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This thesis is entirely my own work, and except where otherwise stated, describes my own research.

Riccardo Angelini, June 2025

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Abstract

Coastal areas are increasingly threatened by sea-level rise due to climate change and anthropogenic pressures, calling for robust and scalable monitoring tools. The first phase of this thesis implements a comprehensive methodology for semi-automatic shoreline extraction through the use of multispectral satellite imagery (Sentinel-2 and PlanetScope). The extracted shorelines are validated using in situ GNSS surveys and high-resolution orthomosaics along three Mediterranean sandy beaches. The shoreline extraction tool works with several spectral indices in combination with thresholding and unsupervised clustering segmentation methods. A high level of performance in the coastline extraction process is achieved using Sentinel-2, with an average sub-pixel accuracy of 4 m (mean absolute deviation, MAD) obtained from a 10 m pixel. A MAD of 2 m is achieved from imagery at 3 m pixel resolution of PlanetScope.

In the second phase of this work, the obtained multispectral satellite shorelines are used to characterize coastal morphologies called megacusps, shoreline undulations with alongshore wavelengths of hundreds of meters and cross-shore amplitudes up to a few tens of meters that can significantly affect beach usability. Subsequent validation with reference data proves satellite-derived shorelines can robustly and accurately describe megacusp parameters such as amplitude and wavelength. Moreover, megacusp evolution can be effectively characterized by combining different types of satellite imagery (Sentinel-2 and PlanetScope), enabling the identification of periods of growth, decay, and migration, even at weekly timescales. This can be a useful tool to manage the impact of these features on Mediterranean beaches.

Another phase involves evaluating and correcting the extracted shorelines with respect to tide excursions and wave setup. Corrections based

on tide gauge and buoy data show that although absolute displacements are limited, assessing them helps eliminate a potential source of error, justifying their integration into high-accuracy workflows. This would also allow applying the developed methodology to meso- or macro-tidal beaches.

Finally, the research incorporates Synthetic Aperture Radar (SAR) imagery (Sentinel-1 and TerraSAR-X) to expand the shoreline extraction tool to periods without light or with clouds, including two other Mediterranean beaches with different characteristics (gravel sediment). The SAR-based shoreline extraction module includes advanced extra-denoising filtering and an outlier detection module, but it maintains the core methodology used in the first phase, demonstrating the flexibility of the developed approach. The results demonstrate unprecedented accuracy and stability for gravel beaches (approximately 6 m of MAD), and for sandy beaches (approximately 7 m of MAD), starting from a 10 m pixel size. In a comparative assessment between the two TerraSAR-X images available and the closest Sentinel-1 in terms of time, the first achieves higher accuracy in terms of MAD (2.5 m) compared to the second one (6.5 m), but only in the image with good meteorological conditions (no differences are obtained in the other date). The study also investigates the influence of radar parameters, such as polarization, wavelength, acquisition geometry, and environmental conditions, on SAR shoreline accuracy. The results show that higher land–sea backscatter contrast, typical of gravel beaches, and moderate wind conditions enhance detection reliability. Conversely, high wind and wave activity reduce contrast and increase errors. Overall, this work offers robust, scalable tools for high-resolution coastal morphology monitoring in Mediterranean beaches using satellite data. These methodologies could be extended to beaches with significant tides and other related fields such as flood mapping. The developed algorithms could be incorporated into operational platforms like early warning systems or interactive WebGIS applications, potentially significantly contributing to local authorities' adaptive coastal zone management strategies.

Resumen

Las zonas costeras están cada vez más amenazadas por la subida del nivel del mar inducida por el cambio climático y por presiones antropogénicas, lo que exige herramientas de monitoreo robustas y escalables. La primera fase de esta tesis implementa una metodología integral para la extracción semiautomática de líneas de costa mediante el uso de imágenes satelitales multiespectrales (Sentinel-2 y PlanetScope). Las líneas de costa extraídas se validan mediante medidas GNSS in situ y ortomosaicos de alta resolución en tres playas de arena mediterráneas. La herramienta de extracción utiliza varios índices espectrales en combinación con métodos de segmentación basados en umbrales y clustering no supervisado. Se logra un alto rendimiento con Sentinel-2, con una precisión subpíxel media de 4 m a partir de píxeles de 10 m, y se obtiene una precisión media de 2 m usando las imágenes con resolución de 3 m de PlanetScope.

En la segunda fase del trabajo, se emplean las líneas satelitales extraídas para caracterizar morfologías costeras conocidas como megacusps, ondulaciones de la línea de costa con espaciados longitudinales de centenas de metros y amplitudes transversales de hasta pocas decenas de metros, que pueden afectar significativamente la usabilidad de las playas. La validación con datos de referencia demuestra que las líneas derivadas por satélite pueden describir de forma robusta y precisa parámetros como la amplitud y la longitud de onda. Además, la evolución de los megacusps puede caracterizarse eficazmente combinando diferentes tipos de imágenes (Sentinel-2 y PlanetScope), permitiendo identificar fases de crecimiento, erosión y migración, incluso a escalas semanales. Esto puede ser útil para gestionar su impacto en las playas mediterráneas.

Otra fase consiste en evaluar y corregir las líneas extraídas respecto a las excursiones de marea y el setup del oleaje. Las correcciones basadas en

datos de mareógrafos y boyas muestran que, aunque los desplazamientos absolutos son limitados, su análisis ayuda a eliminar una fuente potencial de error, justificando su integración en flujos de trabajo de alta precisión. Esto también permitiría aplicar la metodología desarrollada a playas meso- y macro-mareales.

Finalmente, la investigación incorpora imágenes de radar de apertura sintética (SAR) (Sentinel-1 y TerraSAR-X) para ampliar la herramienta de extracción a periodos sin luz o con nubes, incluyendo dos playas mediterráneas adicionales con características distintas (sedimento de grava). El módulo SAR emplea un filtrado avanzado y detección de valores atípicos, pero mantiene la metodología básica de la primera fase, demostrando la flexibilidad del enfoque. Los resultados muestran una excelente precisión y estabilidad para playas de grava (MAD de unos 6 m) y de arena (unos 7 m), partiendo de píxeles de 10 m. En una comparación entre dos imágenes TSX y la más cercana en el tiempo de Sentinel-1, la primera alcanza mayor precisión (MAD de 2.5 m frente a 6.5 m), pero solo en condiciones meteorológicas favorables (no se ven diferencias en la otra fecha). El estudio también analiza la influencia de parámetros como la polarización, la longitud de onda, la geometría de adquisición y las condiciones ambientales en la precisión de las líneas de costa de SAR. Los resultados indican que un mayor contraste de retrodispersión producido por la tierra y el mar, típico en playas de grava, y un viento moderado mejoran la detección. Por el contrario, un viento o oleaje fuertes reducen el contraste y aumentan el error.

En conjunto, este trabajo ofrece herramientas robustas y escalables para la monitorización de alta resolución de la morfología costera de playas mediterráneas mediante datos satelitales. Estas metodologías podrían extenderse a playas con marea o a campos afines como la cartografía de inundaciones. Los algoritmos desarrollados podrían incorporarse en plataformas operativas como sistemas de alerta temprana o aplicaciones WebGIS interactivas, contribuyendo significativamente a las estrategias adaptativas de gestión costera por parte de las autoridades locales.

Resum

Les zones costaneres estan cada cop més amenaçades per la pujada del nivell del mar induïda pel canvi climàtic i per pressions antropogèniques, fet que requereix eines de monitoratge robustes i escalables. La primera fase d'aquesta tesi implementa una metodologia integral per a l'extracció semiautomàtica de línies de costa mitjançant imatges satel·litals multiespectrals (Sentinel-2 i PlanetScope). Les línies de costa extretes es validen mitjançant mesures GNSS in situ i ortomosaics d'alta resolució en tres platges de sorra mediterrànies. L'eina d'extracció utilitza diversos índexs espectrals combinats amb mètodes de segmentació basats en l'landars i clustering no supervisat. S'assoleix un alt rendiment amb Sentinel-2, amb una precisió mitjana subpíxel de 4 m (desviació mitjana absoluta, MAD) a partir de píxels de 10 m, is'obté una precisió mitjana de 2 m amb les imatges de 3 m de resolució de PlanetScope.

En la segona fase del treball, les línies extretes s'utilitzen per caracteritzar morfologies costaneres conegudes com a megacusps, undulacions de la línia de costa amb espaiats longitudinals de centenars de metres i amplituds transversals de fins a poques desenes de metres, que poden afectar significativament la usabilitat de les platges. La validació amb dades de referència demostra que les línies derivades per satèl·lit poden descriure amb solidesa i precisió paràmetres com l'amplitud i la longitud d'ona. A més, l'evolució dels megacusps pot caracteritzar-se eficaçment combinant diferents tipus d'imatges (Sentinel-2 i PlanetScope), permetent identificar fases de creixement, erosió i migració fins i tot a escales setmanals. Això pot ser útil per gestionar el seu impacte en les platges mediterrànies.

Una altra fase consisteix a avaluar i corregir les línies extretes segons les excursions de marea i el setup de l'onatge. Les correccions basades en dades de mareògrafs i boies mostren que, tot i que els desplaçaments absoluts són limitats, la seva anàlisi ajuda a eliminar una font potencial

d'error, justificant-ne la integració en fluxos de treball d'alta precisió. Això també permetria aplicar la metodologia desenvolupada a platges meso- i macro-mareals.

Finalment, la recerca incorpora imatges de radar d'obertura sintètica (SAR) (Sentinel-1 i TerraSAR-X) per ampliar l'eina d'extracció a períodes sense llum o amb núvols, incloent-hi dues platges mediterrànies addicionals amb característiques diferents (sediments de grava). El mòdul SAR empra un filtratge avançat i la detecció de valors atípics, però manté la metodologia bàsica de la primera fase, demostrant la flexibilitat de l'enfocament. Els resultats mostren una excel·lent precisió i estabilitat per a platges de grava (MAD d'uns 6 m) i de sorra (uns 7 m), partint de píxels de 10 m. En una comparació entre dues imatges TerraSAR-X i la més propera en el temps de Sentinel-1, la primera aconsegueix una millor precisió (MAD de 2.5 m enfront de 6.5 m), però només en condicions meteorològiques favorables (no es veuen diferències en l'altra data). L'estudi també analitza la influència de paràmetres com la polarització, la longitud d'ona, la geometria d'adquisició i les condicions ambientals en la precisió de les línies de costa de SAR. Els resultats indiquen que un contrast més alt entre la retrodispersió produït per la terra i el mar, típic de platges de grava, i un vent moderat milloren la detecció. Per contra, un vent o onatge forts redueixen el contrast i augmenten l'error.

