

Article

Automated Detection of Submerged Sandbar Crest Using Sentinel-2 Imagery

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Highlights

What are the main findings?

- The logarithmic band-ratio method applied to Sentinel-2 imagery accurately detects submerged sandbar crests across morphologically distinct Mediterranean beaches.
- The blue–green ratio proves to be the most suitable and consistent approach for sandbar detection, applicable across both microtidal and mesotidal environments.

What is the implication of the main finding?

- The proposed methodology approach provides a cost-free, automated, and scalable solution for long-term sandbar monitoring using satellite imagery.
- The use of the presented methodology supports coastal managers in assessing sediment budgets and shoreline resilience without the need for frequent in situ surveys.

Abstract

Coastal sandbars play a crucial role in shoreline protection, yet monitoring their dynamics remains challenging due to the cost and limited temporal coverage of traditional surveys. This study assesses the feasibility of using Sentinel-2 multispectral imagery combined with the logarithmic band ratio method to automatically detect submerged sandbar crests along three morphologically distinct beaches on the northwestern Mediterranean coast. Pseudo-bathymetry was derived from log-transformed band ratios of blue-green and blue-red reflectance used to extract the sandbar crest and validated against high-resolution in situ bathymetry. The blue-green band ratio achieved higher accuracy than the blue-red band ratio, which performed slightly better in very shallow waters. Its application across single, single/double, and double shore-parallel bar systems demonstrated the robustness and transferability of the approach. However, the method requires relatively clear or calm water conditions, and breaking-wave foam, sunglint, or cloud cover conditions limit the number of usable satellite images. A temporal analysis at a dissipative beach further revealed coherent bar migration patterns associated with storm events, consistent with observed hydrodynamic forcing. The proposed method is cost-free, computationally efficient, and broadly applicable for large-scale and long-term sandbar monitoring where optical water clarity permits. Its simplicity enables integration into coastal management frameworks, supporting sediment-budget assessment and resilience evaluation in data-limited regions.

Keywords: sandbar detection; Sentinel-2; coastal monitoring; morphodynamics



Academic Editor: Gareth Rees

Received: 24 October 2025

Revised: 30 November 2025

Accepted: 22 December 2025

Published: 30 December 2025

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1. Introduction

Among the various features influencing coastal behavior, submerged sandbars are critical morphological elements in many coastal systems, as they dissipate wave energy before it reaches the shoreline, thereby helping to reduce coastal erosion and protect both ecosystems and infrastructure from storm impacts [1,2]. Their morphology and dynamics respond to wave climate, sediment availability, and tidal regimes, making them sensitive to environmental variability [3–6]. Some bars remain constantly submerged (microtidal), while others are submerged only during high tides (macrotidal), which affects both energy dissipation and monitoring. One of the most widely used classifications for single-barred coasts is that of [3], which defines six beach states based on sandbar morphology and wave energy, and several studies have highlighted the importance of describing sandbar systems and their behavior [3,4,7–10]. However, they stress the need for an extensive data set, as a comprehensive understanding of the spatial and temporal variability of submerged sandbars is essential for assessing coastal resilience and guiding sustainable coastal management strategies.

Sandbar dynamics have been extensively investigated since the late 1980s through laboratory experiments [1,11–13], field campaigns [3,5,14], numerical modeling [9,15–17], and video imagery [4,6,18,19]. More recently, satellite imagery has been explored as a tool to detect sandbar crest positions and analyze their evolution. Based on seminal manual techniques to identify sandbar crests from satellite images [20–22], ref. [23] proposed a methodology that combines red, green, and blue bands to enhance spectral responses over sandbars, thereby facilitating and systematizing their detection. Ref. [24] used high-resolution satellite images combined with spectral indices, unsupervised classification, and spatial statistics to extract bar positions. Ref. [25] proposed the SandBar Index (SBI) to detect sandbars at locations where waves break (white foam). Although promising methods for identifying bars using satellite imagery exist, significant potential remains for further improvement, such as multi-beach intercomparison of methodologies or developing straightforward algorithms for large data sets.

Ref. [26] proposed a standard algorithm for estimating depth in shallow waters based on a log-transform band ratio, from wavelengths with different absorption properties in water, to linearize the exponential attenuation of light with depth. The resulting ratio serves as a form of pseudo-bathymetry, enabling the detection of submerged sandbars. More recently, ref. [27] applied high-resolution drone imagery along the coast and proposed a Standardized-Ratio Bathymetric Index (SRBI), based on the ratio of log-transformed green and red bands, to identify sandbar positions. The mentioned contributions suggest a strong dependence on the local optical properties of beach waters, which calls for a systematic assessment of methods across different sites. In this paper, we aim to evaluate the feasibility and accuracy of using Sentinel-2 imagery to detect sandbar crest positions through pseudo-bathymetry derived from the logarithmic band ratio proposed by [26], combining blue and green or red bands. We present a new automated methodology for deriving sandbar crest positions (rather than local depth) from satellite imagery, which is cost-free, computationally efficient, and widely accessible. To assess its robustness and potential for application elsewhere, we applied the method to three different beaches from the NW Mediterranean Sea. Applying the method to different beaches allows for a systematic intercomparison while also highlighting its ability to accurately identify sandbar crests in diverse environments. The method has been applied to three morphodynamically distinct beaches, and a long-term evolution of the system is determined for the available Sentinel-2 dataset, discussing the crest bar migration as a function of the wave energy. Additionally, four more sites have been studied, including it in the Supplementary Materials

to further support the robustness and transferability of the presented method, as well as to provide consistency in the discussions and conclusions drawn from the study.

The paper is structured as follows: The study area is reported in Section 2. The datasets used and the algorithm development are given in Section 3. The results obtained in the selected beaches are presented in Section 4, followed by the discussion in Section 5. Finally, the main conclusions are highlighted in Section 6.

2. Study Area

The selected beaches are located in the NW Mediterranean coast of Spain on the Catalan Coast: Sant Vicenç de Montalt (SVM), Castelldefels-Gavà (CG), and Trabucador (TB) (Figure 1). The area is considered a tideless (0.3 m) and fetch-limited environment with a mixed sea-swell regime [28,29]. Significant wave heights typically range between 0.5 m and 1.5 m, with storm conditions that can achieve up to 7.9 m [29,30]. Wave periods are generally short (3 s–7 s), reflecting the limited fetch, and only during severe storms can they extend up to 10 s. This coast is dominated by episodic storms from the E-NE associated with easterly and northeasterly winds, particularly during autumn and winter, due to low-pressure systems in the western Mediterranean that are most active. In contrast, summer conditions are generally calm, characterized by prolonged periods of low wave energy. Overall, the Catalan coast is characterized by a moderate but highly variable wave climate. Storm events, which exert a critical influence on coastal processes, are the main drivers controlling the morphology and dynamics of beaches along this coastline [31].

In 2010, the *Centre Internacional d'Investigacions dels Recursos Costaners* (CIIRC) carried out a thorough evaluation of the state and spatiotemporal evolution of the Catalan coast [32], which assessed the morphological and hydrodynamic conditions. This report provides detailed insights into the hydro-morphological characteristics of the 331 beaches by compiling data from coastal-oceanographic campaigns and numerical models. Each beach analyzed in this study exhibited a distinct morphodynamic state according to the classification of [3]. SVM shows a reflective model morphodynamic state, CG is classified as between dissipative in the northern transects and intermediate in the southern sections, and TB corresponds to a dissipative beach [32]. The seaward boundary of significant sediment transport, commonly referred to as the depth of closure (DoC), is 6.9 m at SVM, 6.35 m at CG, and 8.07 m at TB, all referenced to mean sea level [32]. This depth represents the limit of net sediment transport over the selected temporal scale [33].

SVM is an open beach (Figure 1a) with a median grain size (D_{50}) of 0.812 mm. It is 80 m wide and 1200 m long. (see the main characteristics summarized in Table 1). The site experiences a mean significant wave height (H_s) of 0.69 m and a peak wave period (T_p) of 6.2 s [32]. This beach features a single sandbar system situated approximately 100 m to 300 m offshore at a depth of 2.5 m–4 m. CG is located near the Llobregat Delta (Figure 1b), approximately 20 km south of Barcelona. It is an open beach composed of sand with a $D_{50} = 0.307$ mm and extends 3640 m in length, with a H_s and T_p of 0.74 m and 6.0 s, respectively [32]. This area exhibits a double-bar system, consisting of a highly dynamic inner bar, also referred to as a “terrace”, and a more stable outer bar [16,34,35]. In the northern sector, the inner bar is located approximately 0 m–100 m from the shoreline, at depths between 0.5 m and 1.5 m. In contrast, in the southern sector, the inner bar is closer to the coast, typically not extending beyond 50 m offshore at 0.5 m–1 m depth. The position of this inner system is strongly influenced by the prevailing wave climate [34]. The outer bar is located in a more fixed position, between 150 m and 200 m from the coast, at depths ranging from 2.5 m to 3.2 m [16,34,35]. TB is a barrier beach (Figure 1c) with a length of 8132 m and a width of 69 m, composed of sand with a $D_{50} = 0.225$ mm. This is a wave-dominated beach [36], with a H_s and T_p of 0.81 m of 5.24 s, respectively [32]. The

beach exhibits a double shore-parallel bar system, as described by [36,37], with the inner bar located at 0.8 m–1.5 m depth, approximately 100 m from the shoreline, and the outer bar at 1.2–2.5 m depth, around 300 m offshore. The four complementary beaches reported in the study (Figure S1), Calafell (CF), Altafulla (AF), Fangar (FG), and Platjola (PJ), are characterized in Tables S1 and S2.

Table 1. Morphological and hydrodynamic features of the studied beaches. D_{50} represents the median grain size (mm), L is the beach length (m), DoC is the depth of closure (m), β represents the beach slope, H_s is the significant wave height (m), and T_p is the peak wave period (s). The type of bar indicates the morphological configuration of the sandbar at each beach.

