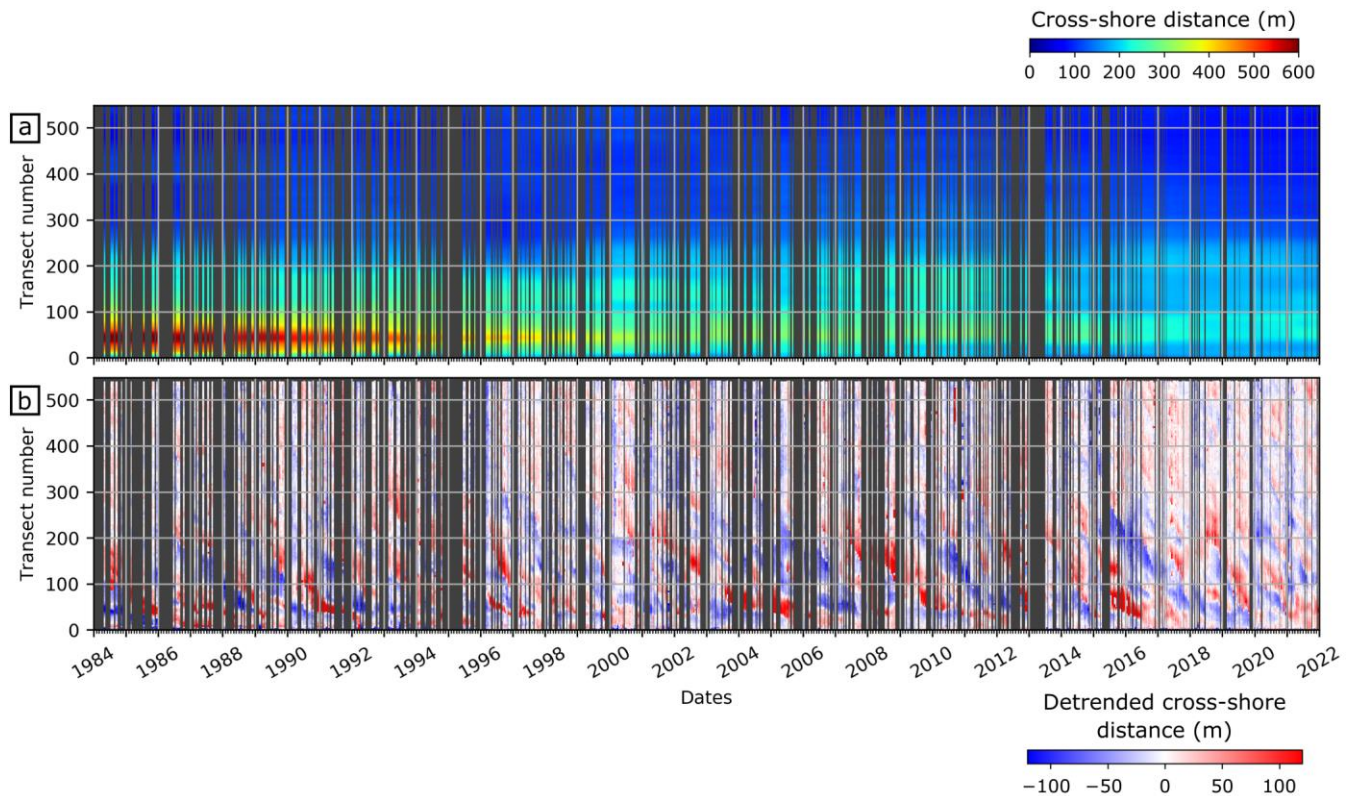


Figure 12. (a) A smoothed timestack of satellite-derived wet/dry line, obtained using a moving average based on a 5-year and 11-transect moving window. (b) Detrended cross-shore distance of the satellite-derived wet/dry line. Dark grey areas denote periods during which wet/dry line extraction from satellite images was not possible. The cross-shore distance is defined as positive seaward.

Computing the spatiotemporal moving average of the timestack of satellite-derived wet/dry line based on a 5-year and 11-transects moving window (Figure 12a) reveals that the long-term erosion trend was present only south of transect no. 200 and was maximum near transect no. 50. North of transect no. 200, the shoreline remained stable in the long term.