En conjunt, aquest treball ofereix eines robustes i escalables per al monitoratge d'alta resolució de la morfologia costanera de platges mediterrànies mitjançant dades satel·litals. Aquestes metodologies podrien estendre's a platges amb marea i a altres àmbits relacionats com la cartografia d'inundacions. Els algorismes desenvolupats podrien integrar-se en plataformes operatives com sistemes d'alerta primerenca o aplicacions WebGIS interactives, contribuint significativament a les estratègies adaptatives de gestió costanera per part de les autoritats locals.

Sommario

Le zone costiere sempre più minacciate dall'innalzamento del livello del mare e dalle pressioni antropiche, necessitano di affidabili sistemi di monitoraggio. La prima parte della tesi intende sviluppare una metodologia per l'estrazione semiautomatica della linea di costa da immagini satellitari multispettrali (Sentinel-2 e PlanetScope). Le linee estratte sono state validate usando rilievi GNSS in situ e ortomosaici ad alta risoluzione su tre spiagge sabbiose nel Mediterraneo. Il tool di estrazione della linea di riva opera utilizzando diversi indici spettrali combinati con metodi di sogliatura e di classificazione non supervisionata. I risultati, in particolare usando Sentinel-2 hanno raggiunto una notevole accuratezza, in media 4 m partendo da una risoluzione spaziale di 10 m per pixel; con PlanetScope è stata ottenuta in media un'accuratezza di 2 m a partire da immagini con 3 m di risoluzione spaziale.

In secondo luogo, le linee di costa ottenute da immagini multispettrali sono state usate per caratterizzare le particolari morfologie costiere chiamate megacuspidi. Successivamente, la validazione con dati di riferimento ha dimostrato che queste morfologie potevano essere descritte accuratamente secondo i parametri di ampiezza e lunghezza d'onda. Inoltre, è stato possibile caratterizzare efficacemente l'evoluzione delle megacuspidi combinando l'utilizzo di più piattaforme satellitari, rendendo possibile l'identificazione di periodi di crescita, decadimento e migrazione, anche a scala settimanale. Questo potrà rivelarsi un importante strumento per gestire l'impatto di questi fenomeni sull'usabilità della spiaggia.

Un'altra sezione riguarda la valutazione e la correzione delle linee di riva ottenuta sulla base delle oscillazioni a breve termine di onde e maree. Le correzioni ottenute dai dati di boe e mareografi hanno mostrato valori limitati di spostamento in termini assoluti. Tuttavia la stima

dello stesso risulta utile a eliminare due potenziali fonti di errore, giustificando l'inserimento di tale correzione all'interno del procedimento sviluppato.

Infine, per espandere le funzionalità del tool sviluppato è stata aggiunta una sezione per consentire l'estrazione della linea di riva da immagini satellitari radar ad apertura sintetica (SAR) (Sentinel-1 e TerraSAR-X). Sono stati aggiunti altri due spiagge mediterranee, stavolta in ghiaia, come casi di studio. Il modulo SAR del tool include tecniche avanzate di limitazione del rumore e filtri di outlier, mantenendo tuttavia il core della metodologia sviluppata per le immagini multispettrali, dimostrando così notevole flessibilità. I risultati mostrano un'eccellente accuratezza e stabilità per le spiagge di ghiaia (circa 6 m in termini di deviazione assoluta (MAD)) e per le spiagge sabbiose (circa 7 m in termini di deviazione assoluta (MAD)) a partire da pixel di dimensione 10 m di lato. Comparando le due immagini TSX disponibili e le più vicine S1 in termini di tempo, nella prima TSX ha ottenuto un'accuratezza di 2.5 m rispetto ai 6.5 m di S1. Tuttavia, nella seconda immagine non sono stati riscontrati miglioramenti significativi a causa delle cattive condizioni meteorologiche che hanno influenzato i dati. Lo studio si è concentrato anche sull'influenza dei parametri radar sull'accuratezza delle linee di riva estratte: polarizzazione, lunghezza d'onda, geometria d'acquisizione e condizioni ambientali. I risultati mostrano che una forte differenza di intensità di ritorno tra mare e suolo, maggiormente riscontrata nelle spiagge di ghiaia e in assenza di vento, favorisce il riconoscimento della morfologia costiera. Al contrario, condizioni meteorologiche avverse riducono tale differenza aumentando la probabilità di errori.

In definitiva, questo lavoro ha condotto alla realizzazione di un tool per il monitoraggio ad alta risoluzione delle morfologie costiere usando dati satellitari ottici e radar, affidabile e scalabile. Inoltre, queste metodologie sono potenzialmente estendibili ad altri campi come la mappatura di aree allagate o il monitoraggio delle zone umide. Gli algoritmi sviluppati possono costituire la base per sistemi di allerta o incorporati in piattaforme WebGIS e possono contribuire alla gestione delle zone costiere da parte delle autorità locali.

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Chapter 1

Introduction

1.1 Motivation

Coastal environments are critical for both natural ecosystems and human societies, as they serve as dynamic transition zones between land and sea. These areas sustain high levels of biodiversity, including essential nursery habitats for numerous marine species, and provide key ecosystem services such as carbon sequestration, nutrient cycling, and coastal protection. They also underpin major economic sectors, including fisheries, tourism, and maritime trade, supporting the livelihoods of millions of people worldwide.

However, coastal zones are increasingly under threat from a combination of natural processes and anthropogenic pressures. Rising sea levels driven by climate change exacerbate erosion and intensify the frequency and impact of flooding events, ultimately leading to the loss of habitats and the exposure of human settlements and critical infrastructure to greater risk [Nicholls and Cazenave 2010]. At the same time, urban expansion, industrial activity, and unsustainable resource use further reduce the resilience of these systems by disrupting their ecological balance and undermining their adaptive capacity [Masselink and Knight 2011]. The degradation of natural coastal defenses such as mangroves, seagrasses, and coral reefs compounds this vulnerability, resulting in significant socio-economic and environmental consequences.

In light of these challenges, the shoreline emerges as a key indicator for understanding and monitoring coastal dynamics. Being the most visible and responsive boundary between land and sea, its position reflects the integrated effect of hydrodynamic forcing, sediment transport, and morphological evolution over multiple temporal scales. Monitoring the shoreline enables early detection of erosion trends, supports spatial planning, and informs adaptive coastal management strategies [Boak and Turner 2005].

Among the geomorphological patterns observable along the shoreline, megacusps deserve particular attention. These alongshore rhythmic undulations, consisting of alternating protruding horns and eroded embayments with spacings of 100 to 1000 m, are associated with morphodynamic instabilities and represent localized erosion hotspots. Their formation, migration, and decay are tightly linked to nearshore sediment dynamics and hydrodynamic variability, offering valuable insights into beach stability and resilience. Moreover, detailed data about megacusp dynamics is essential for validating morphodynamic models. Megacusps,

and the associated erosional hotspots can also affect the usability of beaches and must thereby be taken into account by managers.

Given the complex and rapidly changing nature of the coastal environment, remote sensing technologies play a fundamental role in providing consistent, scalable, and timely observations. Multispectral sensors such as Sentinel-2 and PlanetScope offer fine spatial resolution and rich spectral information, but are limited by atmospheric conditions and daylight availability. Conversely, Synthetic Aperture Radar (SAR) systems like Sentinel-1 and TerraSAR-X operate independently of weather and illumination, allowing for continuous data acquisition even during cloudy days or at night. The integration of these two types of satellite data improves the reliability and frequency of shoreline monitoring.

Compared to traditional surveying methods, such as GNSS field surveys, airborne LiDAR, or orthophoto interpretation, which provide high-resolution data but are often limited in spatial extent and temporal frequency, satellite remote sensing offers broad-scale, repeatable, and cost-effective monitoring capabilities. This makes it an ideal approach for long-term shoreline studies and operational decision-making in vulnerable coastal zones.

Exploring these topics is essential to improve our understanding of the dynamic boundary between land and sea, as well as the morphologies that emerge from its variability. In particular, the development of advanced methodologies for shoreline detection and megacusp characterization using both multispectral and radar satellite data offers new opportunities for scalable and repeatable coastal monitoring. Validating these approaches across multiple environmental conditions and study sites supports the generation of robust datasets, contributing to more adaptive and informed strategies for coastal management and geomorphological analysis.

1.2 Background

1.2.1 Shoreline dynamics and definition

The term shoreline generally refers to the dynamic interface between land and sea. The shoreline position can fluctuate at a wide range of time scales. The fastest motion is at 1-20 seconds and is related to each wave's swash. Wave groupiness and infragravity waves produce a lower frequency variability up to some 10 minutes. At the time scale of hours, there are water fluctuations related to astronomical tidal cycles and storm surges (temporary sea level rises typically associated with cyclonic storms). Erosional processes related to storms move sediment from the dry beach to the submerged area and typically leave a signal in the shoreline visible at a daily scale. The beach recovery, with the post-storm waves transporting the sediment back to the dry beach, occurs during the subsequent weeks. Finally, chronic erosion or accretion trends occur at interannual or decadal scales [Morton 1991].