Beach	Morphological Features					Hydrodynamic Conditions	
	D_{50} (mm)	L (m)	DoC(m)	β	Type of bar	H_s (m)	T_p (s)
SVM	0.812	1200	6.9	0.23	Single bar system	0.6	6.2
CG	0.307	3640	6.35	0.25–0.08	Single/double bar	0.7	6
TB	0.225	8132	8.07	0.06	Double shore bars	0.8	5.2

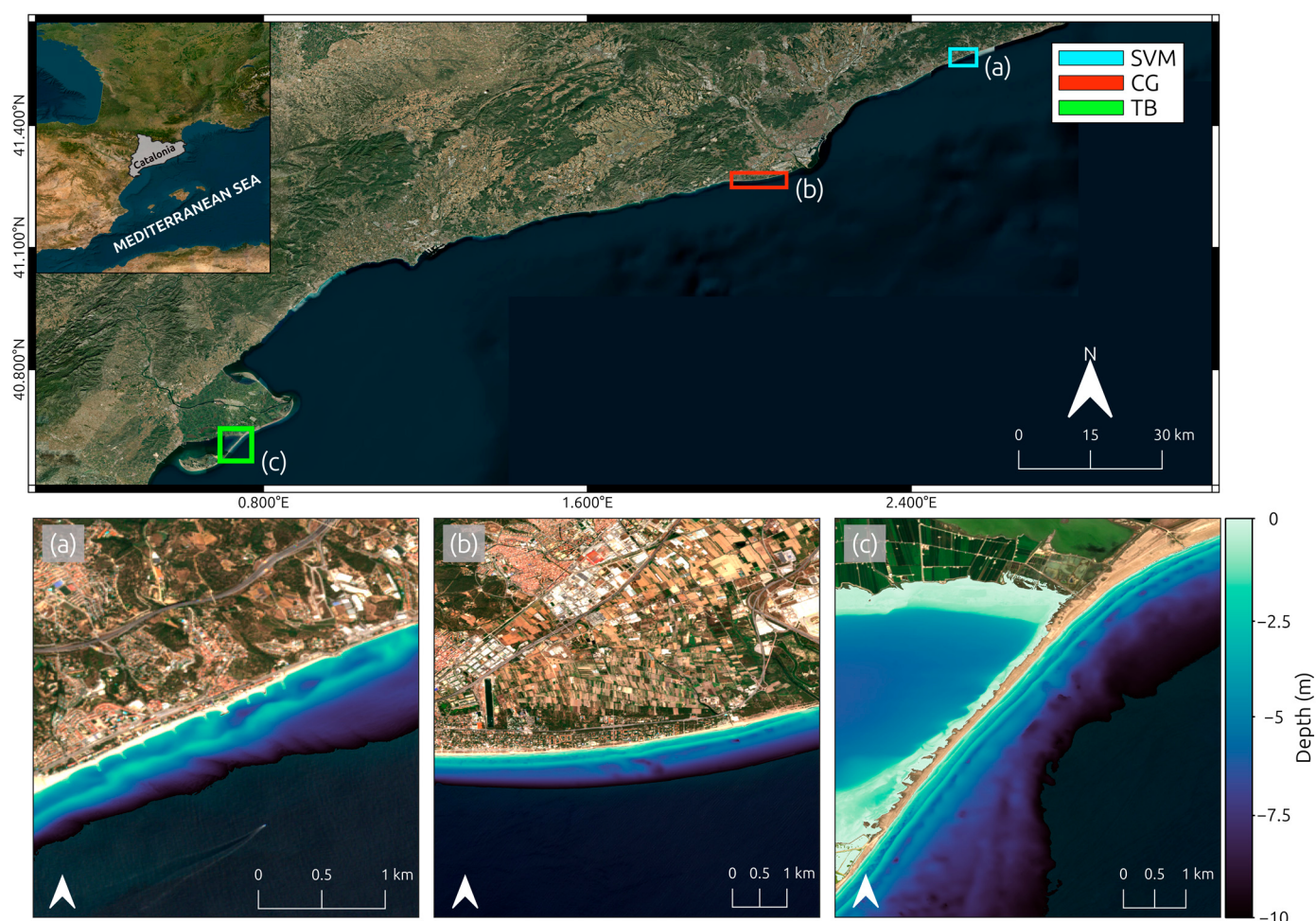


Figure 1. Location of the three study sites (SVM, CG, and TB beaches) along the Catalan coast (NW Mediterranean Sea). The **upper** panel shows the regional context with the areas of interest (a–c) indicated by colored boxes (SVM-cyan, CG-red, TB-green). The **lower** panels (a–c) display Sentinel-2 imagery, including true-color composites and bathymetry in situ, with depth values ranging from 0 m to –10 m.

3. Materials and Methods

In this contribution, the satellite-derived sandbar positions using the log-band ratio as a pseudo-bathymetry were evaluated by comparing them with in situ bathymetry data from the *Institut Cartogràfic i Geològic de Catalunya* (ICGC) for three beaches obtained in July 2022 and July 2023. Additionally, a qualitative assessment of sandbar dynamics at CG over three years (August 2018 to August 2021) was performed using reference data and hydrodynamic conditions from modeled wave data (i.e., hindcast product). This analysis enhances our understanding of the potential of this methodology for large-scale sandbar position monitoring. Figure 2 illustrates the overall methodological approach adopted in this study. A preprocessing analysis of Sentinel-2 imagery was first conducted, followed by the extraction of the shoreline. A set of cross-shore transects was defined, along which bar crests were identified using the finite differences method.

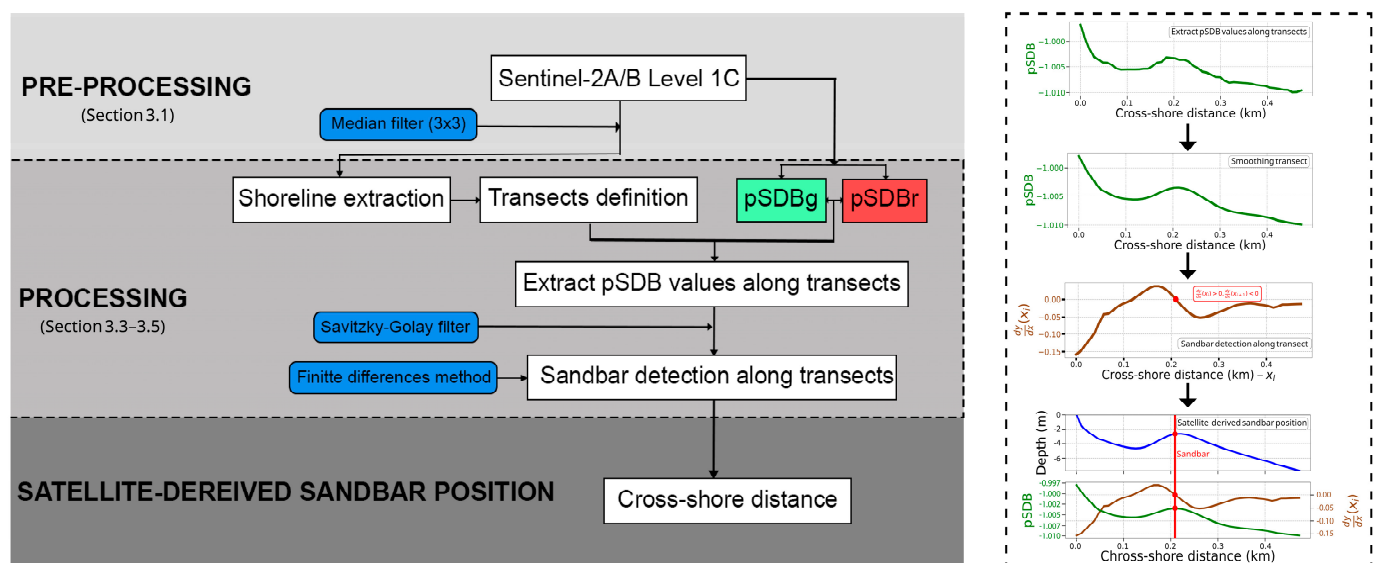


Figure 2. Methodology flowchart followed in the study. The right column shows a visual representation of the processing workflow. pSDBg: blue-green ratio; pSDBr: blue-red ratio.

3.1. Satellite Data and Pre-Processing

The Sentinel-2 mission, launched by European Space Agency (ESA), covers the entire globe and deployed two twin satellites: 2A (launched in 2015) and 2B (launched in 2017). Equipped with Multispectral Instruments (MSI), the mission delivers multispectral images with high spatial (10 m, 20 m, and 60 m), temporal, and spectral resolution across 13 bands [38]. For this study, Sentinel-2 Level-1C images with 10 m resolution were downloaded (Figure S2(a.1–c.1)) using the Python (Version 3.14.2) API of Google Earth Engine (GEE) (version 1.5.24) [39]. These images are downloaded with geographic coordinates, referenced to the World Geodetic System-1984 (WGS84), to be consistent with the bathymetric data. L1C A/B images are radiometrically and geometrically corrected at the top-of-atmosphere (TOA), in contrast to L2A images, which include atmospheric correction. Although atmospheric corrections have a significant impact on image quality for extracting Satellite-Derived Bathymetry (SDB) [40–44], it was not applied to the downloaded images. This facilitates the eventual processing of large data sets of imagery for long-term monitoring.

Our purpose is to assess the viability of pseudo-bathymetry using SDB techniques based on the logarithmic band ratio model [26]. Therefore, a preprocessing stage was conducted to identify appropriate images, specifically those devoid of turbidity and cloud

cover. To select the best image, a criterion was established, prioritizing scenes with less than 30% cloud cover and low water turbidity.

A 30% cloud-cover threshold was applied to exclude highly clouded scenes while retaining enough usable images. Since Level-1C Sentinel-2 data lack the Scene Classification Layer (SCL), we combined this threshold with visual inspection, discarding scenes with cloud interference where clouds block the water surface or cast shadows and thin clouds that significantly alter the reflectance.

To identify low-turbidity conditions, regression analyses were performed between the Near-infrared (NIR), blue, and green reflectance bands from land-masked images. In low-turbidity waters, reflectance in all bands increases approximately linearly with turbidity, whereas in highly turbid waters, the visible bands, particularly blue and green, tend to saturate and lose sensitivity [45,46]. By regressing the NIR band against the blue and green bands, areas affected by significant turbidity and potential saturation can be identified. Only cases with a coefficient of determination (R^2) exceeding 0.65 were considered, as this threshold indicates a sufficiently strong linear relationship between bands, as for that the light reflected from the water captures the morphological features. Images below this threshold are assumed to correspond to considerable turbidity, enough to reduce confidence in capturing seabed morphological features.