Computing the detrended timestack of satellite-derived wet/dry line (Figure 12b) highlights the existence of numerous planview shoreline undulations all along the tip of the Cap Ferret sand spit that migrated southward throughout the study period. A transition in terms of spatial scales and duration is visible between transects nos. 250 and 300 (Figure 12b). North of this transition area, the shoreline undulations generally developed each year during late spring or summer and disappeared during the following winter, with cross-shore amplitudes (from trough to crest) that rarely exceeded 50 m and with wavelengths of about 500 m. In contrast, shoreline undulations reaching or developing within and south of this transition area have generally persisted for some years (e.g., between 2002 and 2006), with larger cross-shore amplitudes up to 100–200 m and larger wavelengths generally ranging between 500 and 1200 m.

Visual inspection of Figure 12b suggests that there was not a clear link between the alongshore position (i.e., transect number) and the migration speed of shoreline undulations. Nonetheless, rough estimates of migration speed indicate that the shoreline undulations migrated on average at a rate of around 2–3 m/day north of transect no. 150,

which increased slightly to 3–3.5 m/day between transects nos. 50 and 150. South of transect no. 50, the shoreline undulations migrated on average at a slower rate of around 1 m/day and eventually flattened as they got closer to the sand spit extremity (i.e., transect no. 1). It should be noted that between transects nos. 50 and 150, the maximum migration speed of an individual shoreline undulation could reach 5–10 m/day, whereas elsewhere, it was mostly less than 5 m/day. Figure 12b also shows that south of transect no. 250, the migration speed of shoreline undulations was quite variable throughout the study period, with sometimes alternating periods of stagnation and rapid southward displacement. Rough estimates of migration speed suggest that overall shoreline undulations migrated slightly faster during the fall and winter seasons (around 3 m/day) than during the spring and summer seasons (around 2 m/day).

As they developed and migrated along the tip of the Cap Ferret sand spit, these shoreline undulations caused large fluctuations in cross-shore shoreline positions on timescales related to their lifetime and migration speed. North of transect no. 300, the seasonal variability in cross-shore shoreline positions (shown in Figure 11a,b) was certainly accentuated by the dynamics of these shoreline undulations. However, south of transect no. 250, the dynamics of these shoreline undulations have apparently been the main driver of cross-shore shoreline variability on timescales ranging from season to several years (shown in Figure 11c–e).

5. Discussion

5.1. Limitations and Advantages

In this work, lidar-derived MWH shorelines could only be compared to wet/dry lines derived from Landsat 8 images (Figure 6) and Sentinel-2 images (Figure 7). Comparisons with wet/dry lines derived from Landsat 5/7 and SPOT 1/2/4/5 images were not possible because beach surveys along Cap Ferret sand spit began in 2008 and were sparse until 2014. Landsat 8 and Sentinel-2 satellites are equipped with improved sensors compared to the other satellites. The accuracy of the wet/dry lines to reproduce the MWH shorelines could, therefore, be reduced when derived from Landsat 5/7 and SPOT 1/2/4/5 images. A meticulous inspection of Figure 12b suggests that the timestack of the detrended cross-shore position of the wet/dry line is a little bit noisier prior to the Landsat 8 and Sentinel-2 era. However, at timescales greater than the seasonal scale, the detection and characteristics of the shoreline undulations seem to be relatively unaffected. The method introduced here should be applied to meso- or macrotidal sites where long-term coastal monitoring programs exist in order to better assess its accuracy when using Landsat 5/7 and SPOT 1/2/4/5 images.

A tolerance of ± 7 days around the lidar dates was applied in the search for satellite-derived wet/dry lines that could be compared with lidar-derived MWH shorelines. The underlying hypothesis is that the upper beach morphology does not change over this period of time. Analysis of past wave conditions and tide levels indicates that there was no major morphogenic event (e.g., storm) between image and lidar acquisitions, except for the comparison matchup of January 2020 (Figure 7d). For this matchup, involving a Sentinel-2 image acquired on 9 January 2020 and a lidar acquired on 11 January 2020, the assumption of stability is not valid due to the occurrence of very energetic offshore waves ($H_s = 5\text{--}6$ m, $T_p = 14\text{--}15$ s) concomitant with a moderate spring tide on 10 January 2020. The morphology of the beach may have changed significantly as a result of this event. The comparison shown in Figure 7d should, therefore, be interpreted with caution. Indeed, visual inspection of satellite images acquired over the weeks before and after reveals a sharp decrease in the dry beach width near the sand spit tip after 9 January 2020. This could

explain the significant seaward offset of the wet/dry line observed between transects nos. 1 and 100 in Figure 7d.