In an ideal sense, the shoreline is defined as the precise physical boundary where water meets land at a given time [Boak and Turner 2005]. In practice, however, this definition is problematic because the true land–water boundary is constantly moving due to tides, waves, and other factors [Boak and Turner 2005], as previously explained. Consequently, coastal scientists and engineers have introduced a variety of shoreline definitions or proxy indicators that make the concept of “shoreline” more practical and measurable [Boak and Turner 2005]. These definitions differ based on the data available and the intended application, such as short-term monitoring versus long-term planning [Moore 2000]

Given the inherent variability of instantaneous shorelines, a widely adopted approach anchors shoreline definitions to consistent tidal datums, such as Mean High Water (MHW), Mean Low Water (MLW), or Mean Sea Level (MSL). These tidal-based definitions represent statistical averages of water levels, providing a more stable and reproducible reference than instantaneous waterlines [Moore 2000]. For example, the MHW line is frequently utilized in coastal mapping, management, and legal contexts, representing the intersection of the land surface with the average high tide level [Pajak and Leatherman 2002]. Such tidal-based definitions are especially valuable because they mitigate short-term noise and enhance comparability across time and space. However, applying tidal-based definitions demands accurate local tidal measurements or tidal modeling, and the shoreline

position defined by tidal datums can vary spatially due to variations in tidal range and coastal morphology.

Closely related are datum-based shoreline definitions that employ fixed vertical references (such as geodetic datums) to consistently define the shoreline. Shorelines defined by fixed elevation contours relative to a vertical datum are advantageous because they provide an objective, reproducible position that can be precisely mapped with modern technologies like airborne or terrestrial LiDAR and GNSS surveys [Moore 2000]. This method has seen widespread adoption in recent large-scale shoreline-change assessments, allowing rigorous analyses of long-term coastal evolution and providing a stable reference frame against short-term variability [Stockdon et al. 2002]. Nevertheless, this definition requires precise, spatially extensive elevation data, thus limiting its applicability.

In addition, morphological shoreline indicators are used, employing natural coastal features as proxies for shoreline position. These morphological definitions include vegetation lines, dune toes, bluff edges, beach berm crests, and erosion scarps, each representing distinct physical or ecological boundaries influenced by marine processes [Crowell et al. 1991]. For example, in some sites the vegetation line coincides with the highest extent of regular tidal inundation and wave influence, making it a robust indicator for longer-term coastal evolution and management applications [Crowell et al. 1991]. Similarly, erosion scarps or dune toes can indicate positions impacted by episodic storm events, thereby providing insights into both short-term and long-term coastal dynamics. Although morphological indicators integrate environmental conditions over extended periods, their interpretation may introduce subjectivity unless a clearly defined criteria are utilized.

In recent years, the exponential increase in high-resolution satellite imagery has made the definition of the instantaneous shoreline, the visible land–water boundary at the exact time of image capture, particularly popular in remote sensing applications [Pucino et al. 2022]. This approach leverages the distinct visual contrasts on beaches, marking transitions between water and sand, to delineate the shoreline. However, because an image captures a single moment, the instantaneous shoreline may reflect arbitrary tidal and wave conditions, causing its position to vary significantly depending on the time of image acquisition. For instance, short-term shoreline positions can deviate by several meters, or even several tens of meters on ocean-exposed beaches, due to transient water-level fluctuations caused by tides, storm surges, or wave run-up. Despite these limitations, the widespread

availability of historical aerial and satellite imagery has increased the use of instantaneous shorelines in coastal studies [Dominici et al. 2019].

1.2.2 Satellite platforms

In the last decade, the use of satellites that offer free medium-resolution images like Sentinel-2 (S2) from the European Space Agency (ESA) Copernicus program, as well as the Landsat family, has been widely adopted for shoreline monitoring of large areas [Luijendijk et al. 2018, Qiao et al. 2018]. S2 is a European mission that encompasses a pair of wide-swath, high-resolution, multispectral imaging satellites, orbiting in tandem along the same path but staggered 180° apart, aiming to achieve a rapid revisit rate of 5 days at the Equator. Equipped with Multispectral Optical Instruments (MSIs), S2 captures imagery across thirteen spectral bands: four bands with a spatial resolution of 10 m (Figure 1.1b), six bands at 20 m, and three at 60 m. The coverage width of its orbital swath extends to 290 km [ESA 2015]. S2 images are provided at different processing levels. In this study, L2A (orthorectified and atmospherically corrected) images were used.

One disadvantage of the use of medium resolution satellite products is attributable to the spatial resolution, between 10 and 30 m, which prohibits the recognition of small features. Recently, PlanetScope (PLN) (CubeSat satellites) (Figure 1.1a) provided free 3 m spatial resolution images for research purposes [PlanetScope 2023]. The PLN constellation captures visible to near-infrared (NIR) surface reflectance with a global median average revisit time of 30.3 h. The technology behind the PLN satellites has developed across three generations: Dove-Classic (PlanetScope-0), Dove-R (PlanetScope-1), and SuperDove (PlanetScope-2), each featuring unique specifications. The PlanetScope-0 and PlanetScope-1 sensors capture imagery across four spectral bands: blue, green, red, and near-infrared (NIR). The PlanetScope-2 sensor, meanwhile, offers bands with characteristics akin to those of the S2 satellite, also including the red-edge band [PlanetScope 2023].

Multispectral sensors are highly sensitive to atmospheric conditions, with cloud cover and sun glint often limiting their usability, particularly in regions prone to persistent overcast conditions. Moreover, the dependence on solar illumination restricts their ability to collect data at night, leading to temporal gaps in coverage [Wu et al. 2024]. SAR imagery has emerged as a powerful alternative for environmental studies, overcoming some of the limitations of optical sensors. Operating in the microwave spectrum, SAR systems actively emit signals and measure the

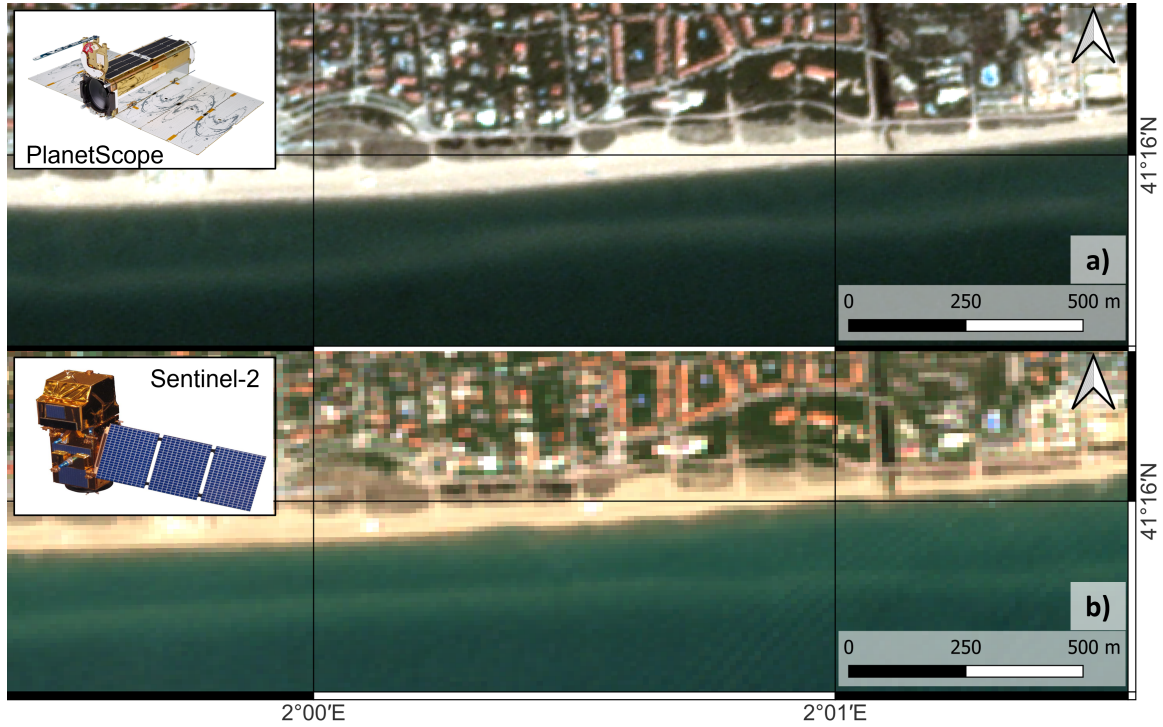


Figure 1.1: Plot a) shows the PLN platform RGB image, which provides a 3 m spatial resolution; plot b) shows the Sentinel-2 platform RGB image, which provides a 10 m spatial resolution.

backscattered energy, enabling observations regardless of the weather or lighting conditions. The unique characteristics of SAR data, such as its sensitivity to surface roughness, dielectric properties, and geometry, make it particularly well suited for delineating the land-water boundary.

Sentinel 1 (S1) is a radar imaging mission within the European Copernicus program. The mission consists of two satellites, Sentinel-1A and Sentinel-1B (at the moment, Sentinel-1C is available in substitution of 1B), operating in C-band and orbiting in a sun-synchronous configuration with a 180° phase shift. This setup enables a revisit time of 6 days at the Equator. The S1 radar operates in four exclusive acquisition modes: Stripmap (SM), Interferometric Wide Swath (IW), Extra Wide Swath (EW), and Wave (WV) [Torres et al. 2012] (Figure 1.2). The Interferometric Wide Swath mode used in this study provides an initial spatial resolution of 20×22 m and a swath width of 250 km. Data are delivered as Level-1 Ground Range Detected products, which are radiometrically calibrated and georeferenced. The S1 images are freely available and can be accessed through the ESA Copernicus Browser.

Among SAR platforms, there is also the option to select paid or on-demand

resources such as TerraSAR-X (TSX). TSX, launched by the German Aerospace Center (DLR), is an X-band radar satellite. It operates at a central frequency of 9.65 GHz and offers a range of imaging modes, including Spotlight, Stripmap, and ScanSAR, with resolutions varying from 1 m to 40 m, depending on the mode. The high spatial resolution compared with the Sentinel constellation can be clearly appreciated in Figure 1.2. The satellite is equipped with flexible imaging geometry, allowing the selection of polarization modes (single, dual, or quad) to suit specific applications. TSX orbits in a sun-synchronous path with a repeat cycle of 11 days. However, interferometric acquisitions can be achieved with a revisit time of less than 24 h when paired with its twin satellite, TanDEM-X. TSX data are provided as Single Look Slant Range Complex or Multi-look Ground Range Detected products. Comprehensive TSX data are distributed by ESA with an approved project proposal or by commercial vendors.