Among the selected images, the one with the best fit was subsequently chosen for analysis. To further improve data quality, inter-pixel variability and noise were reduced using a 3×3 median filter. Finally, the selected images were acquired close to the bathymetric survey dates, with a maximum difference of two days (Table 2). For the temporal analysis of bar positions in CG, an automated optimization procedure was applied to select the most appropriate image for processing, following the quality standard previously established.

Table 2. List of Sentinel-2 images selected for each study location, including the dates of the bathymetric data obtained and corresponding satellite acquisition dates.

Location	Satellite		Date of the Bathymetric Campaign
	Date	Sensor	Date
SVM	21 July 2022	S2B MSIL1C	19 July 2022
CG	6 July 2023	S2B MSIL1C	13 July 2023
TB	11 July 2022	S2B MSIL1C	19 July 2022

3.2. In Situ Bathymetry

The ICGC provides high-resolution topobathymetric data, where each grid point represents orthometric elevation in meters at a 1×1 m resolution. The dataset covers the entire range from the emerged beach zone to a depth of 50 m. Data were acquired on different dates (see Table 2) through a combination of aerial LiDAR, single- and multi-beam echosounders, and topographic profiles. Shallow waters (0 m–3 m) were surveyed using single-beam echosounders mounted on Unmanned Surface Vehicles (USVs), while deeper areas (3 m–50 m) were mapped using multibeam echosounders deployed from vessels. Topographic profiles were recorded to bridge the transition between emerging and submerged terrain, and terrestrial LiDAR was used to capture the emergent zones. The merged data were processed and, through georeferencing and overlap, integrated to produce a continuous model. These data are available in various formats. The raster dataset was downloaded in 32-bit Cloud Optimized GeoTIFF format with a 1 m grid resolution. Geographic coordinates were originally provided in the European Terrestrial Reference System 1989 (ETRS89) and subsequently transformed to the WGS84 to align with the Sentinel-2 imagery. Bathymetric data from depths of 0 m to −10 m have been used for the beaches (Figure 1a–c).

3.3. Shoreline Extraction

To evaluate the position of the sandbars, the satellite-derived locations were compared with in situ cross-shore distances from the shoreline to the bars. For this purpose, the shoreline was extracted (Figure S2(a.2–c.2)) from each Sentinel-2 L1C image (10 m resolution), following the methodology proposed by [47]. The satellite-derived shoreline was obtained using the Red-minus-Blue (RmB) spectral index, and the optimum threshold to distinguish water from sand was the Weighted Peaks (WP) thresholding method [47,48] calculated as follows:

$$WP = x_{water} - 0.7 \times (x_{sand} - x_{water}) \quad (1)$$

where x_{sand} and x_{water} are the RmB values of the sand and water pixel peaks in the bimodal distribution, respectively. The marching squares algorithm [47,49], which creates a continuous contour line by linear interpolation between neighboring cells, was used to extract the coastline contour based on the ideal threshold. The extracted shorelines used as a baseline to measure the cross-shore distance between the sandbar and the shoreline were validated using the data provided by the ICGC (See Figure S3).

3.4. Retrieving Log-Transformed Reflectance Band Ratio

The Beer-Lambert law (BLL) states that light attenuation decreases exponentially with depth and is wavelength-dependent. This principle underlies empirical models to retrieve the SDB [50]. This work uses the log band-ratio formulation proposed by [26] to extract the pseudo-bathymetry and subsequently the submerged sandbar crests. The exponential attenuation of light with depth is linearized by the model using a log-transformed band ratio of water reflectance from wavelengths with various absorption characteristics. The resulting ratio is hereinafter referred to as pSDB, representing a pseudo-depth derived from satellite data, which is dimensionless (Equation (2)).

$$pSDB = \frac{\ln(1000\pi R(\lambda_i))}{\ln(1000\pi R(\lambda_j))} \quad (2)$$

In this study, pSDB was calculated using reflectance $R(\lambda)$, combining the blue band (490 nm, λ_i) with either green band (560 nm, λ_j), yielding pSDBg ratio, or red band (665 nm, λ_j), yielding pSDBr ratio. For each image, the pSDBg (Figure 3(a.1–c.1)) and pSDBr ratios (Figure 3(a.3–c.3)) were computed to evaluate their capabilities in detecting bars. A key question is which of these two band ratios provides higher accuracy for this purpose. Blue light attenuates slowly with depth, penetrating down to 25 m, whereas red and green light attenuate more rapidly [41]. Several studies indicate that the red band, due to the faster attenuation of the red light, is more accurate for shallow waters, while the green band better captures information from deeper areas [41,42,51,52].

3.5. Sandbar Detection and Extraction

Shoreline extraction was followed by the definition of cross-shore transects (Figure S2(a.2–c.2)). These transects were automatically generated, extending 500 m offshore and spaced at 50 m intervals along the shoreline, this spacing allows the spatial variability of the sandbars to be captured adequately, as well as their potential migrations. Moreover, it ensures that, even in exceptional cases, the transect length is sufficient to capture the sandbars. A total of 60 transects were created for SVM, 130 for CG, and 94 for TB. The sandbar position is retrieved along the transects defined orthogonal to the reference coastline (Figure 3(a.2–c.2)). The pSDB values extracted along each transect were resampled to equally spaced points using cubic interpolation, with the corresponding geographic coordinates interpolated to the same positions to preserve spatial correspondence. This

procedure ensures that all transects are represented by the same number of points while maintaining the original spatial information data. To reduce noise in the transects, several filter approaches were evaluated to smooth the pSDB profiles. Finally, the pSDB values on the cross-shore transects were smoothed using a Savitzky–Golay filter, which fits a second-order polynomial over a moving window of 12 points, preserving the relevant morphological features (i.e., sandbars). These cross-shore profiles are visible in Figure 3 and in Figures S4–S6.

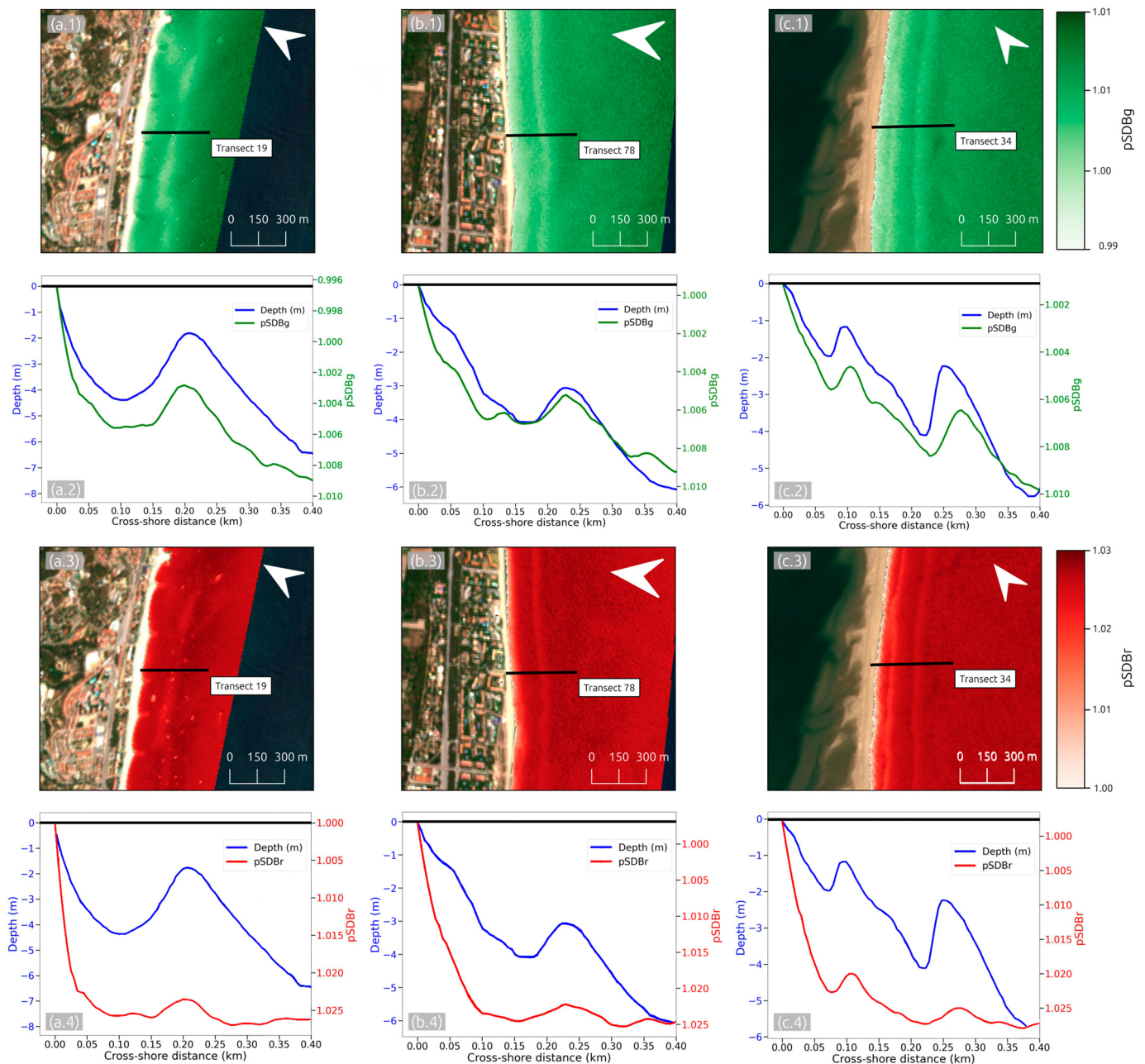


Figure 3. Spatial distribution of pSDBg and pSDBr ratios along SVM (a.1–a.4), CG (b.1–b.4), and TB (c.1–c.4), and cross-shore distance profiles compared with in situ bathymetry. Panels (a.1–c.1) show pSDBg ratio maps and transect locations, while panels (a.2–c.2) display the corresponding cross-shore profiles. Panels (a.3–c.3) present pSDBr ratio maps, and panels (a.4–c.4) show the respective cross-shore profiles. Blue profiles represent in situ bathymetry, and green and red lines correspond to pSDBg and pSDBr ratios, respectively. pSDB maps are rotated to align with the cross-shore profiles and the white arrows indicate north.