As for waterline-based SDS, the accuracy of wet/dry-line-based SDS can be adversely affected by some local environmental conditions. First, a landward offset of the wet/dry line in relation to the MHW shoreline is expected for extractions made from satellite images acquired at a time when the total water level was higher than the MHW level. This happens at the high tide of a spring tide or at any other time close to the high tide if it occurs synchronously with the onset of storm surge or high-energy waves causing large wave setup and runup values. The 27.5 m landward bias associated with the wet/dry line extracted on 17 October 2014 when compared to the lidar-derived MHW shoreline of October 2014 (Figures 6a and 13a,b) arises from such a particular situation. The satellite image used to extract the wet/dry line was acquired at the high tide of a neap tide under high-energy wave conditions characterized by H_s of 2.9 m and T_p of 13.9 s. Based on the formula of [89], these wave conditions can cause a wave setup and runup of about 0.5 m and 1.3 m, respectively. This may have led to a total water level of about 2.1 above MSL, which is about 0.6 m above the MHW level. Similar to waterline-based SDS, a water level correction could be applied to attempt to reduce landward bias induced by such environmental conditions.

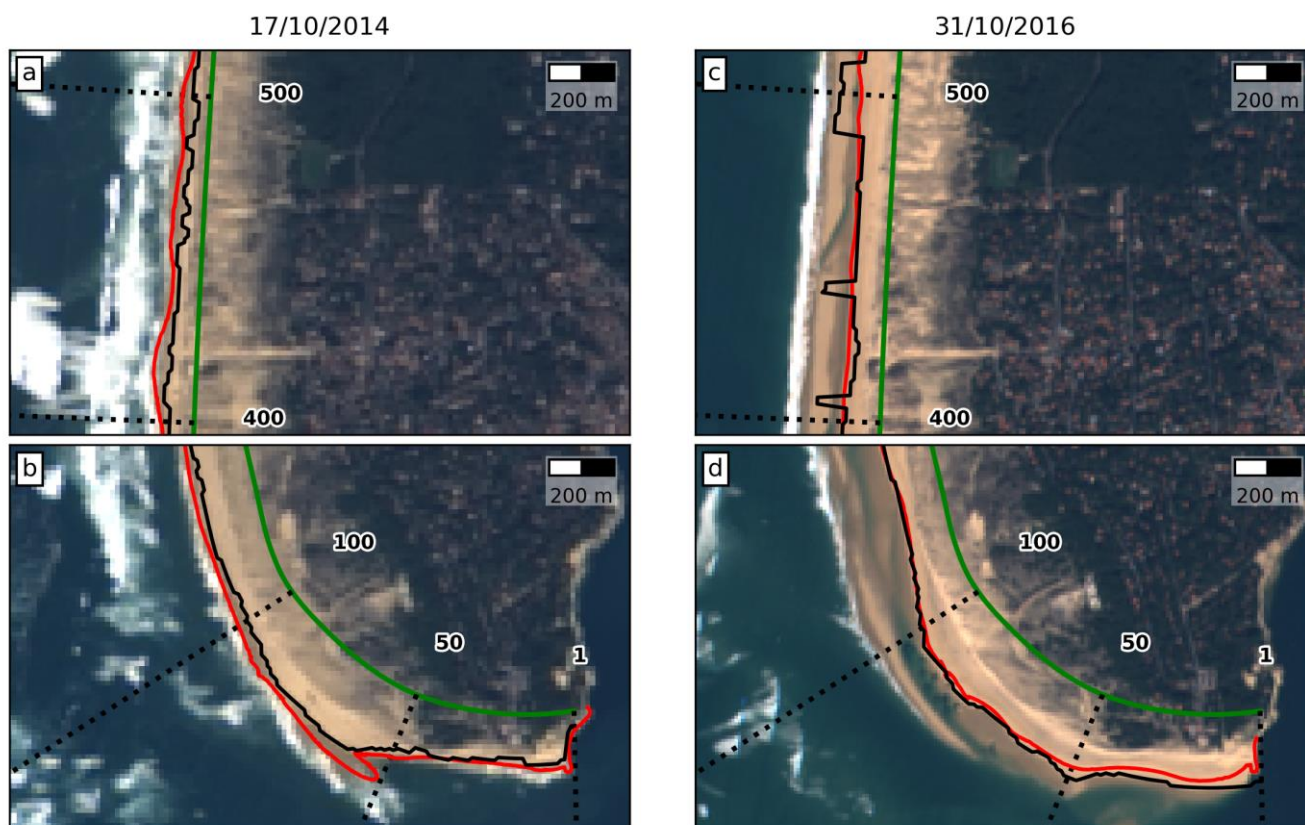


Figure 13. A comparison between the satellite-derived wet/dry line (black curve) and the lidar-derived MHW contour (red curve) for two matchups. (a,b) Lidar of 23 October 2014 with Landsat 8 RGB image of 17 October 2014 acquired at a high neap tide. (c,d) Lidar of 29 October 2016 with Sentinel-2 RGB image of 31 October 2016 acquired at a low spring tide. In panels (a–d), the green curve indicates the baseline defining the transect origin and the dotted black lines indicate specific transects, whose numbers are given in black.

Second, even if the wet/dry line is argued to remain close to the past high water line over a falling and rising tidal cycle [38,39], drying factors such as the sun, the temperature, the wind, and the time to the previous high tide may cause the wet/dry