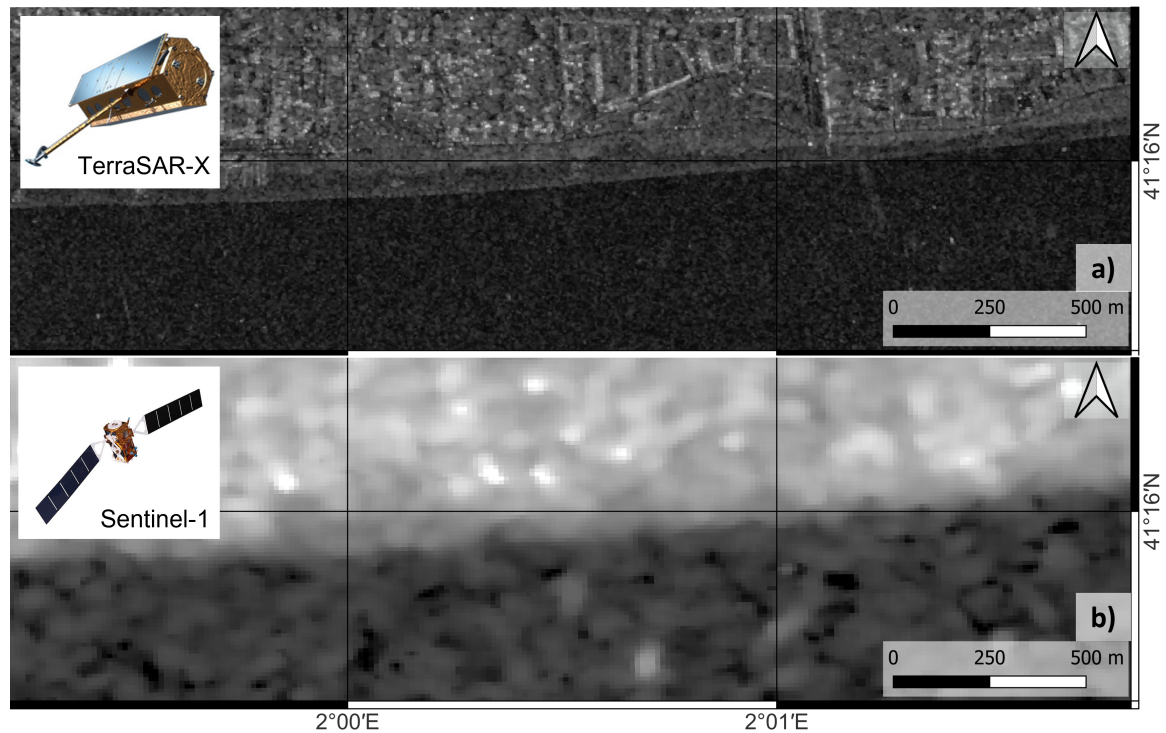


Figure 1.2: Radar satellite platform and relative amplitude images. Plot a) shows the TSX platform and its HH polarization image, which provides a 3 m grid image; plot b) shows the Sentinel-1 platform with its VV polarization, which provides a 10 m grid image.

1.2.3 Segmentation methods

In order to identify the shoreline in satellite images of certain bands (or combinations of bands in certain indices), standard methods are based on classifying the pixels according to their band or index values. This thesis deals with various algorithms for image segmentation, from simple thresholding methods to more complex unsupervised clustering techniques, focusing on separating water and land.

Thresholding Methods

Thresholding is an image segmentation approach where one or more intensity thresholds partition the image into distinct classes. In satellite imagery, thresholding can separate features (e.g., land vs. water) based on pixel intensity values. The methods below highlight both *global thresholding* (single threshold for the whole image) and *local or adaptive thresholding* (varying thresholds per neighborhood).

- **Otsu's Method.** Otsu's method [Liao et al. 2001] is a global automatic thresholding approach that finds an optimal single intensity threshold to separate the image into two classes (foreground and background) by maximizing the between-class variance in the intensity histogram. Let the image histogram be $p(i)$ for intensity level i . For a candidate threshold t , the pixels are divided into class 0 ($i < t$) and class 1 ($i \geq t$). Define $\omega_0(t)$ and $\omega_1(t)$ as the probabilities (histogram sums) of each class and $\mu_0(t)$, $\mu_1(t)$ as the mean intensities of each class. Otsu's criterion is to choose t that maximizes the between-class variance:

$$\sigma_B^2(t) = \omega_0(t)(\mu_0(t) - \mu_T)^2 + \omega_1(t)(\mu_1(t) - \mu_T)^2, \quad (1.1)$$

where μ_T is the total image mean. This criterion can be shown to be equivalent to minimizing the within-class variance. Otsu's algorithm performs an exhaustive search over t to find the optimum. It is non-parametric and assumes only that a meaningful separation will reflect as bimodality in the histogram.

- **Multiclass Otsu (Multi-level Thresholding).** Otsu's original work also extended the thresholding concept to multiple classes by selecting multiple thresholds instead of one [Otsu 1979]. The multi-class Otsu method maximizes the sum of pairwise between-class variance terms for all K classes.

While the computational cost increases with K , dynamic programming and heuristic strategies have been introduced to make the method tractable.

- **Niblack Thresholding.** Niblack’s method [Milyaev et al. 2013] is a local thresholding technique that computes a threshold for each pixel based on the statistics of its local neighborhood. For a given pixel, the threshold T is defined as the local mean plus a bias proportional to the local standard deviation:

$$T = \mu_w + k \sigma_w, \quad (1.2)$$

where μ_w is the mean intensity in a window around the pixel, σ_w is the standard deviation in that window, and k is a constant (typically $k \approx -0.2$ as originally suggested by Niblack). This yields a binary segmentation that adapts to local contrast, making it useful when illumination is non-uniform.

Clustering Methods

Clustering-based segmentation approaches treat pixel values (or feature vectors derived from pixels) as samples from different groups or distributions, and attempt to partition these samples into clusters such that pixels in the same cluster are likely part of the same region or land-cover type. Unlike thresholding (which operates on one feature like intensity and often yields hard binary masks), clustering methods can operate in multidimensional feature spaces and naturally handle multi-class unsupervised segmentation. A common limitation of clustering methods such as K-means and GMM is that they require the number of clusters K to be known a priori. Selecting an appropriate K is not always straightforward, and when no prior information is available, one usually relies on model selection criteria such as the Akaike Information Criterion (AIC) or the Minimum Description Length (MDL) to guide the choice.

- **K-means.** K-means [Hartigan and Wong 1979] is an iterative classification algorithm that divides the data into K clusters by minimizing the within-cluster sum of squared distances. In the context of images, K-means can be applied to pixel intensities, color vectors, or other features to group pixels into coherent regions. The algorithm starts with K initial cluster centroids, usually randomly chosen, and then alternates between an assignment step (assigning each pixel to the nearest centroid) and an update step (recomputing centroids):

$$\min_{S_1, \dots, S_K} \sum_{k=1}^K \sum_{x \in S_k} \|x - \mu_k\|^2, \quad (1.3)$$

where S_k is the set of pixels in cluster k and μ_k is the mean of cluster k . The process continues until the centroids stabilize. However, this iterative scheme typically converges to a local minimum of the objective function, depending on the initial positions of the centroids. To mitigate this, the algorithm is often repeated N times with different random initializations, and the solution yielding the lowest overall distortion is selected. The method produces a “hard” segmentation (each pixel belongs to one cluster) and is computationally efficient in practice, making it suitable for large datasets.

- **Gaussian Mixture Models (GMM).** A GMM [Zhuang et al. 1996] models the data as a combination of K Gaussian distributions:

$$p(x) = \sum_{k=1}^K \pi_k \cdot \mathcal{N}(x \mid \mu_k, \Sigma_k), \quad (1.4)$$

where π_k is the weight of the k -th Gaussian, and $\mathcal{N}(x \mid \mu_k, \Sigma_k)$ is the multivariate normal distribution with mean μ_k and covariance Σ_k . Pixels are assigned to the component with the highest posterior probability. Parameter estimation is typically carried out via the Expectation-Maximization (EM) algorithm [Dempster et al. 1977], which iteratively refines cluster responsibilities and updates the parameters to maximize likelihood. GMM provides a more flexible description of the dataset compared to K-means, as it not only models the location of each cluster (through the mean) but also allows for different shapes and orientations by learning the full covariance matrix for each Gaussian component.

1.2.4 Shoreline detection from multispectral satellite imagery

Recently, the increasing availability of MSI satellite data has facilitated the emergence of various tools for shoreline extraction from multispectral imagery, such as CoastSat [Vos et al. 2019], SHOREX [Sánchez-García et al. 2020], CASSIE [Almeida et al. 2021], and SAET [Palomar-Vázquez et al. 2023]. These tools, both open- and closed-source, can achieve subpixel accuracy in delineating shorelines, particularly in micro-tidal coastal environments. During the image preprocessing stage, which often involves a classification step, a variety of pixel- and object-based techniques are implemented to assign land, water, or other class labels to each pixel [Toure et al. 2019]. Among the most widely adopted techniques for distinguishing between land and water pixels is the use of water indices [Kelly and Gontz 2018],

which rely on pixel-level operations across multiple spectral bands. These indices exploit the sharp decrease in surface reflectance from visible to near-infrared wavelengths as the primary criterion for differentiation. A range of classification methods can be employed to distinguish water from land, including single-threshold approaches with fixed or adaptive thresholds that can be user-defined or computed automatically [Toure et al. 2019]. In recent years, the adoption of machine learning (ML) techniques has further enhanced this step, enabling the automatic extraction of shorelines over extensive spatial scales and the identification of complex patterns not easily detectable with traditional methods [Tsiakos and Chalkias 2023].