To detect the sandbar, we assumed that the bathymetric and the pSDB transect could be described as a scalar function $y = y(x)$, represented discretely by a set of pairs:

$$\{(x_i, y_i)\}_{i=0}^{N-1}, \quad (3)$$

where $x_i \in \mathbb{R}$ is the domain, in this case, the distance along the transect, and $y_i = y(x_i)$ the depth. This continuous function was discretized during the equally spaced points interpolation. The first-order derivative $\left(y'(x) = \frac{dy}{dx}\right)$ at x_i was approximated using the central finite difference scheme:

$$\frac{dy}{dx} \approx \frac{y_{i+1} - y_{i-1}}{x_{i+1} - x_{i-1}} + O(h^2), \quad (4)$$

where $h = x_{i+1} - x_i$, and the associated truncation error is of order $O(h^2)$, implying that the accuracy is quadratic concerning the step size. At the domain boundaries, forward and backward differences were used instead. This method has quadratic accuracy with respect to the discretization step. After obtaining the numerical approximation of the first-order derivative, $\frac{dy}{dx}(x_i)$, a local maximum is identified at positions where the derivative changes sign from positive to negative (Figure 2), corresponding to the crests of the sandbars along the pSDB profiles (Equation (5)).

$$\frac{dy}{dx}(x_i) > 0, \quad \frac{dy}{dx}(x_{i+1}) < 0 \quad (5)$$

3.6. Validation

3.6.1. Single Validation and Uncertainty

To evaluate the accuracy of using pseudo-bathymetry to extract sandbar crests, the cross-shore positions of submerged bars derived from in situ bathymetry provided by the ICGC were compared to those extracted from satellite imagery. The sandbar in situ and satellite positions are identified using the algorithm described in Section 3.5, which detects the local maximum along the depth and pSDB profiles corresponding to the submerged bars. To maintain consistency between datasets and facilitate direct comparison between in situ and satellite-derived positions, the shorelines extracted from Sentinel-2 (Section 3.3) are adopted as a fixed baseline. This approach ensures that all bar crest positions are measured with respect to the same reference line, so that only the differences between in situ and satellite-derived sandbar positions are evaluated, thereby avoiding external deviations and providing methodological coherence.

Validation was performed using satellite imagery acquired temporally closest to the bathymetric data (Table 2). Scene selection was based on the prioritization of images with minimal atmospheric interference, such as cloud cover or sunglint. The dates of the satellite images and the corresponding bathymetric data coincided with relatively calm periods in the northwestern Mediterranean Sea (July 2022 and July 2023). The positions of the sandbars from Sentinel-2 were extracted using the finite difference algorithm described previously. This procedure was applied to SVM, CG, and TB. To validate the sandbar position extracted from satellite imagery against in situ observations, the correspondence between both datasets was quantified using several error metrics: R^2 , mean absolute error (MAE), mean absolute percentage error (MAPE), root mean square error (RMSE), standard deviation (STD), and residual error (RE), where y_i represents the observed sandbar position (from in

situ measurements), $\hat{y}_i$ denotes the predicted or estimated sandbar position (from satellite imagery), $\bar{y}$ is the mean of the observed values, and n is the total number of observations.

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (6)$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (7)$$

$$MAPE = \frac{100}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right| \quad (8)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (9)$$

$$STD = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (y_i - \bar{y})^2} \quad (10)$$

$$RE_i = y_i - \hat{y}_i \quad (11)$$

3.6.2. Time Series Qualitative Validation

Since no in situ reference data are available for long-term comparison, the validation of the proposed method is complemented by a qualitative assessment of the temporal evolution of sandbars. Sandbar positions were analyzed along the transect defined at site CG, covering the period from August 2018 to August 2021. We selected CG, given the extensive literature on this specific site [16,34,35] where the inner bar does not always form, and when it does, it is often difficult to distinguish it from the inner terrace, and tend to be very shallow and are located close to the shoreline [16,34,35]. Due to the limited spatial resolution of satellite imagery and the restricted capacity of reflectance data to capture such subtle bathymetric variations, our analysis focuses exclusively on the detection and monitoring of the outer bar, which is consistently observed at 150 m–200 m offshore. One image per month was selected based on cloud coverage (<30%), resulting in 31 images. The shoreline and sandbar positions were extracted from each image. For long-term analysis, sandbar crest positions are measured from the start of the transect inland, because using the instantaneous shoreline as a reference for the cross-shore distance in each image would incorporate its positional uncertainty into the measurement. This approach provides a consistent reference distance of the sandbar position relative to the baseline, so that the measurement of sandbar migration is affected only by the accuracy of sandbar extraction and not by shoreline uncertainty. In order to better understand the behavior of sandbars, hydrodynamic data were downloaded from the nearest SIMAR point database maintained by *Puertos del Estado* (Spanish Ports Authority). Specifically, wave height (H_s), mean wave period (T_m), and wave direction (Dir) time series were obtained.

4. Results

4.1. Validation and Uncertainty Assessment

The positions of the submerged bars at SVM, CG, and TB, extracted using the pSDBg and pSDBr ratios, are shown in Figure 4 (see also Figure S7). The results showed that both methods captured the sandbar, although the positions extracted by pSDBr ratio exhibited greater dispersion. Although, the double shore-parallel sandbar system in TB is accurately depicted with similar cross-shore distance values for both ratios.

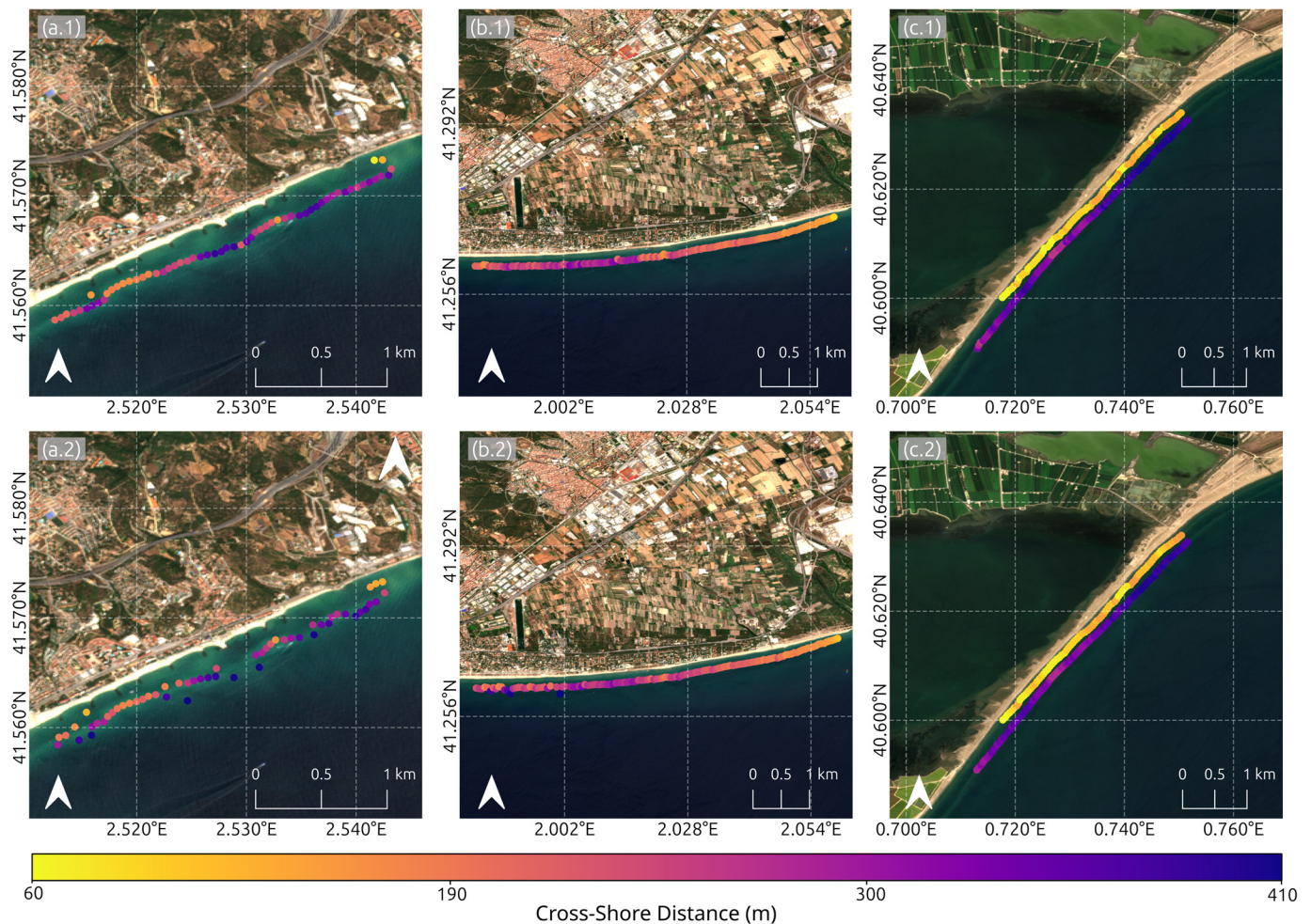


Figure 4. Cross-shore distance for SVM, CG, and TB beaches (**Left**, **center**, and **right** columns). Top panels (a.1–c.1) show the cross-shore distance (m) extracted from pSDBg ratio, and **bottom** panels (a.2–c.2) illustrate the cross-shore distance (m) derived from pSDBr ratio.