line to move seaward to its original position. Under the influence of such factors, a seaward offset of the wet/dry-line-based SDS in relation to the MHW shoreline could occur (e.g., Figure 13d). This may explain the large seaward bias of 27.1 m obtained with a wet/dry line derived from the Landsat 8 image of 17 October 2020. This image was acquired about one hour after the low tide of one of the highest spring tides of the year (Figure 6d) concomitant with drying weather conditions. In contrast to the high-water-level-driven landward offset, this seaward offset cannot be mitigated using a water-level correction. Further investigations based on field experiments, including wet/dry line tracking under varying environmental conditions, are potentially required to assess the impact of sand drying out on the overall skill of the wet/dry line at reproducing the MHW shoreline.

When strongly exacerbated, these drying factors could also lead to partial drying out of emerged intertidal sandbars (e.g., Figure 13c) and, in turn, to the extraction of the wrong wet/dry line in case the most seaward line is systematically taken. In this work, an extraction rule was applied to prevent the extraction of wet/sand lines belonging to sandbars visually detached from the upper beach (see Section 3.4, Figure 5a,b). However, this fails to pick out the correct wet/dry line in the case of partially dried-out sandbars located very close to the upper beach. This is highlighted by some inaccurate cross-shore positions of the wet/dry lines extracted on 29 October 2016 from a Landsat 8 image (Figure 6b) and on 31 October 2016 from a Sentinel-2 image (Figures 7a and 13c) between transects nos. 400 and 548. The extraction method used here is relatively simple and could be improved by adding additional processing steps such as the use of a contouring function (e.g., the marching squares) and the removal of wet/dry contours having a length below a specific threshold (e.g., [21,24]). Applying a contouring function to a grayscale image of a radiometric index that discriminates well the wet sand from the dry sand, rather than applying it to a classified image, would pave the way for subpixel wet/dry line detection. However, the search for a radiometric index that satisfies this constraint is beyond the scope of this study and is left for future research.