Among the different water indices, the Normalized Difference Water Index (NDWI)—which combines the green and near-infrared (NIR) spectral bands—remains one of the most frequently used tools in coastal research [Apostolopoulos and Nikolakopoulos 2021b]. In the CASSIE tool [Almeida et al. 2021], NDWI is first applied to a multispectral image. If the resulting histogram is not bimodal, a multi-threshold Otsu algorithm [Liao et al. 2001] is subsequently used to classify pixels into land, water, and intertidal zone classes, followed by a fixed threshold that separates the combined water–intertidal area from land. However, NDWI may fail under conditions of significant wave-induced foam, which alters surface reflectance [Pardo-Pascual et al. 2018]. To address this limitation, the Coast-Sat tool [Vos et al. 2019] uses the Modified Normalized Difference Water Index (MNDWI), incorporating the short-wave infrared (SWIR–1) band, which is less sensitive to foam effects. The tool then applies a supervised classification to distinguish between land, water, and whitewater (foam), and final land–water separation is achieved through Otsu thresholding [Liao et al. 2001], using only the pixel histogram of the land and water classes.

The more recently introduced SAET tool [Palomar-Vázquez et al. 2023] is capable of employing multiple indices, such as Automated Water Extraction Index (AWEI) and MNDWI, to mitigate the influence of shadows and dark surfaces. It also provides multiple land–water classification options, including K-means clustering and Otsu thresholding (both bimodal and multimodal). Furthermore, it builds upon the shoreline extraction capabilities of the earlier SHOREX tool [Sánchez-García et al. 2020] by incorporating the gradient information from the SWIR–1 band. Pucino et al. (2022) evaluated a variety of such spectral indices, including the Water Index (WI), which demonstrated improved performance in challenging shoreline delineation scenarios. In addition to conventional thresholding ap-

proaches, they also employed a Convolutional Neural Network (CNN) based on a Unet+++ architecture with Deep Supervision.

Among the existing open-source solutions, CoastSat is currently the only one that supports both S2 and PLN imagery (in its latest versions). This tool relies on a single water index and a thresholding-based approach, which may not be optimal for our target environments. MSI satellite imagery, taking advantage of strong visible-to-NIR land-water contrast across multiple spatial resolutions, is now routinely used for automated shoreline detection. However, SAR imagery—obtained by transmitting microwave pulses and recording the backscatter—provides weather- and illumination-independent observations whose sensitivity to surface roughness, dielectric contrasts, and geometry makes it well suited for delineating the land-water boundary.

1.2.5 Shoreline detection from SAR satellite imagery

A variety of studies have employed SAR data for shoreline detection using approaches ranging from classical edge-detection algorithms to state-of-the-art machine learning techniques. [Zollini et al. \(2023\)](#) proposed a semi-automatic shoreline detection method based on the J-Net Dynamic algorithm, which was applied to both SAR and multispectral datasets from two microtidal beaches. In their study, S1 and S2 images were co-registered and preprocessed, with speckle noise filtering applied to SAR images and spectral indices computed for optical data. Shorelines extracted from these data were validated against GNSS measurements, yielding positional accuracies ranging between one and two pixels of the S1 imagery. [Wu et al. \(2024\)](#) implemented the DeepLabv3+ architecture to perform pixel-level semantic segmentation on S1 data, demonstrating strong performance across diverse coastal settings. Their results were attributed to the clear contrast in backscatter intensity between land and sea, driven by differences in surface roughness and dielectric constants. The highest accuracy, corresponding to 0.9 S1 pixels, was achieved at a site with coarser sediment. Certain additional researches explored the influence of tidal variations, meteorological conditions, and scene geometry on the accuracy of S1-derived shorelines [[Savastano et al. 2024](#)]. In these studies, segmentation-based algorithms were used to extract shorelines, and their accuracy was evaluated using high-resolution ground-truth data. The temporal variability of tidally influenced environments was also assessed to investigate the robustness of such approaches across different geomorphological contexts [[Savastano et al. 2024](#)]. Further studies have examined the use of deep learning algorithms for

the identification and extraction of coastlines from SAR imagery [Passarello et al. 2024]. The role of radar polarization and incidence angle in enhancing land-water boundary detection has also been investigated; Wu et al. (2019), for example, identified HH polarization as offering the highest land-sea contrast, while incidence angles between 30° and 50° were found to yield optimal delineation accuracy.

In addition, the impact of radar wavelength on intertidal zone mapping has been addressed. Kim et al. (2007) found that shorter radar wavelengths were better suited for mapping low-slope beaches due to the Bragg wave resonance effect. Other investigations have analysed how variations in sediment grain size affect SAR backscatter responses [Mann et al. 2024], revealing that fine-grained beaches exhibit lower backscatter intensity due to smoother surfaces, whereas coarse-grained beaches produce stronger backscatter signals owing to increased surface roughness. From a methodological standpoint, Mao and Splinter (2025) developed an approach that integrates S1 SAR data with Landsat multispectral imagery in scenarios where optical data are unavailable due to cloud cover. A synthetic Modified Normalized Difference Water Index (MNDWI) was reconstructed by training a neural network on S1 data.

1.2.6 Megacusp dynamics and presence

The shoreline can exhibit a variety of alongshore rhythmic undulations at different spatial scales, consisting of horns projected towards the sea and embayments in between. For example, beach cusps are ubiquitous in many beaches and exhibit wavelengths ranging between 1 and 50 m [Ribas et al. 2015]. Megacusps have considerably longer wavelengths (Figure 1.3), often in the order of hundreds of meters (up to about 1000 m). Finally, km-scale shoreline sand waves are larger-scale features, with spacings from a few to tens of km [Ribas et al. 2015].

This thesis investigates the characteristics of the intermediate-scale patterns called megacusps. In each megacusp, the horn corresponds to an area of sediment deposition and shoreline advancement, while the embayment is characterized by shoreline retreat due to erosion [de Swart et al. 2022b]. Megacusps amplitudes can range from a few to tens of meters (Figure 1.3), and their embayments can constitute erosive hot spots that decrease the usable width of the beach.

Megacusps arise from morphodynamic instabilities of the coupling between seabed and hydrodynamics, through feedback interactions between wave motions, induced currents, and alongshore sediment transport. They are typically part of a larger morphodynamic system, involving not only the shoreline but the whole

surf zone and the nearshore sand bars occurring there [Wright and Short 1984], as can also be seen in the middle panel of Figure 1.3. These patterns form under specific combinations of wave conditions, pre-existing morphology, and sediment transport regimes. Typically, their emergence is linked to periods characterized by low-energy wave conditions, particularly following storm events, during which nearshore sandbars migrate shoreward, promoting coastal accretion [Segura et al. 2018]. Under these conditions, an inner crescentic sandbar tends to connect its horns to the shoreline, giving rhythmic undulations to the coastline by forming protrusions aligned with bar horns and embayments where rip channels occur. Observational studies have shown that megacusps formations often develop just a few days after the formation of crescentic sandbars in the nearshore zone, and they persist as long as the bars remain stable under low-energy wave conditions [de Swart et al. 2022b]. The dynamics of these morphological features are closely related to a specific hydrodynamic circulation: divergent flow currents at the horns and convergent currents within embayments redistribute sediments, reinforcing deposition on horns and erosion within embayments [Thornton et al. 2007]. Under certain conditions, megacusps can also form under more energetic wave forcing, such as during intense storms, if strong spatial variations in wave dynamics (such as focusing or refraction of waves alongshore) exist. These variations generate stationary rip channels, leading to intensified erosion within embayments and promoting the formation of erosive megacusps [Castelle et al. 2015]. Once established, megacusps can slowly migrate alongshore, driven by oblique coastal currents; alongshore migration rates of tens of meters per day have been documented.

The evolution and stability of these coastal features rely on a delicate balance between wave-forcing conditions and morphological feedback mechanisms. When favorable wave conditions persist (moderate energy, nearly shore-normal incidence), megacusps may remain stable for extended periods. Conversely, drastic changes in wave conditions (e.g., new energetic storms with significant wave obliquity) usually erase megacusps, reverting the shoreline to a more linear profile (Figure 1.3). Importantly, no simple, direct relationship consistently links them with specific wave parameters. For instance, a study conducted along a Mediterranean coastline found no clear dependency solely on wave conditions; instead, megacusps formation was almost always associated with crescentic bar presence, rather than spontaneously emerging along an initially uniform coastline [de Swart et al. 2022b]. This observation strongly suggests that morphological coupling between

the sandbars and shoreline plays a crucial role: megacusps are most likely to form when a rhythmic nearshore seabed pattern (bars and channels) already exists, providing a hydro- morphological setting that reinforces shoreline undulations at the initiation of megacusps.

Megacusps occur globally on sandy coasts in both micro-, meso- and macrotidal tidal wave-dominated environments. Examples include:

- **Microtidal, limited-fetch beaches (Mediterranean Sea):** Castelldefels beach, Spain, shows frequent megacusp formation ($\sim 24\%$ of the observation period), wavelengths of 100–700 m, and cross-shore amplitudes of 3–8 m, strongly linked to crescentic bar presence [de Swart et al. 2022b]. Saint-Cyprien (France) similarly exhibits megacusps (~ 300 m spacing) associated with inner crescentic bars [Feyssat et al. 2024].
- **Microtidal, high-energy beaches (Pacific Ocean):** Monterey Bay (California) has persistent megacusps (~ 200 m spacing) coupled with stationary rip currents, significantly amplifying dune erosion during storms [Thornton et al. 2007]. Lighthouse Beach (Australia) also documents megacusps (~ 500 m spacing), morphologically coupled with transverse surf-zone bars [Short 2016].
- **Meso- macrotidal high-energy beaches (Atlantic Ocean):** Megacusps occur on high tidal range coasts such as Gironde (France), a meso- macrotidal environment. Here, calm conditions induce stable megacusps linked to crescentic bars, while energetic storms cause transient erosive megacusps acting as erosion hotspots (~ 300 – 400 m spacing) [Castelle et al. 2015]. Similar features occur along the English, Welsh coast, demonstrating global ubiquity and scale consistency despite tidal differences [Castelle et al. 2015].