Figure 5 shows the validation of cross-shore distance for SVM, CG, and TB, using in situ data (i.e., bathymetry) in terms of regression analysis (including the error metrics) and residual error as a function of cross-shore distance. The results obtained at SVM using pSDBg ratio demonstrated its ability to skillfully extract sandbar positions at a depth of 2.5 m–4 m (Figure 5(a.1,b.1)) in comparison to pSDBr ratio (Figure 5(c.1,d.1)). For pSDBg ratio, the comparison between the distance from the shoreline to the bar crest using in situ data and the distance extracted from the model performed with high accuracy ($R^2 = 0.97$), with an average MAE of 5.63 m and a MAPE of 2.49%. The STD showed that the errors were constant, being low dispersion (STD = 6.89 m). In contrast, the results of the use of the pSDBr ratio at SVM highlighted that the error metrics (MAPE = 14.41%) were lower, showing reduced correlation ($R^2 = 0.46$) with high dispersion of errors (STD = 47.25 m). The results obtained at this beach using pSDBg ratio demonstrated its capability to accurately extract sandbar positions at depths of 2.5–4 m.

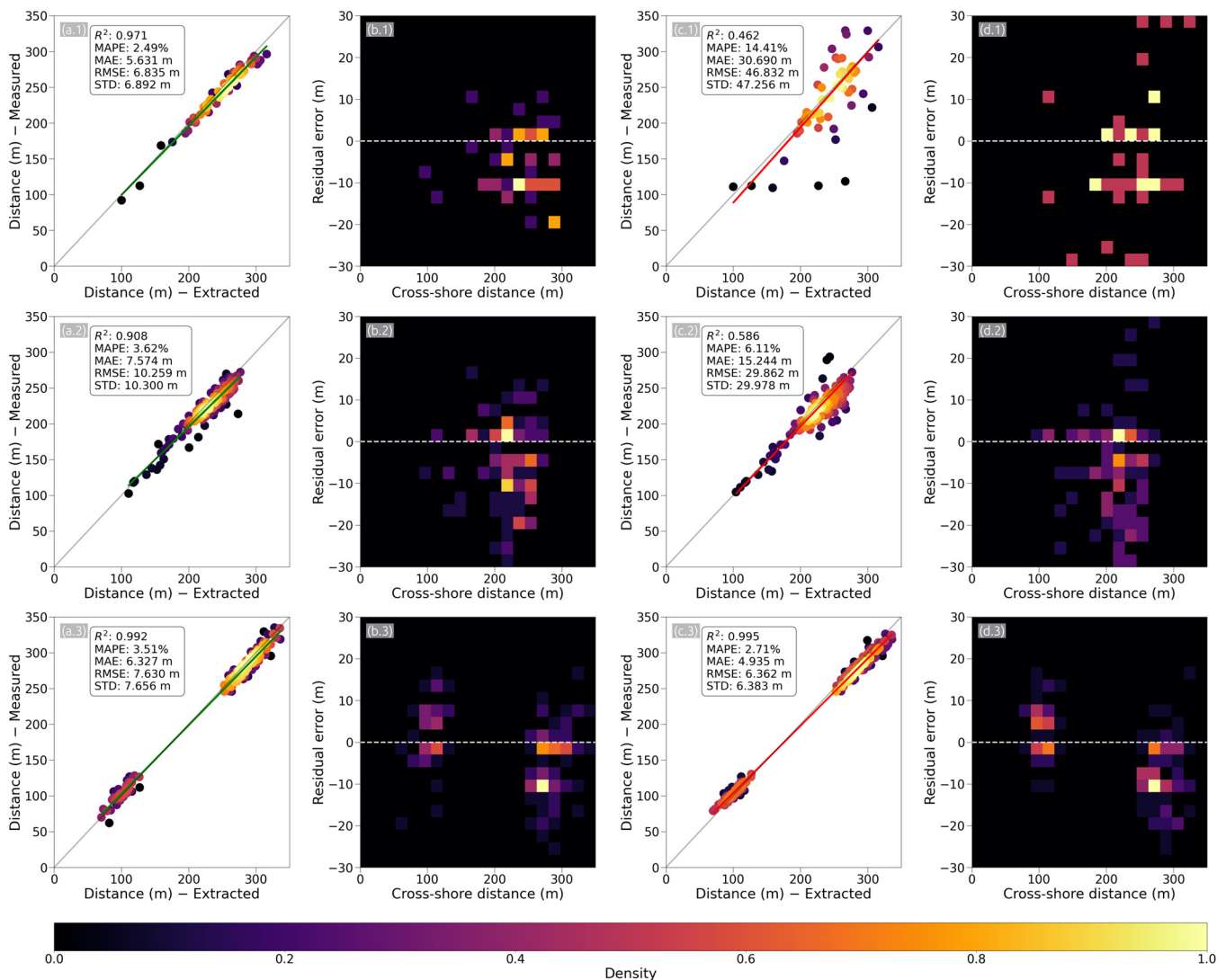


Figure 5. Validation of the extracted sandbar crest positions for the three study sites: SVM (Top panels), CG (Middle panels), and TB (Bottom panels). Panels (a.1–a.3) and (c.1–c.3) show the linear regression analyses comparing the measured and extracted cross-shore distances using the pSDBg and pSDBr ratios, respectively. The gray line represents the 1:1 reference line, while the colored line denotes the regression fit. The statistical metrics (R^2 , MAPE, MAE, RMSE, and STD) are included in each panel. Panels (b.1–b.3) and (d.1–d.3) display the corresponding 2D histograms of residual errors as a function of cross-shore distance, where the horizontal dashed line indicates zero error. The color bar represents the density of the observations.

At CG, where the bar is fully parallel and located between 2.5 m and 3.2 m water depth, the sandbar position extracted from the satellite image using pSDBg ratio (Figure 5(a.2,b.2)) showed a strong correspondence with the in situ measurements ($R^2 = 0.90$, MAE = 7.57 m, MAPE = 3.62%). The STD of the detected positions is 10.30 m, indicating limited variability. By comparison, the sandbar positions extracted using pSDBr ratio (Figure 5(c.2,d.2)) showed lower correlation ($R^2 = 0.58$) and reduced positional accuracy, as reflected by higher variability (STD = 29.97 m) and larger median error (MAE = 15.24 m).

TB exhibited a double-bar system parallel to the coastline, studied from the 1990s to the present [36,37]. This system consists of relatively narrow bars, with the first located 90 m–100 m from the shoreline and the second at 200 m–300 m. The sandbar crest positions extracted using the pSDBg ratio (Figure 5(a.3,b.3)) performed slightly worse than the pSDBr ratio, showing a similar correlation ($R^2 = 0.99$) but with high errors (MAE = 6.32 m) and

widely dispersed values (STD = 7.65 m). In contrast, the pSDBr ratio (Figure 5(c.3,d.3)) captured the bar positions with high accuracy ($R^2 = 0.99$), although some shallower bars were not detected. The error relative to the actual bar positions was low (MAE = 4.93 m) with an STD of 6.38 m, corresponding to a MAPE of 2.71%.

The aggregate results obtained for the three sites (Figure 6) demonstrated the ability of satellite imagery, using a specific band for pseudo-bathymetry, to accurately identify the position of submerged bars. The bar positions extracted from the pSDBg ratio (Figure 6(a.1)) satellite images showed a strong agreement with in situ observations ($R^2 = 0.98$), with a MAPE of 3.38% and a mean error of 6.73 m. The results also indicated that bars located within 100 m of the shoreline had errors closer to zero, although some variability of up to ± 10 m was observed. Bars located further offshore tended to be overestimated in their position, with discrepancies of up to 20 m. In contrast, the bar positions extracted from satellite imagery using the pSDBr ratio (Figure 6(a.2)) showed a lower correlation with in situ observations ($R^2 = 0.85$) compared to the pSDBg ratio, with a median error of 13.12 m. Although the spatial distribution of errors was more scattered, the highest concentration occurred around 250 m from the shoreline, with differences of up to ± 10 m. For the sandbars closest to the coast, the mean error was about 5 m, while variability remained relatively high in this zone.

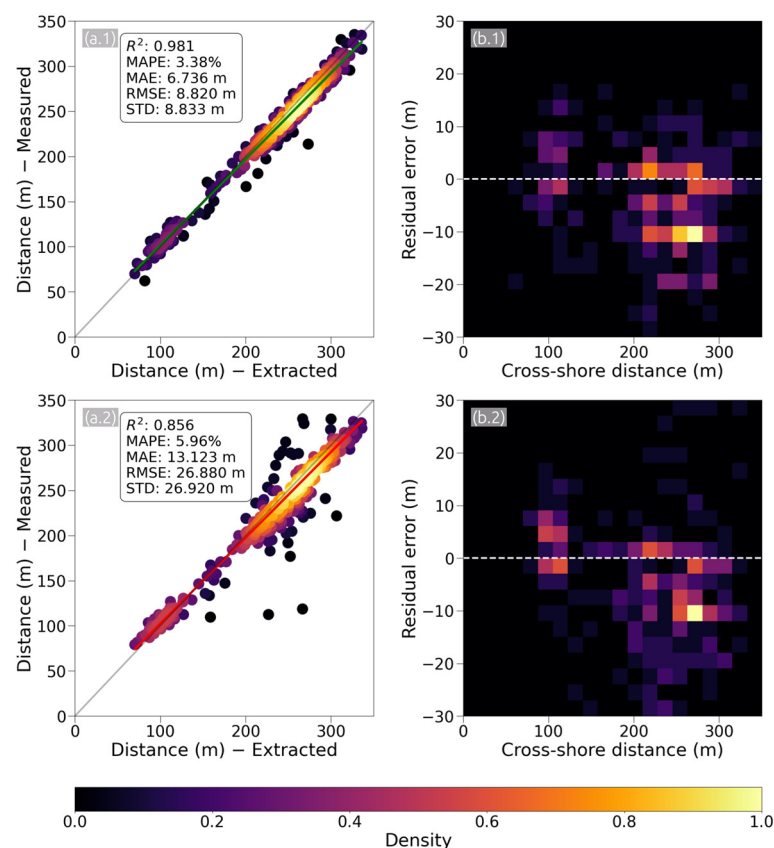


Figure 6. Validation of the extracted sandbar crest positions combining the three study sites (SVM, CG, and TB) for the pSDBg and pSDBr ratios results. The top panels (a.1,b.1) correspond to the pSDBg ratio results, while the bottom panels (a.2,b.2) show the pSDBr ratio results. Scatter plots (left column) compare measured and extracted cross-shore distances, including error metrics (R^2 , MAPE, MAE, RMSE, and STD). The gray line represents the 1:1 reference line, and the colored line denotes the regression fit. The 2D histograms (right column) show residual errors as a function of cross-shore distance, where the horizontal dashed line indicates zero error. The color bar represents the density of the observations.