A crucial step of the method introduced here is the supervised classification of satellite images and, more specifically, the building of the training sample datasets that feed the classifiers. Because spectral signatures of the wet sand and dry sand are close, the selection of the training samples must be performed with care. In this work, several working days were devoted to this task. Applying this method to other beaches with different sand characteristics (e.g., composition, color) would require the building of new training sample datasets. These constraints currently prevent it from generalizing its application to sandy coasts worldwide. If such an objective is sought, the use of waterline-based algorithms is still more appropriate. Indeed, the performances of these algorithms can be less sensitive to the quality of the training sample datasets due to very different spectral signatures of the water and sand (whether dry or wet). Nevertheless, in the case of in-depth studies at a limited number of meso- and macrotidal sites, the use of the wet/dry line to generate satellite-derived shorelines, as an alternative to the waterline, should be seriously considered. Future work should address the speeding up of the classifier training step, which could probably be achieved by combining the use of existing databases of surface spectral signatures with unsupervised classification.

5.2. Comparison with the Waterline-Based Shoreline Detection

Our results show that even without reducing errors caused by water levels above the MWH or by the drying out of the intertidal beach, the use of the wet/dry line extracted at pixel-scale enables the monitoring of the alongshore and cross-shore MHW shoreline variability at this meso-macrotidal site on seasonal and interannual scales. The occasional and punctual inaccuracies in detecting the MHW shoreline obtained here are most of the

time compensated for by the multiplicity of the usable satellite images on such temporal scales. The skill of the wet/dry line of reproducing the MHW shoreline (Figures 8c and 9, Table 3) also appears much better than that obtained at the 6 km away Truc Vert beach using non-corrected waterlines (RMSE = 31.4 m, bias = 22.5 m, R^2 = 0.42, number of images used for skill assessment (n) = 226 images) and slightly better when using tide-only corrected waterlines (RMSE = 15.6 m, bias = −8.0 m, R^2 = 0.53) [28], especially in terms of bias and R^2 . Using only satellite images acquired at tide levels greater than 0.2 m above MSL (n = 164 images) and accounting for the wave runup in the water level correction step, the skill of the waterline-based SDS of reproducing the MHW shoreline was significantly improved, with RMSE = 10.3 m, bias = 7.1 m and R^2 = 0.78 [28]. However, this resulted in the exclusion of about 27% of the available cloud-free images, which represents a significant loss of data for the assessment of shoreline change on seasonal and shorter timescales.

Table 3. Shoreline detection skills obtained in this study and in other studies that have applied the waterline-based shoreline detection algorithm CoastSat at distinct meso- and macrotidal sandy coasts. The number of satellite images used for skill assessment (n) is indicated in the last column. Abbreviation n/a means not applicable.

Site [Study]	Detection Based on	Tidal Range (m)	Target Datum-Based Shoreline	Water Level Correction	Image Exclusion	RMSE (m)	Bias (m)	R^2	n
Cap Ferret sand spit [this work]	wet/dry line	3.8	MHW	none	none	20.2	1.7	0.86	11
Truc Vert [28]	waterline (CoastSat)	3.7	MHW	none	none	31.4	22.5	0.42	226
				tide-only	none	15.6	−8.0	0.53	226
				tide and wave runup	low-tide images	10.3	7.1	0.78	164
Slapton Sands [90]	waterline (CoastSat)	4.4	MHW	none	none	18.1	10.2	n/a	147
				tide-only	none	14.0	6.5	n/a	147
Perranporth [90]	waterline (CoastSat)	6.3	MHWN	none	none	138.2	16.2	n/a	93
				tide and wave runup	none	22.2	−4.2	n/a	93

Even if not fully demonstrated here, we anticipate that using the wet/dry line allows for using most of the available cloud-free images and opens larger perspectives in the study of shoreline changes along meso- and macrotidal coasts. Additionally, the authors of [28] relied on offshore wave conditions extracted from a regional wave hindcast to estimate wave runup at Truc Vert beach and to feed water level corrections. Closer to the tip of the Cap Ferret sand spit, inshore waves experience complex transformations due to the proximity of the tidal inlet and the complex arrangement of nearshore sandbars (Figure 1b) and may not be well reflected by those offshore wave conditions. The inclusion of the accurate wave wave runup contribution into water level corrections in this area would, therefore, require an additional step of inshore wave modeling. This would make the satellite-based monitoring of shoreline changes highly complex. In contrast, the use of the wet/dry line may simplify the overall workflow while ensuring sufficient accuracy in detecting shoreline changes.