1.2.7 Megacusp monitoring

Only a few studies have performed detailed monitoring of megacusp dynamics. In situ GNSS surveys provide high-resolution data but are spatially limited and lack sufficient temporal resolution [de Swart et al. 2022a]. Airborne imagery requires costly, dedicated campaigns, resulting in scarce temporal coverage. Long-term, high-frequency monitoring has mainly been achieved through video systems [van de Lageweg et al. 2013, de Swart et al. 2022a], which offer continuous observations but are limited to beach stretches of about 1 km. Exceptionally, weekly LiDAR data

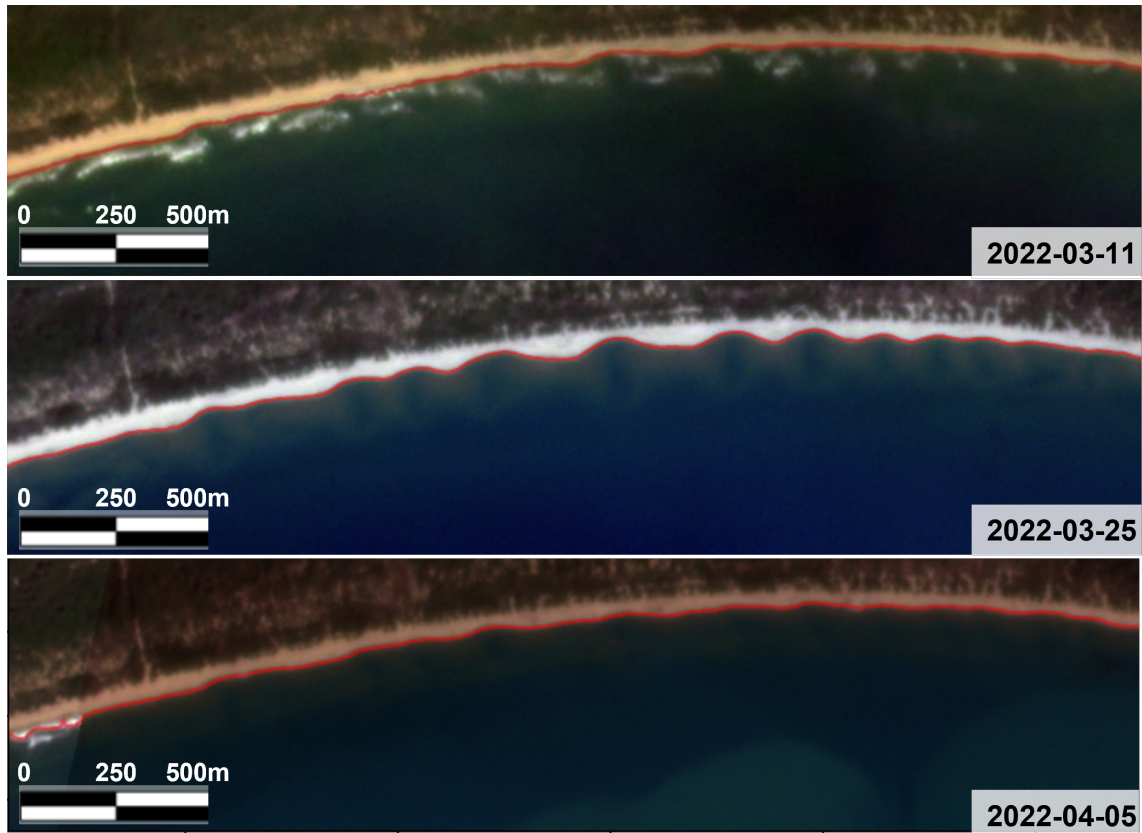


Figure 1.3: Rapid development and disappearance of megacusps in a Mediterranean microtidal beach (Fegnolia beach, in the Italian Tyrrhenian Sea) in March-April 2022 event.

have been used to monitor megacusps, though restricted to a 2 km sector and one year [Matsumoto et al. 2020].

Satellite data, despite enabling regional-scale analysis, have been constrained by their spatial resolution (10–30 m). Recently, higher-resolution imagery from PLN (3 m) has become freely available for research [PlanetScope 2023], and platforms like Google Earth Engine (GEE) [Gorelick et al. 2017] have improved data accessibility and management for long-term monitoring. Although megacusps can be visually detected in satellite imagery [Leuci et al. 2022] (see also Figure 1.3), no studies have yet quantified their characteristics from space. Developing a methodology to characterize and follow the megacusps dynamics could complement video-based studies. The combination of S2 and PLN imagery could enable the analysis of megacusp evolution at weekly to daily timescales.

1.3 Aim and Objectives

This research aims to advance the use of remote sensing for monitoring coastal morphology through satellite imagery by employing both multispectral data (Sentinel-2 and PlanetScope) and SAR data (Sentinel-1 and TerraSAR-X), specifically focusing on ‘instantaneous’ shoreline extraction and the characterization of its megacusp undulations. The study looks to contribute to the state of the art in this field by developing a new methodology that is as validated, repeatable, and scalable as possible across different satellite products. This thesis focuses on Mediterranean beaches, which are characterized by limited-fetch wave conditions and an almost negligible tidal range (20 cm), a setting that has received comparatively less attention in the scientific literature.

To achieve this, the research aims at reaching the following specific objectives:

- **Develop an automated shoreline extraction methodology for multispectral imagery.**

Design and implement a robust procedure for detecting instantaneous shorelines from multispectral data sources (e.g. S2, PLN) that maintains the shoreline undulations. To ensure adaptability on various study sites, different combinations of spectral indices and segmentation methods have been incorporated.

- **Detect and characterize megacusps using multispectral data.**

Apply the newly developed satellite-multispectral-based methodology of shoreline extraction to identify and characterize shoreline undulations called megacusps, including the quantification of their wavelength and amplitude. Emphasis is placed on the potential of PLN’s high revisit time to capture the weekly-scale dynamics of these features.

- **Quantify and account for shoreline detection errors caused by wave and tide variability.**

Quantify shoreline displacements due to tides and waves, and integrate the corresponding corrections into the developed shoreline extraction methodology to improve the reliability of the collected information. This would be essential for extending the research to higher-resolution satellite products in macrotidal environments.

- **Adapt and refine the automated shoreline extraction methodology for SAR imagery.**

Extend the shoreline-detection approach to SAR imagery by introducing specific preprocessing for radar data and improve the typical 10–15 m accuracy often reported for SAR-derived shorelines. Implement an additional denoising step to reduce the characteristic speckle noise present in radar imagery and test outlier detection methods, issues commonly associated with shoreline extraction attempts from SAR images in the literature.

- **Investigate key factors affecting land–sea backscatter contrast in SAR.**

Analyse how polarization mode, sea surface state (wind, waves), and beach grain size (sandy, gravel) influence radar backscatter, to gain understanding of the different error sources. This step seeks to advance the understanding of shoreline delineation through SAR imagery.

1.4 Thesis Outline

This thesis is structured into four chapters in addition to the introduction. Chapter 2, introduces the study areas and the satellite datasets employed throughout the analysis. It details the selection of five representative Mediterranean coastal sites, chosen for their varied geomorphological characteristics and data availability. The chapter also describes the multispectral (S2, PLN) and radar (S1, TSX) imagery used, along with reference shoreline data and auxiliary measurements such as wave, tide, wind, and elevation data.

Chapter 3, presents the methodological development of a new multispectral shoreline extraction tool. It consists of a set of algorithms for preprocessing satellite imagery, extracting shorelines, and validating them through comparisons with in situ and orthophoto-derived shoreline data. Based on the extracted shoreline, another section provides a tool for characterizing megacusp undulations. The two methodologies are validated in three Mediterranean sandy beaches. This chapter includes a detailed assessment and discussion of the results of different classification and segmentation techniques (e.g., Otsu, Niblack, K-means, GMM).

Chapter 4, shifts to radar-based shoreline detection, introducing preprocessing techniques specific to SAR data and assessing the performance of various denoising and classification combinations. It compares results from S1 and TSX imagery, discusses the sensitivity of shoreline detection to environmental and sensor-specific parameters, and addresses the role of backscatter dynamics in SAR shoreline mapping. The methodology is validated in two sandy and two gravel Mediterranean beaches.

Finally, Chapter 5, synthesizes the findings of the thesis, highlighting key results and potential perspectives for future research. The chapter concludes with reflections on the broader applicability of the developed tools for coastal monitoring and management under changing contexts and environmental conditions.

To conclude, Appendix A focuses on evaluating how wave and tidal variations influence the accuracy of shoreline positions derived from satellite imagery in three Mediterranean sandy beaches. It investigates the potential for correcting shoreline displacements caused by these short-term hydrodynamic undulations.

Chapter 2

Study sites and Dataset

2.1 Study Sites

The research within this thesis was conducted on five coastal areas located in the Western Mediterranean Basin (Figure 2.1). They were selected to capture a variety of coastal morphologies and sediment types, needed in two different works related to Multispectral Satellite Image-Shoreline Extraction (MSI-SE) and megacusp (MC) detection (Chapter 3), and Synthetic Aperture Radar - Shoreline Extraction (SAR-SE, Chapter 4). All sites are subject to similar wave and tidal conditions, with weak tidal fluctuations of approximately 20 cm and alternating periods of calm seas with occasional short, intense storms with limited fetch. However, the effect of these oscillations was tested on these beaches in Appendix A.

The Southern Llobregat Delta (SLD) in Spain spans a 10 km stretch along the coast in front of the towns of Castelldefels, Gavà, and Viladecans. This semi-anthropized coast exhibits variable beach widths and is backed by hard structures. It is mainly composed of sand with a median grain size of 270 μm , and the wave energy predominantly originates from two directions: east-southeast (with an average mean wave direction of 100°) and south-southwest (with an average mean wave direction of 176° , measured from the north) [de Swart et al. 2020].