4.2. Sandbar Crest Temporal Evolution: Example

The qualitative evaluation of the bar crest temporal evolution from transect number 74 of CG is shown in Figure 7, jointly with the wave conditions and H_s^2 (m^2), to identify the wave energy content [53]. This transect is representative of the mean conditions of a principal bar profile in the southern region of CG. The results of hydrodynamic conditions are limited to waves that impact the beach due to its geometric orientation (waves from 90° to 270°).

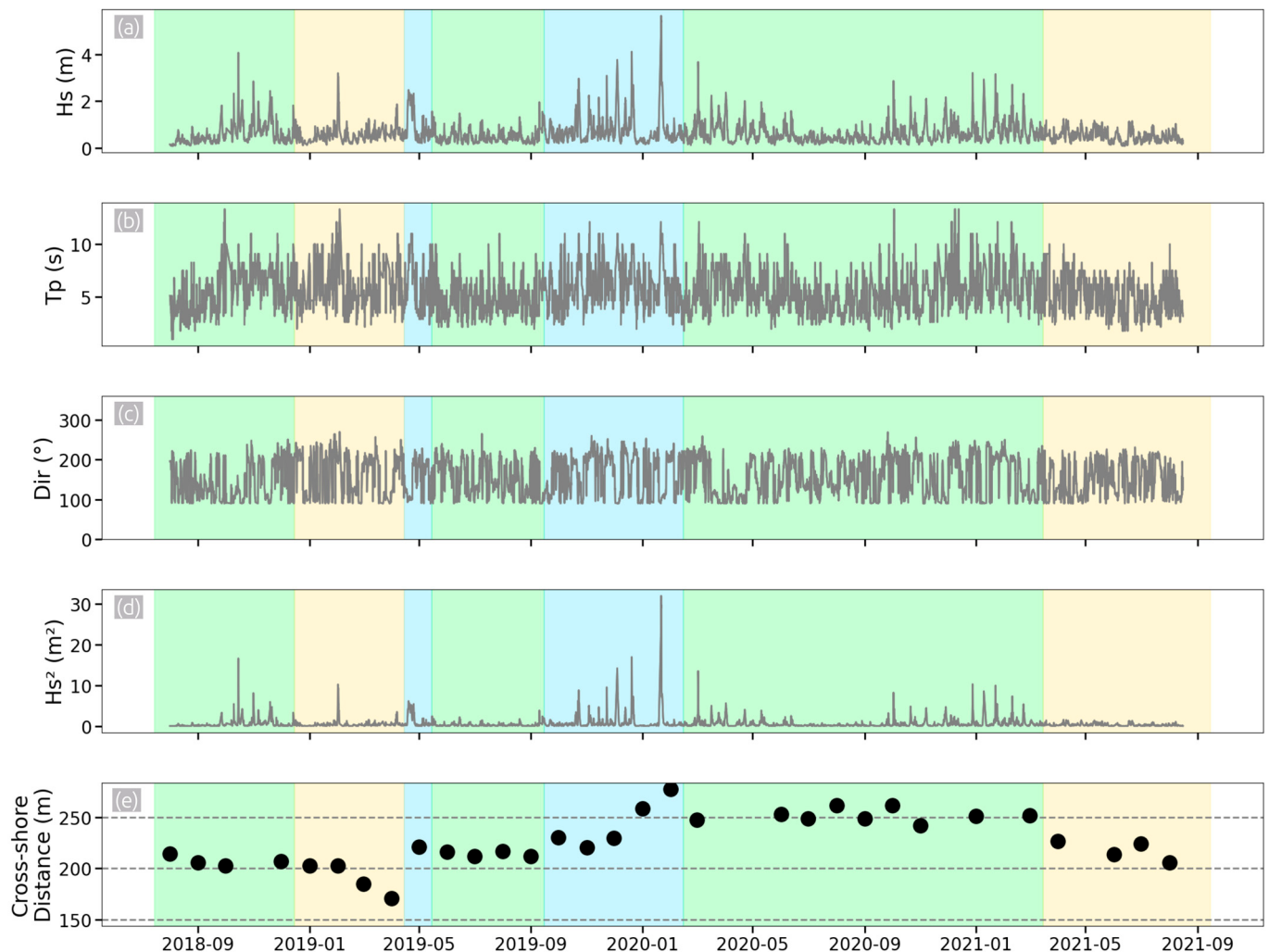


Figure 7. Time series of offshore wave and shoreline dynamics. (a) Significant wave height (H_s , m), (b) peak wave period (T_p , s), (c) wave direction (Dir , $^\circ$), and (d) wave energy content (H_s^2 , m^2); (e) displays the cross-shore shoreline distance (m) extracted from satellite-derived observations using, where the color scale represents the temporal distribution of measurements. Green panels represent the stable sandbar position, yellow indicates a landward migration, and blue indicates seaward migration.

Results show that the bar crest remained relatively stable (~ 200 m) with respect to the baseline during the initial months (August–November 2018). Although storms occurred during this period (October–December 2018), their short duration and limited intensity were insufficient to alter significantly the crest position. In the following months (January–April 2019), a landward migration was detected under moderate wave energy conditions, which favored onshore sediment transport and drove the bar closer to the shoreline. A storm in May 2019 induced additional offshore migration, after which the bar remained stable until November 2019. At that time (October–December 2019), a sequence

of consecutive storms forced the bar seaward, reaching its farthest recorded position during the major storm event of early 2020, known as Storm Gloria [54]. Subsequently, the bar crest gradually migrated landward, stabilizing at ~250 m from the baseline. During the final phase of the study period (April–August 2021), the bar exhibited another landward migration, once again associated with low to moderate wave energy conditions.

5. Discussion

5.1. Methodological Framework

The detection of submerged sandbars from optical satellite imagery remains challenging due to their diffuse morphology, temporal variability, and sensitivity to local hydrodynamic and optical conditions [22,25,55]. Existing approaches using video imagery [4,19] or satellite data [25], often relied on wave-breaking locations to identify the position of the sandbar crest [4,19]. Other methods combine bands from the visible spectrum to amplify spectral responses over the sandbars [23] or integrate spectral indices with spatial analysis techniques [24]. Although these methods can yield accurate results under specific circumstances, they are typically constrained by site-dependent calibration and the need for extensive preprocessing.

The approach developed in this study provides a streamlined, physically based alternative for sandbar extraction from Sentinel-2 imagery by exploiting slope variations in the extracted pSDB cross-shore profiles. Unlike approaches relying on wave-breaking detection [25], strongly dependent water optical properties [23], or complex spatial filtering and multi-directional analyses [24], our method leverages the behavior of the first derivative of pSDB profiles to identify inflection changes associated with bar crests. To contextualize the relevance of this contribution, methods such as those in [24] identify maximum neighborhood pixels in multiple directions, refined with cross-shore and longshore transects to generate smoothed crest polylines. Alternatively, ref. [25] applies a prominence algorithm, and [23] uses a moving window to detect local maxima in bathymetric signals. These techniques rely on signal processing, often requiring parameter tuning, and do not directly exploit the morphological characteristics of the seabed. In contrast, the present approach exploits the physical signature of a morphological element (the bar crest) in the pSDB profile through a straightforward derivative based criterion. This reduces methodological complexity while retaining sensitivity to morphological gradients. The suitability of each method and its complementarity likely depend on site-specific conditions, making it challenging to identify the most suitable. In any case, the method presented here contributes to the discussion on sandbar detection and offers an alternative perspective that complements existing approaches in the literature.

The comparative analysis between pSDBg and pSDBr demonstrates that band selection is a critical determinant of detection accuracy. The use of the pSDBg ratio outperforms the use of pSDBr to detect the sandbar positions (pSDBg, $R^2 = 0.98$; pSDBr, $R^2 = 0.85$) with fewer errors (pSDBg, MAE = 6.73 m; pSDBr, MAE = 13.12 m) than the pSDBr ratio (Figure 6). These results contrast with other studies [52], which indicates that, in general, pSDBg combinations yield better results than pSDBr combinations for extracting SDB across all depth ranges. The pSDBg ratio demonstrated superior performance to the pSDBr ratio in identifying sandbars located deeper (SVM and CG), while for shallower bars (TB), both ratios showed comparable performance (MAE for TB is equal to 6.32 m and 4.93 m pSDBg and pSDBr, respectively). These results are in agreement with those obtained by [41,42,51,52,56,57], in which pSDBr yields less correlation and encounters difficulties in detecting deeper depths (note that TB is shallower than CG and SVM), which is also observed in AF (Figure S9), where bars are located at 2 m depth. The above-mentioned references determined that the use of red bands on the band ratio model performs better

for shallow waters (<3 m), being TB sandbars located between 1.2 m and 2.5 m. This is also consistent with the results from the complementary beaches studied, CF, FG, and PJ (Figures S8, S10 and S11), where bars located at 1–2 m are detected slightly more effectively with pSDBr than with pSDBg.

The error metrics divergence between bands was highlighted by [26] who investigated the differential absorption characteristics of visible bands in the water column. As water depth increases, reflectance decreases in all bands. However, bands with higher absorption (i.e., red) attenuate much more rapidly than those with lower absorption (i.e., green), which limits their penetration to very shallow depths [26,58–60]. This means that the sea bottom reflected signal in the red band can be detected better in shallow waters, where the effect of the water column is minor [52]. In contrast, at SVM and CG, where the bars are deeper (depths between 2.5 m and 3.8 m), the green band penetrated more effectively into deeper waters while maintaining a low level of noise, consistent with previous examples of SDB [52,56,57,61–63]. For this reason, SVM and CG presented better error metrics for pSDBg compared to the pSDBr (SVM: pSDBg, $R^2 = 0.97$; pSDBr, $R^2 = 0.46$; CG: pSDBg, $R^2 = 0.90$; pSDBr, $R^2 = 0.58$).