Comparisons of waterline-based SDS with observed high-tide datum-based shorelines at macrotidal sites are also found in [90] (Table 3). At the reflective and steep beach of

Slapton Sands, comparing non-corrected waterlines with MHW shorelines resulted in an RMSE of 18.1 m and a bias of 10.2 m ($n = 147$ images). Applying tide correction to the waterlines increased slightly the skill with an RMSE of 14.0 m and a bias of 6.5 m. At the dissipative and flat beach of Perranporth, comparing non-corrected waterlines with mean high water neap (MHWN) shorelines resulted in an RMSE of 138.2 m and a bias of 16.2 m ($n = 93$ images). Applying tide and runup corrections to the waterlines improved drastically the skill with an RMSE of 22.2 m and a bias of -4.2 m. Even if a direct comparison is not possible between the Cap Ferret sand spit and these two sites, the use of the wet/dry line seems to provide a benefit, particularly in terms of bias reduction.

5.3. Shoreline Variability Along the Cap Ferret Sand Spit

Thanks to the availability of a long and dense archive of free satellite images, the shoreline variability along the Cap Ferret sand spit occurring on seasonal and decadal scales since 1984 has been depicted here for the first time (Figure 11). This study has revealed a progressive change of the dominant modes of shoreline variability along the tip of the Cap Ferret sand spit, with a transition between transects nos. 250 and 300, i.e., approximately 2.5–3 km away from the sand spit extremity. North of this transition area, the cross-shore shoreline changes were rather in phase (Figures 11 and 12b), regardless of their location. Seasonal and interannual cycles are also similar to those observed elsewhere along the sand spit and away from the tip, such as at the G16 and G17 transects of the Observatoire de la côte de Nouvelle-Aquitaine [7] or at Truc Vert beach [28]. In contrast, south of transect no. 250, the seasonal and interannual cycles were quite uncorrelated from one alongshore location to another (Figures 11 and 12b), with greater amplitudes of shoreline change than those observed further north, away from the tip. Analysis of spatiotemporal diagrams of shoreline changes (Figure 12b) has evidenced that this shift in the dominant modes of shoreline variability on seasonal and interannual scales was mostly related to the existence of shoreline undulations south of transect no. 250 that migrated southward with variable migration speeds, visually uncorrelated to seasons. Such shoreline undulations have already been observed along other km-scale sand spits (e.g., [58,59]). Shoreline undulations have also been systematically observed in the north of the study area but with limited cross-shore amplitudes and with lifetimes in phase with the typical accretion/erosion seasonal cycles. This latter alongshore variability corresponds to the formation of accretive beach megacusps [76,77].

The progressive changes in environmental settings (coastal orientation, distance to the inlet) that are observed south of transect no. 300 are inherent to inlet-adjacent coast sections and may affect the hydrodynamics and, in turn, the dynamics of local ridge–runnel systems and the shoreline dynamics [91,92]. For instance, the coastline orientation shifts from a N-S orientation at transect no. 300 to a W-E orientation at transect no. 1. Therefore, incident waves, predominantly coming from the WNW to NW direction, reach the breaking zones with increasing incidence angles as the distance to the sand spit extremity reduces. This could favor the onset of high-angle-wave shoreline instabilities, thus partly explaining the development of the shoreline undulation in this area [61,93,94] or the amplification of beach megacusps reaching this area. Tidal currents, which develop within the ebb delta of the Arcachon lagoon, also interact with inshore wave conditions and modify the longshore sediment transport patterns at the tip of the sand spit [54]. This likely contributes to the growth, stabilization, and vanishing of these morphological features. Visual inspection of the satellite images has also revealed a change in the characteristics of the ridge–runnel systems that migrated southward from transect no. 300 (e.g., Figure 14). These changes include a widening of intertidal sandbars and an increase in cross-shore extent over which they have developed. Large hook-shaped

intertidal sandbars have also frequently developed from the apex of shoreline undulations and have sometimes reconnected to the upper beach. These bar attachments have generally led to an increase in the spatial scales of shoreline undulations and an apparent migration of their downdrift flank (Figure 14d,e). Thus, self-organizing processes occurring within the intertidal zone should also be considered as potential drivers in the dynamics of shoreline undulations observed along the tip of the Cap Ferret. More in-depth investigations of these dynamics would, however, require additional modeling and measurement of waves, currents, and morphological changes.