Feniglia (FNG) beach in Italy is part of a natural beach/dune ridge system enclosing the Orbetello Lagoon. Extending for about 6 km and anchored landwards by the Ansedonia promontory, FNG is composed of fine sand (detailed grain size data are unavailable) and faces predominantly south. It is directly exposed to waves from the southern directions, with those from the southeast and south affecting the entire coastline. In contrast, waves from the southwest primarily impact the eastern sector due to sheltering by Monte Argentario [Pranzini et al. 2020].

The Northern Ombrone Delta (NOD) is a sandy area in Italy covering the northern section of the Ombrone River Delta and facing the town of Marina di Grosseto. Starting at the port of Marina di Grosseto, it extends for about 5 km towards the river mouth. This site is characterized by a grain size of approximately 700 μm and a prevailing wave direction from the south [Pranzini et al. 2020].

Platja el Marjal (MRJ) is a gravel beach situated in Spain, south of the Ebro Delta and facing the town of Alcanar. It extends approximately 3 km in length, has an average width of 30 m, and is located in a semi-urban environment. The beach is characterized by a mean orientation of 241° relative to the North [de Swart et al. 2020].

Ribera de Cabanes (RDC) is a gravel barrier beach in Spain, located north of Castelló de la Plana. Extending for about 8 km, RDC exhibits a primary orientation of 35° relative to the north and features a berm morphology with low height and width, a steep slope facing the sea, and a gentler gradient toward the continent. Wave energy in this area is generally low, with 96% of recorded wave heights below 2 m; the most energetic waves, common during autumn and winter, come from the northeast and east-northeast [Mateu 1982].

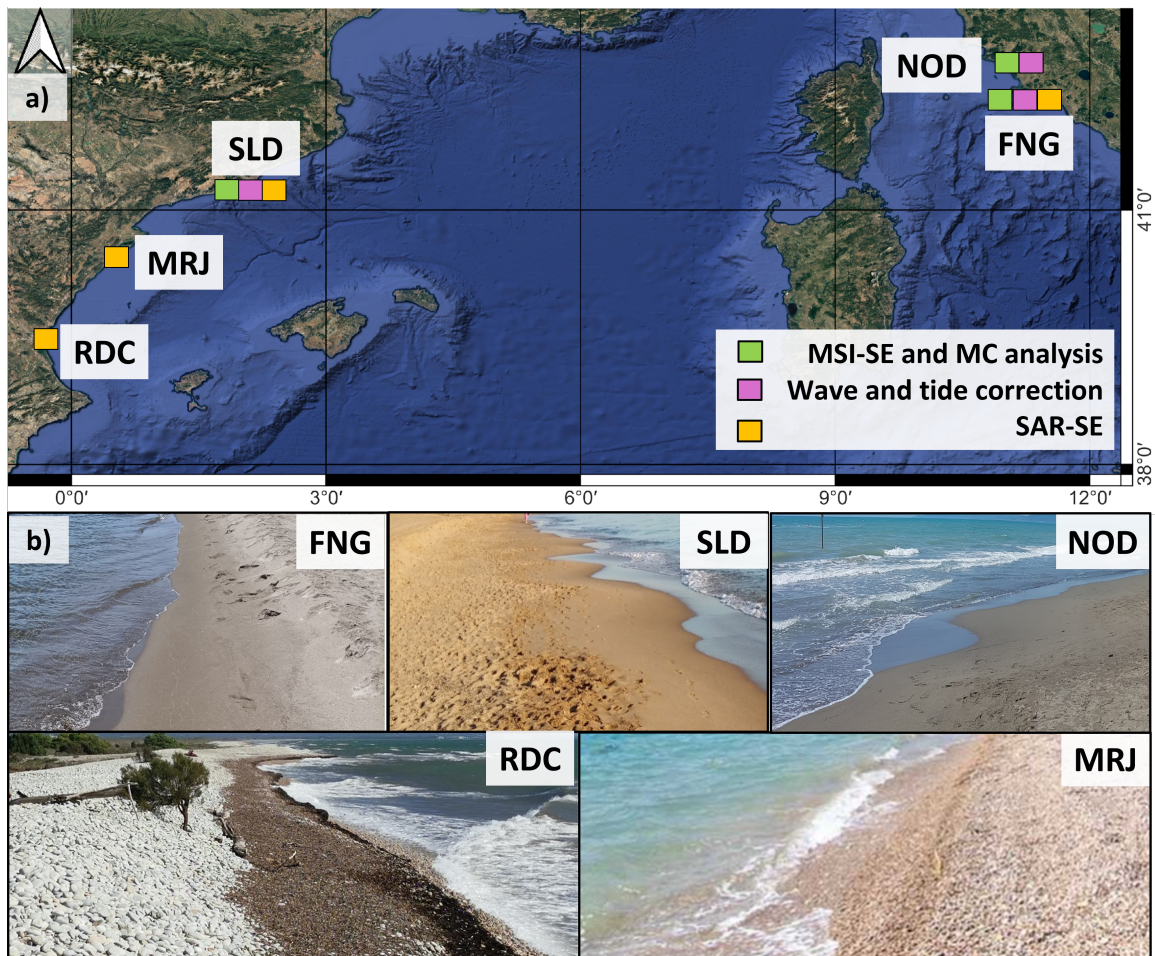


Figure 2.1: In panel a), study areas are specified based on the particular research investigation for which they were used. The coordinate reference system is WGS84. In panel b) pictures of Feniglia beach (FNG, top left, Italy), Southern Llobregat Delta (SLD, Spain, panel b) top center), Northern Ombrone Delta (NOD, Italy, panel b) top right), Playa del Marjal (MRJ, Spain, panel b) bottom left) and Ribera de Cabanes (RDC, Spain, panel b), bottom right) are shown.

2.2 Satellite Dataset

2.2.1 Multispectral dataset for shoreline identification and megacusp characterization

In Chapter 3, satellite images served two purposes. In the validation phase of the satellite-derived shorelines, the satellite images with acquisition times closest to those of the reference shorelines in the three beaches were selected. A total of 12 S2 level-2A (L2A) images and 12 Planet images were employed (Table 2.1). Despite S2 providing imagery across thirteen spectral bands, including four at 10m, six at 20m, and three at 60m spatial resolution, in Chapter 3, only the bands at 10m and 20m resolution were selected. Regarding PLN images, they capture visible to near-infrared (NIR) surface reflectance with a spatial resolution of 3 m, achieving a global median average revisit time of 30.3 h. PLN imagery is not freely available, but it can be accessed for free for research and academic purposes by applying to the Planet Education and Research Program. Some SLD reference shorelines were also used to assess the feasibility of detecting megacusps, due to the presence of these phenomena in some of the high-resolution orthomosaics close to a satellite image date. Subsequently, tens of images for studying two megacusp events, one at the SLD coast and another at FNG beach, were also downloaded. The dataset for the event on FNG beach comprised nineteen S2 L2A images and sixteen PLN images, between February and June 2022. The event on the SLD coast was tracked with twenty S2 images and twenty PLN images, between March and October 2023.

Table 2.1: Acquisition date of the reference products, either aerial orthophotos (*) or GNSS (**), used to validate satellite-derived shorelines, and the corresponding Sentinel-2 and PlanetScope imagery dates and relative time gaps in the three sites (SLD, FNG, and NOD, see the Abbreviations list). Some orthomosaics in the SLD are also used for the validation of the methodology for megacusp characterization (°).

Reference Shoreline Date	S2 Imagery Date	Time Gap (Days)	PLN Imagery Date	Time Gap (Days)
SLD				
25 May 2017 *°	23 May 2017	2	27 May 2017	2
31 May 2017 **	02 June 2017	2	31 May 2017	0
20 November 2017 **	19 November 2017	1	20 November 2017	0
18 January 2018 **	18 January 2018	0	18 January 2018	0
14 March 2018 **	14 March 2018	0	16 March 2018	2
23 May 2019 *°	23 May 2019	0	23 May 2019	0
09 June 2021 *°	11 June 2021	2	08 June 2021	1
FNG				
19 July 2019 *	23 July 2019	4	19 July 2019	0
20 July 2021 *	22 July 2021	2	20 July 2021	0
05 April 2023 **	03 April 2023	2	06 April 2023	3
NOD				
19 July 2019 *	23 July 2019	4	19 July 2019	0
20 July 2021 *	22 July 2021	2	20 July 2021	0

2.2.2 Radar Dataset for shoreline detection

In Chapter 4, the processed S1 SAR images were downloaded free of charge from the Copernicus Browser (<https://browser.dataspace.copernicus.eu/>, accessed on 21 December 2024). S1 mission consists of two satellites, Sentinel-1A and Sentinel-1B, operating in C-band (5.40 GHz of central frequency) and orbiting in a sun-synchronous configuration with a 180° phase shift. This setup enables a revisit time of 6 days at the Equator in a full operating condition. The approach consisted of downloading, for each validation date, the pair of images in Ascending (ASC) and Descending (DESC) mode closest to that date, with a total of 20 S1 images (Table 2.2). The Interferometric Wide Swath mode used in this study provides a spatial resolution of 20×22 m and a swath width of 250 km. Data are delivered as Level-1 Ground Range Detected (GRD) products, which are radiometrically cal-

ibrated, georeferenced, and finally distributed with a 10 m pixel spacing. The S1 images were downloaded freely through the ESA Copernicus Browser in IW GRD mode.

The TerraSAR-X dataset was provided by CTTC and consists of 2 X-Band (9.65 GHz of central frequency) images acquired with the SM mode in ascending orbit, with HH polarization, covering the SLD area with a pixel size of 1.4 m x 1.9 m. TSX orbits in a sun-synchronous path with a repeat cycle of 11 days. However, interferometric acquisitions can be achieved with a revisit time of less than 24 h when paired with its twin satellite, TanDEM-X. Comprehensive TSX data are distributed by ESA with an approved project proposal or by commercial vendors.

Table 2.2: Acquisition date of the reference products from aerial orthophotos (*) or PLN high-resolution images (**), used to validate satellite-derived shorelines, and the corresponding S1 and TSX (in bold) imagery dates, relative time gaps, and orbit information in the four sites (SLD, FNG, MRJ, and RDC).