This result suggests that pSDBr is suitable for detecting inner or low-relief bars, whereas pSDBg offers greater robustness and generalizability across depth ranges. The observed performance across multiple beach types and sandbar configurations (Figure 5 and Figures S8–S11) supports the transferability of the method. The bar detection analysis is particularly relevant due to its strong linkage between satellite-derived imagery and water depth, especially in tide-dominated environments. In areas with a high tidal range, shallow bars may become submerged at considerable depths and vice versa. Therefore, one might assume that the selection of a specific spectral band depends on local hydrodynamic conditions. However, the results of our study indicate that, for shallow bars, the pSDBr method performs slightly better than pSDBg. Conversely, the latter demonstrates greater robustness and high accuracy in both shallow and deeper environments, making it more suitable for upscaling and eventual large-scale application using cloud-based geospatial platforms such as GEE. Although band-ratio models are often affected by factors such as turbidity or sunglint, these can underestimate in SDB [55,56]. Our objective was not to retrieve absolute depth but to delineate sandbar position. In this context, the method presented here yields a form of pseudo-bathymetry, and thus, potential biases in depth estimation become irrelevant. Overall, the model proves to be a robust and primarily filter-independent approach that may be translated elsewhere, as it has been tested across three different sites with varying beach types and sandbar crest morphologies.

As suggested by [23–25,27,55,64], application under turbid and wave-breaking conditions is particularly challenging. Nonetheless, using images from Storm Gloria on 23 January 2020 (Figure 8), the method was tested and qualitatively demonstrated to capture the positions of the bars under forced conditions. Along the transect, the bars were clearly identified and consistently located near the wave-breaking zone. In this case, it was necessary to alter the Savitzky–Golay filter applied to the profiles and introduce prior distance constraints to eliminate false detection as a function of the number of bars expected. Under such hydrodynamic conditions, our results indicate that the method developed by [25] is the most effective and should be used for retrieving sandbar dynamics in high-energy wave conditions (during wave-breaking conditions).

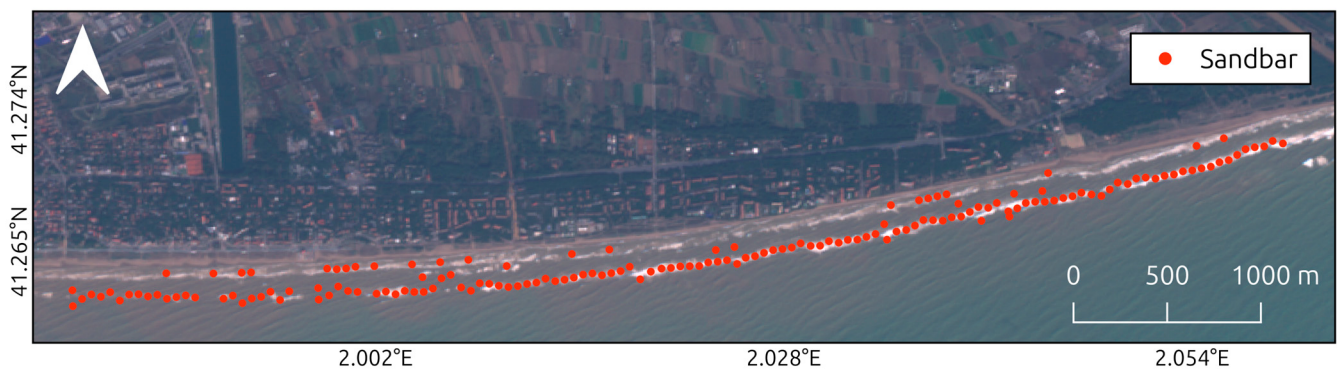


Figure 8. Sentinel-2 image showing the beach area (CG) during the Gloria storm and the sandbars detected with the location of the bar's crest indicated by red dots.

Nevertheless, certain limitations persist, as sandbar detection is inherently constrained by both spatial and temporal resolution. In this study, Sentinel-2 Level-1C imagery provides a spatial resolution of 10 m and a revisit time of 5 days. High spatial resolution satellites (<5 m) are available, but access is limited and costly, and there is no direct platform, such as GEE, for automated data retrieval. Additionally, high-resolution imagery is more susceptible to issues such as turbidity, sunglint, and noise generated by hydrodynamic processes [65,66]. Another limitation arises from the inability to capture small-scale features due to spatial constraints [22,67]. We observed this limitation in the long-term monitoring of sandbars at site CG, where the inner bars are located very close to the shoreline, exhibit minimal elevation, or sometimes appear as inner terraces. These subtle morphological features are difficult to capture with current optical sensors. Temporal resolution also poses a challenge, as it does not allow for the monitoring of processes occurring at short time scales [22,55,67]. Additionally, the effective spatial resolution is influenced by prevailing cloud conditions, since a specific percentage of images may be cloud-covered. Another limiting factor is the spectral resolution, which depends on the wavelength intervals recorded by the sensor, as well as the radiometric resolution, which reflects the sensor's ability to distinguish between objects with similar reflectance values [22,55,68]. Our method is subject to these limitations, despite these challenges, the demonstrated capability of Sentinel-2 imagery to accurately delineate bar positions represents a major step toward operational, mid-resolution monitoring of nearshore morphology.

5.2. Practical Implications

The long-term evolution of bars is crucial for understanding coastal dynamics [22,55]. By providing a remote and scalable monitoring tool, it enables coastal managers to track bar dynamics over wide areas with high temporal frequency, reducing reliance on costly in situ surveys. This supports evidence-based decisions on beach safety, sediment management, and coastal risk reduction, while offering timely information for storm impact assessment and adaptation planning. The Gloria storm, which caused significant damage along the Mediterranean coast [54], stresses the importance of considering long-term processes, as they play a key role in beach evolution and defense.

The results at the CG case are consistent with the widely accepted behavior of sandy beaches [8,13,14]. During energetic events, the sandbar undergoes offshore migration, whereas during less energetic periods, the profile recovers and the bar migrates back towards the shore. Similarly, during the studied period, a series of energetic events progressively displaced the sandbar offshore from October to December 2019 until the arrival of Storm Gloria in January 2020, which caused extensive damage to the NW Mediterranean coast [54]. The events preceding this major storm gradually displaced the sandbar until

April 2019, when the equilibrium profile began to recover, remaining relatively stable thereafter. Even during the energetic periods of 2021, the bar maintained its position due to the large displacement it had previously undergone. Our long-term results (Figure 7) further highlight the influence of extreme events on bar crest evolution. Under prolonged or sequential storm conditions (see Figure 7d), the sandbar tends to migrate offshore, leading to a reduction in the available emerged sediment stock. The intensity of this displacement has a direct correlation with the wave energy impacting the coast. This behavior is consistent with previous studies [37,69,70], which reported that storms can induce rapid offshore migration of sandbars, with the outer bar stabilizing at depths where subsequent, less energetic waves cannot mobilize the seabed further. The equilibrium profile, located approximately 200 m from the baseline (Figure 7d), returned to its original position by April 2021. Crucially, these findings were derived from satellite imagery analysis, allowing the quantification of offshore sand mobilization associated with different storm conditions without the need for expensive and time-consuming bathymetric field surveys. These results shown here align with the expected behavior of sandbar dynamics and highlight a reliable method for extracting sandbar positions from satellite images under non-breaking wave conditions. This methodology contrasts with previous approaches [25] and provides a valuable and cost-effective tool for monitoring coastal dynamics, particularly when integrated with satellite-derived shoreline analysis frameworks [71–73].

Regular sandbar position retrieval allows managers to track sediment exchange, detect storm-driven erosion, and observe recovery phases along large stretches of coastline. This remote and automated monitoring capability reduces reliance on in situ surveys and enhances the temporal continuity of coastal datasets, key requirements for adaptive coastal zone management [22,48,55]. Importantly, sandbar crest positions can serve as functional indicators of coastal protection capacity. When bar crests are located farther offshore, wave energy dissipation begins earlier, reducing the impact on the backshore. Conversely, onshore migration or bar degradation may indicate reduced buffering potential, serving as an early warning for erosion risk. In this context, integrating satellite-derived bar dynamics with shoreline and sediment budget analyses could improve coastal vulnerability assessments and resilience planning. While the present approach performs reliably across a range of environments, further refinement is warranted for more complex settings. Future developments should address detection in multi-bar systems, nearshore bars located within the swash zone, and highly turbid or optically variable waters. Combining the pSDB approach with advanced Machine Learning or multi-temporal compositing strategies could enhance detection reliability under suboptimal imaging conditions.

5.3. Future Perspective

Future developments should focus on extending sandbar detection to more complex settings, including multi-bar systems, low-lying bars, nearshore bars located within the dynamic swash zone, and highly turbid or optically variable waters. These environments present additional challenges due to overlapping morphological signals, rapid temporal changes, and reduced optical clarity. Combining the pSDB approach with advanced machine learning techniques, multi-temporal compositing, or data fusion strategies could further improve detection reliability under suboptimal imaging conditions. Furthermore, the method's simplicity and computational efficiency make it particularly well-suited for upcoming higher-resolution satellite missions. Anticipated improvements in temporal and spatial resolution, as well as in atmospheric correction methods, from these platforms are expected to enhance the accuracy of pSDB retrievals, thereby expanding the applicability of this methodology to a wider range of coastal morphodynamic studies.

6. Conclusions

This study confirms the feasibility of using Sentinel-2 multispectral imagery and the log-band ratio approach for detecting submerged sandbar crests in diverse coastal settings. The method proved capable of accurately retrieving sandbar positions without requiring atmospheric correction or extensive preprocessing. Validation against high-resolution *in situ* bathymetry demonstrated that the pSDBg ratio provides the highest accuracy, while the pSDBr ratio performs slightly better in very shallow waters (<3 m). These results highlight the wavelength-dependent behavior of light attenuation in water and the importance of spectral band selection for reliable sandbar detection.

The application across three morphodynamically distinct beaches along the NW Mediterranean coast confirmed the robustness and transferability of the approach. Temporal analysis at CG revealed sandbar migration patterns consistent with storm-driven hydrodynamic forcing, supporting the use of satellite-derived sandbar detection for tracking coastal morphodynamics.