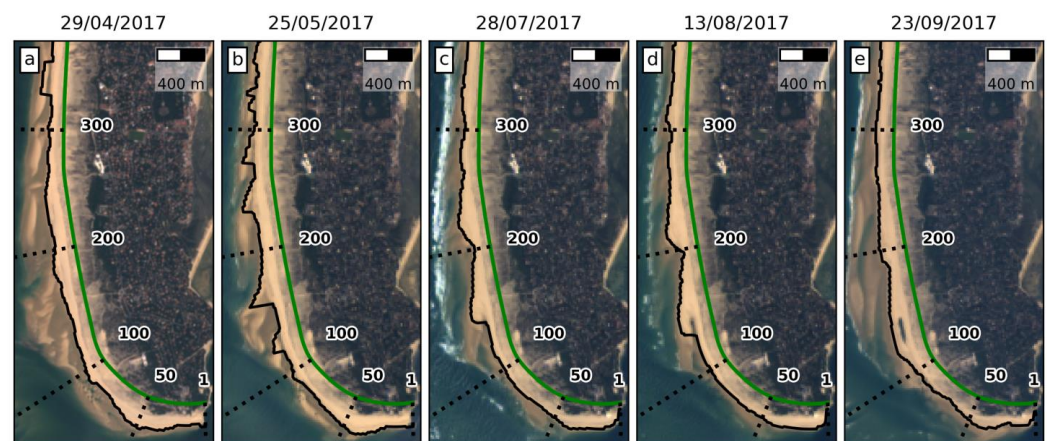


Figure 14. Successive satellite RGB images from 29 April 2017 to 23 September 2017 (a–e) showing the transformation of ridge–runnel systems along the tip of the Cap Ferret sand spit and the development of shoreline undulations. In panels (a–e), the black curve indicates the satellite-derived wet/dry line, the green curve indicates the baseline defining the transect origin, and the dotted black lines indicate specific transects, whose numbers are given in black.

5.4. New Opportunities for Coastal Monitoring

Shoreline change assessment based on satellite imagery along meso- and macrotidal coasts (e.g., [28,29,34,90]) has generally disregarded the cross-shore shoreline variability occurring on seasonal and shorter timescales and/or the alongshore shoreline variability occurring at spatial scales lower than hundreds of meters. This choice was usually motivated by the need to smooth out in space and time potential errors inherent to waterline-based SDS in such environments [34,90]. The results shown in this work suggest that it is still possible to investigate shoreline changes occurring on these spatial and temporal scales along meso- to macrotidal coasts using satellite imagery, pending the use of the wet/dry line.

The use of historical and recent aerial photographs [7,9] has already enabled the characterization of the chronic erosion affecting the southern extremity of the Cap Ferret sand spit over the last decades, with a dune-foot erosion trend estimated up to about -9 m/year over the 1985–2014 period. Using waterline-based SDS from 1984 to 2019, the authors of [28] computed an erosion trend of -8.38 m/year at a location near transect no. 50. Here, the erosion trend at transect no. 50 computed from satellite-derived wet/dry lines was estimated to be -8.71 m/year over the 1984–2021 period (Figure 11e), which is in agreement with these earlier studies. The wet/dry-line-based SDS can, therefore, be used to estimate shoreline change trends at decadal scales as an alternative to other state-of-art methods. This can be particularly interesting for meso- and macrotidal sites where long-term monitoring programs have not been carried out and when some input data of waterline-based SDS algorithms cannot be provided (e.g., tidal levels, inshore wave conditions, beach slope). The method introduced here was applied to a high-energy sandy coast, where water fluctuations related to wave runup can be a predominant source of error

when satellite images are acquired close to the high tide (e.g., Figure 6a). The application of this method at low-energy sandy coasts should result in an improved accuracy in shoreline detection due to the lower values of wave runup.

Although not the purpose of this work, major shoreline changes could even be analyzed on a weekly or monthly basis during several periods with a few gaps in usable satellite images and, in particular from March 2017, with the commissioning of the second satellite of the ESA Sentinel-2 constellation (Figure 2). Commissioning of the Landsat 9 satellite by NASA and the USGS at the end of November 2021 provides an additional source of free satellite imagery and will certainly make it possible to further densify the database of usable images from this date.

Operational satellite-based monitoring of changes in the upper beach width over short timescales could be of great interest to coastal managers, particularly on sandy coasts where the dry beach acts as a buffer against storm waves that could reach and erode the dune. Along the tip of the Cap Ferret sand spit, a few sparse observations in the field have shown that storm-driven erosion of the dune mainly occurs where the dry beach is narrow. Results of this study have shown that beach narrowing is strongly related to the development and migration of shoreline undulations. Setting up a regular monitoring of shoreline undulations and their dynamics using the method introduced here should help anticipate dune erosion and encourage local coastal managers to undertake pre-storm beach nourishments only on erosion-exposed segments.

6. Conclusions

The use of the satellite-derived wet/dry sand line has enabled the depiction for the first time of the shoreline changes along the tip of the Cap Ferret sand spit on seasonal and decadal scales. It has evidenced the importance of having information on these timescales to understand the particular dynamics of the site and, in particular, the alongshore gradient in the dominant modes of variability in the last few kilometers of the sand spit. Over the last 2 km of the sand spit, the shoreline has chronically retreated on the decadal scales and is strongly affected by the onset and migration of large shoreline undulations that lead to a dominance of the interannual variability over the seasonal variability. In this area, the shoreline undulations are usually characterized by a wavelength of 500–1200 m and a cross-shore amplitude of 100–200 m. Their migration speed is on average between 1 and 3.5 m/day. Migration speed can occasionally reach 5–10 m/day, except near the tip where shoreline undulations tend to stagnate and flatten out. In contrast, away from the sand spit extremity, at distances greater than around 3 km, the shoreline is relatively stable in the long term, with a dominance of seasonal and interannual variability.

Although, there is room for substantial improvements in accuracy, the method introduced here has already proven its ability to track the dynamics of shoreline undulations having cross-shore and longshore extents greater than a few tens of meters. This work brings new arguments in favor of the use of the wet/dry line to monitor shoreline changes along meso- and macrotidal sandy coasts. Coastal observatories should take advantage of this opportunity to increase their capabilities in shoreline detection and to provide more detail on past shoreline changes. Future research should involve the application of the method introduced here to other coastal environments, such as low-energy and/or microtidal sandy coasts. Speeding up the classifier training step, for example, by using unsupervised classification and existing databases of surface spectral signatures, should help generalize the application of this method to other sandy coasts worldwide. Finally, upgrading this method toward a subpixel approach should improve the shoreline detection accuracy and enable capturing alongshore variability with more detail.

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Data Availability Statement: Landsat 5/7/8 and Sentinel-2 images were downloaded from the Google Earth Engine platform (<https://earthengine.google.com>, accessed on 23 March 2025). Spot 1/2/4/5 images were downloaded from the former Kalideos Littoral platform of the Centre National des Etudes Spatiales, which are now available at processing level 1A from the SPOT World Heritage database (<https://regards.cnes.fr/html/swh/Home-swh3.html>, accessed on 23 March 2025). Beach profiles and lidar DTMs used in this study are freely available on the website of the Observatoire de la côte de Nouvelle-Aquitaine (<https://www.observatoire-cote-aquitaine.fr/SIG-OCA-Collecte-et-diffusion-des-donnees>, accessed on 23 March 2025). Other data supporting the conclusions of this article will be made available by the authors upon request.

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Abbreviations

The following abbreviations are used in this manuscript:

CNES	Centre National des Etudes Spatiales
DTM	Digital Terrain Model
ESA	European Space Agency
GNSS	Global navigation satellite system
Hs	Significant wave height
IGN	Institut national de l'information Géographique et forestière (France)
LA	Landsat
MHW	Mean high water
MHWN	Mean high water neap
MSL	Mean sea level
NASA	National Aeronautics and Space Administration
NGF	Nivellement général de la France
no.	Number
n/a	Not applicable
RMSE	Root-mean-square error
R ²	Determination coefficient
SE	Sentinel
SDS	Satellite-derived shoreline
SP	SPOT
Tp	Peak wave period
USGS	United States Geological Survey

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