Overall, the proposed framework is cost-free, computationally efficient, and easily scalable within cloud-based platforms such as GEE. Further improvements in the bar detection system, particularly for turbid waters, multi-bar configurations, nearshore bars located very close to the coastline, and low-lying bars, remain challenges for future research aiming at enhancing the reliability of coastal remote sensing techniques. It offers a valuable tool for large-scale and long-term monitoring of nearshore morphology. By integrating this technique into coastal management practices, decision-makers can enhance sediment-budget assessments, improve coastal resilience evaluation, and support adaptive strategies in the face of climate-driven coastal change.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/rs18010132/s1>, Figure S1: Location of the four additional study sites (CF, AF, FG, and PJ beaches) along the Catalan coast (NW Mediterranean Sea). The left panel shows the regional context with the areas of interest (a–d) indicated by colored boxes (CF-cyan, AF-red, FG-green, PJ-purple). The right panels (a–d) display Sentinel-2 imagery, including true-color composites and bathymetry *in situ*, with depth values ranging from 0m to –10 m; Table S1: Morphological and hydrodynamic features of the studied beaches. D50 represents the median grain size (mm), L is the beach length (m), DoC is the depth of closure (m), β represents the beach slope, Hs is the significant wave height (m), and Tp is the peak wave period (s). The type of bar indicates the morphological configuration of the sandbar at each beach; Table S2: List of Sentinel-2 images selected for each study location, including the dates of the bathymetric data obtained and corresponding satellite acquisition dates; Figure S2: Sentinel-2 true-color composites illustrating SVM (a.1), CG (b.1), and TB (c.1), highlighting the position of sandbars (white arrows), while lower panels (a.2–c.2) depict the extracted shoreline (black line) and transects used for the analysis (yellow lines); Figure S3: Comparison of the horizontal error between the shoreline extracted from Sentinel-2 and the *in situ* shoreline, showing the effect of applying tide correction. Dark boxes represent non-corrected data, and light boxes represent tide-corrected data; Figure S4: Cross-shore distance pSDB profiles for SVM along transects 14 (a), 27 (b), and 55 (c), compared with *in situ* bathymetry. Panels (a.1–c.1) show the cross-shore distance extracted from the pSDBg ratio, while panels (a.2–c.2) display the cross-shore distance derived from the pSDBr ratio. In each panel, the *in situ* bathymetry is included as blue profiles, and the pSDBg and pSDBr estimates are shown as green and red lines, respectively. Only transect-based cross-shore profiles are presented; no spatial distribution maps are included. Gray and pink rectangles represent the sandbar crest positions measured *in situ* and derived from satellite, respectively; Figure S5: Cross-shore distance pSDB profiles for GC along transects 55 (a), 86 (b), and 113 (c), compared with *in situ* bathymetry. Panels (a.1–c.1) show the cross-shore distance extracted from the pSDBg ratio, while panels (a.2–c.2) display the cross-shore distance derived from the pSDBr ratio. In each panel, the *in situ* bathymetry is included as blue profiles, and the pSDBg and pSDBr estimates are shown as

green and red lines, respectively. Only transect-based cross-shore profiles are presented; no spatial distribution maps are included. Gray and pink rectangles represent the sandbar crest positions measured *in situ* and derived from satellite, respectively; Figure S6: Cross-shore distance pSDBg profiles for TB along transects 30 (a), 50 (b), and 70 (c), compared with *in situ* bathymetry. Panels (a.1–c.1) show the cross-shore distance extracted from the pSDBg ratio, while panels (a.2–c.2) display the cross-shore distance derived from the pSDBr ratio. In each panel, the *in situ* bathymetry is included as blue profiles, and the pSDBg and pSDBr estimates are shown as green and red lines, respectively. Only transect-based cross-shore profiles are presented; no spatial distribution maps are included. Gray and pink rectangles represent the sandbar crest positions measured *in situ* and derived from satellite, respectively; Figure S7: Cross-shore distance for beaches SVM, CG, and TB (left, center, and right columns, respectively). The figure shows a zoomed-in view of the SVM, CG, and TB areas. The top panels (a.1–c.1) display the cross-shore distance derived from the pSDBg ratio, while the bottom panels (a.2–c.2) show the cross-shore distance obtained from the pSDBr ratio. In each panel, the *in situ* data are also included, represented by green crosses; Figure S8: Validation of the extracted sandbar crest positions for the CF. The top panels show results for pSDBg, and the bottom panels for pSDBr. Panels (a.1–a.2) display extracted positions over the Sentinel-2 image with *in situ* points (green for pSDBg, red for pSDBr, and white for *in situ*). Panels (b.1–b.2) show the linear regression analyses comparing the measured and extracted cross-shore distances using the pSDBg and pSDBr ratios, respectively. The grey line represents the 1:1 reference line, while the colored line denotes the regression fit. The statistical metrics (R^2 , MAPE, MAE, RMSE, and STD) are included in each panel. Panels (c.1–c.2) present 2D histograms of residual errors as a function of cross-shore distance, where the horizontal dashed line indicates zero error. The color bar represents the density of the observations; Figure S9: Validation of the extracted sandbar crest positions for the AF. The top panels show results for pSDBg, and the bottom panels for pSDBr. Panels (a.1–a.2) display extracted positions over the Sentinel-2 image with *in situ* points (green for pSDBg, red for pSDBr, and white for *in situ*). Panels (b.1–b.2) show the linear regression analyses comparing the measured and extracted cross-shore distances using the pSDBg and pSDBr ratios, respectively. The grey line represents the 1:1 reference line, while the colored line denotes the regression fit. The statistical metrics (R^2 , MAPE, MAE, RMSE, and STD) are included in each panel. Panels (c.1–c.2) present 2D histograms of residual errors as a function of cross-shore distance, where the horizontal dashed line indicates zero error. The color bar represents the density of the observations; Figure S10: Validation of the extracted sandbar crest positions for the FG. The top panels show results for pSDBg, and the bottom panels for pSDBr. Panels (a.1–a.2) display extracted positions over the Sentinel-2 image with *in situ* points (green for pSDBg, red for pSDBr, and white for *in situ*). Panels (b.1–b.2) show the linear regression analyses comparing the measured and extracted cross-shore distances using the pSDBg and pSDBr ratios, respectively. The grey line represents the 1:1 reference line, while the colored line denotes the regression fit. The statistical metrics (R^2 , MAPE, MAE, RMSE, and STD) are included in each panel. Panels (c.1–c.2) present 2D histograms of residual errors as a function of cross-shore distance, where the horizontal dashed line indicates zero error. The color bar represents the density of the observations; Figure S11: Validation of the extracted sandbar crest positions for the PJ. The top panels show results for pSDBg, and the bottom panels for pSDBr. Panels (a.1–a.2) display extracted positions over the Sentinel-2 image with *in situ* points (green for pSDBg, red for pSDBr, and white for *in situ*). Panels (b.1–b.2) show the linear regression analyses comparing the measured and extracted cross-shore distances using the pSDBg and pSDBr ratios, respectively. The grey line represents the 1:1 reference line, while the colored line denotes the regression fit. The statistical metrics (R^2 , MAPE, MAE, RMSE, and STD) are included in each panel. Panels (c.1–c.2) present 2D histograms of residual errors as a function of cross-shore distance, where the horizontal dashed line indicates zero error. The color bar represents the density of the observations.

Author Contributions: Conceptualization, B.C.; methodology, B.C., V.G. and M.G.; software, B.C.; validation, B.C.; formal analysis, B.C.; investigation, B.C.; resources, B.C., V.G., M.G. and E.P.-F.; data curation, B.C.; writing—original draft preparation, B.C.; writing—review and editing, B.C., V.G., M.G. and E.P.-F.; visualization, B.C. and E.P.-F.; supervision, B.C., V.G., M.G. and E.P.-F.; project

administration, V.G., M.G. and E.P.-F.; funding acquisition, V.G., M.G. and E.P.-F. All authors have read and agreed to the published version of the manuscript.

Funding: This work has received funding from the European Union’s Horizon Europe research and innovation programme under grant agreement No 101213138—COAST-SCAPES Project—HORIZON-MISS-2024-CLIMA-01.

Data Availability Statement: All the images used in this study are available on Google Earth Engine. The results presented in this study are available from the corresponding author upon request, as the research project is still ongoing. Once the project is completed, all data will be made publicly available in an open repository.

Acknowledgments: The authors would like to acknowledge the *Institut Cartogràfic i Geològic de Catalunya* for providing the bathymetric data. We also acknowledge the support of the Grant funded with the support of the AGAUR-FI predoctoral fellowship program (2023 FI-SDU 00329) from the Secretariat for Universities and Research of the Department of Research and Universities of the Government of Catalonia and the European Social Fund Plus, as well as Puertos del Estado (Spanish Ministry of Transport and Sustainable Mobility) for providing the wave data used in this study. The authors would also like to thank Xavier Sánchez Artús for his valuable comments and suggestions before publication. Finally, we would like to thank Mercè Calvillo for her valuable artistic perspective on the figures.

Conflicts of Interest: The authors declare no conflicts of interest. The funders and data providers had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

Abbreviations

The following abbreviations are used in this manuscript:

SRBI	Standardized-Ratio Bathymetric Index
SBI	SandBar Index
SVM	Sant Vicenç de Montalt
CG	Castelldefels-Gavà
TB	Trabucador
CF	Calafell
AF	Altafulla
FG	Fangar
PJ	Platjola
CIIRC	Centre Internacional d’Investigacions dels Recursos Costaners
DoC	Depth of closure
D ₅₀	Grain size
H _s	Wave height
T _p	Peak wave period
ICGC	Institut Cartogràfic i Geològic de Catalunya
ESA	European Space Agency
MSI	MultiSpectral Instrument
GEE	Google Earth Engine
WGS84	World Geodetic System-1984
TOA	Top-of-atmosphere
SDB	Satellite-Derived Bathymetry
SLC	Scene Classification Layer
NIR	Near-infrared
R ²	Coefficient of determination
ETRS89	European Terrestrial Reference System 1989
USVs	Unmanned Surface Vehicles
RmB	Red-minus-Blue

WP	Weighted Peaks
pSDB	Log-transformed ratio
pSDBg	Blue-green ratio
pSDBr	Blue-red ratio
BLL	Beer-Lambert law
MAE	Mean absolute error
MAPE	Mean absolute percentage error
RMSE	Root mean square error
STD	Standard deviation
RE	Residual error

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