Reference Shoreline Date	SAR Imagery Date	Orbit	Time Gap (Days)
SLD			
26 October 2017 **	24 October 2017	-	2
	27 October 2017	DESC	1
	28 October 2017	ASC	2
19 May 2018 **	19 May 2018	DESC	0
	20 May 2018	ASC	1
	21 May 2018	-	2
24 May 2023 **	23 May 2023	DESC	1
	24 May 2023	ASC	0
04 June 2023 **	04 June 2023	DESC	0
	05 June 2023	ASC	1
FNG			
19 July 2019 *	18 July 2019	DESC	1
	18 July 2019	ASC	1
20 July 2021 *	19 July 2021	DESC	1
	19 July 2021	ASC	1
MRJ			
10 July 2016 *	04 July 2016	ASC	6
	10 July 2016	DESC	0
29 June 2021 *	02 July 2021	DESC	3
	02 July 2021	ASC	3
RDC			
01 June 2019 *	01 June 2019	DESC	0
	01 June 2019	ASC	0
06 June 2022 *	02 June 2022	DESC	4
	03 June 2022	ASC	3

2.2.3 Multispectral dataset for wave and tide effect evaluation

The dataset used in Appendix A consists of three S2 and three PLN images, one for each site. S2 level-2A (L2A) products, orthorectified and georeferenced, have been selected, while PLN images are already orthorectified, georeferenced, and radiometrically adjusted to S2 bands. The characteristics of the MSI images used are the same as those described in Section 2.2.1. The images for SLD sites were georeferenced in ETRS89 UTM 31N, while the images for FNG and NOD shared the ETRS89 UTM 32N reference system. The images were selected as close as possible to the dates of the reference orthomosaics (Table 2.3), with a maximum time gap of 4 and 3 days, respectively, for the S2 and PLN imagery.

Table 2.3: Dates of reference orthomosaics and temporal discrepancy (in days) of S2 and PLN imagery from reference data used to validate satellite-derived shorelines, and the corresponding Sentinel-2 and PlanetScope imagery dates and relative time gaps in the three sites (SLD, FNG, and NOD, see the Abbreviations list).

Site	Reference Date	S2 Time Gap (Days)	PLN Time Gap (Days)
SLD	25 May 2017	2	2
FNG	05 April 2023	2	1
NOD	20 July 2019	4	0

2.3 Reference Shorelines

In this thesis, a large portion of the reference shorelines was derived by manually digitizing them in orthomosaics. The manual digitization of the instantaneous shoreline was performed using QGIS 3.22 software, and the shoreline points were positioned at the center of the swash zone, corresponding approximately to the intermediate position between wave runup and rundown. The areas for which orthomosaics were acquired include SLD, NOD, FNG, MRJ, and RDC.

Orthomosaic products for the FNG and NOD beaches were downloaded from the Tuscany Region's GEOscopio WMS service. Two orthomosaics, corresponding to the operational period of the S2, S1, and PLN missions, were selected. These open-access products are distributed in four bands (NIR, red, green, and blue) with a spatial resolution of 20 cm per pixel. The FNG and NOD beaches are covered by the same flight campaign; thus, the available acquisition dates coincide. FNG orthomosaics were employed throughout all the main chapters of the thesis, while NOD orthomosaics were used exclusively in Chapter 3.

Regarding the SLD and MRJ beaches, orthophotos provided by the Institut Cartogràfic i Geològic de Catalunya were used. These products consist of three bands and have a spatial resolution of 25 cm per pixel. For RDC, orthomosaics were obtained from the Institut Cartogràfic Valencià, which also offers three-band products with a spatial resolution of 25 cm per pixel (details in Section 2.2.2). The orthophotos of SLD were used in all the main chapters of the thesis, whereas MRJ and RCD products were employed exclusively in Chapter 4, dedicated to SAR data analysis.

Moreover, GNSS surveys were conducted along a 1.2–1.4 km stretch of the SLD coastline, using an Ashtech Pro.Mark2 system from Thales Navigation (El Camino Real, Santa Clara, CA). Additionally, a survey of the FNG beach was conducted using an Emlid Reach RS2 multifrequency GNSS receiver. On both beaches, shoreline positions were recorded using the same Differential Global Navigation Satellite System (dGNSS). The base receiver was established as a permanent station in a known location, while the rover receiver was operated in RTK (Real-Time Kinematic) mode, recording positions at a rate of one point per second for SLD and every 0.2 s for FNG. The surveys were conducted by experienced researchers who systematically walked along the center of the swash zone to ensure consistency between GNSS-derived shorelines and those digitized from orthomosaics. The planimetric and elevation errors associated with these GNSS campaigns were both

on the order of 10 cm. These data were used only in the study related to MSI-SE and MC characterization (Chapter 3).

Only for the SAR-focused section (Chapter 4), manually digitized instantaneous shorelines from PLN imagery were also used as reference data across the study sites. In the case of SLD, this followed the same rationale adopted for orthomosaic-derived shorelines. Although the spatial resolution of PLN imagery (3 m) is lower than that of orthomosaics, its near-daily coverage enabled the selection of images closely aligned with the SAR acquisition dates, including data from both the S1 and TSX platforms.

2.4 Auxiliary data

2.4.1 Wind, Waves and Tidal data

The position of the shoreline has a strong intrinsic variability that depends on tide and wave conditions. The latter produce shoreline movements toward land or sea, due to various phenomena such as astronomical and meteorological tides, wave setup or storm surges. The analyzed coastal stretches (Figure 2.1), although in a micro-tidal Mediterranean environment, share a low beach slope. Moreover, there is sometimes a time gap between the reference data and the satellite images. Therefore, a quantitative evaluation of the potential errors in shoreline detection related to wave and tide conditions is carried out in the different studies. The pebble beaches, RDC and MRJ, have steeper slopes, which mitigate these effects, reducing the tide- and wave-induced migration of the shoreline. In these cases, weather and sea conditions were controlled only to avoid extreme events. However, a quantitative evaluation of the effect of wave and sea-level variability was conducted on the three sandy beaches (SLD, FNG, NOD).

The sea level data were obtained from the Barcelona 2 tide gauge of Barcelona harbor (Puertos del Estado, Spain) for the SLD coast. The Tarragona tide gauge was used for MRJ, and the Mareógrafo de Sagunto was employed for RDC. Civitavecchia Tide Gauge (Italy) was used for FNG beach, and Marina di Campo harbor for the NOD coast.

The wave conditions were obtained from the Barcelona Buoy II (managed by Puertos del Estado, Spain) for the SLD coast, from the Tarragona Buoy for MRJ beach (the latter two from Puertos del Estado, Spain). For RDC, data was obtained from the SIMAR virtual buoy number 2087122 (Puertos del Estado). Regarding the Italian coasts, data were obtained from the Giannutri buoy for FNG beach, and from the Castiglione della Pescaia buoy for the NOD coastal stretch (the latter two from Servizio Idrologico Regionale, SIR Toscana portal, Italy).

Regarding wind data, important in the radar work of Chapter 4, measurements for FNG were obtained from the SIR Toscana portal, specifically from the Orbetello weather station. For the Spanish beaches (SLD, MRJ, and RDC), wind data were obtained from the same locations as the respective tide gauges, accessed through the Puertos del Estado portal.

2.4.2 Elevation data

Available LiDAR-based Digital Surface Models (DSMs) were used to compute the beach swash slope β , needed to estimate the wave- and tide-induced migration of the shoreline. A DSM with 1 m of spatial resolution, provided by the Tuscany Region, was used to gather the elevation data and assess the slope of the NOD and FNG beaches, matching the same frames as the corresponding orthomosaics. Instead, for the SLD beach, LiDAR data were downloaded from the Geoportal de Cartografia of the Area Metropolitana de Barcelona (AMB), which provides a grid with 1 m spatial resolution. The obtained average swash slopes were 0.08 in the SLD, 0.07 in the FNG, and 0.06 in the NOD.

Chapter 3

Multispectral imagery shoreline extraction and megacusp detection

3.1 Introduction

Coastal zones, particularly sandy beaches, are highly dynamic environments subject to various natural and anthropogenic forcings (details in Section 1.2.1). The instantaneous shoreline is a widely used indicator of beach changes in image-based applications, and it can display undulations at different spatial and temporal scales. Megacusps, periodic seaward and landward shoreline perturbations are an example of such undulations that can significantly modify beach width and impact its usability (details in Section 1.2.6). Traditionally, the study of these phenomena relied on video monitoring systems, which provide high-frequency imagery but limited spatial coverage (details in Section 1.2.7). Instead, the objective of this methodological study is to test the potential of employing multispectral satellite-derived shorelines, specifically from Sentinel-2 (S2) and PlanetScope (PLN) platforms, for characterizing and monitoring megacusps formation and their weekly dynamics over time.

A recurring conclusion across many of the previous studies on shoreline extraction from multispectral satellite images is the absence of a universally applicable shoreline extraction method (see a detailed background on Section 1.2.4). As a result, algorithms must be tailored and validated for each specific coastal setting [Kelly and Gontz 2018, Pucino et al. 2022, Bishop-Taylor et al. 2019]. It is also worth noting that most existing tools have been designed to capture large-scale shoreline evolution, whereas the focus of this study lies in identifying small- and short-term shoreline fluctuations associated with megacusps. To overcome these limitations, this chapter also aims at developing a fully automatic, in-house shoreline detection algorithm compatible with both S2 and PLN data. This tool must be highly flexible, allowing for multiple combinations of spectral indices, classification strategies, and shoreline smoothing levels to be tested to maximize detection accuracy before megacusp characterization. The algorithm incorporates various spectral indices derived from the bands available in both satellite platforms, and includes both global and local thresholding techniques, as well as two unsupervised classification methods: deterministic K-means and the probabilistic Gaussian Mixture Model (GMM). In parallel, the well-known CoastSat tool is also applied to all satellite images to serve as a benchmark for comparison.

First, the shoreline extraction tool is developed and validated to guarantee accurate results that maintain the megacusp undulations (Section 3.2.2). Validation of this shoreline detection phase is performed on three micro-tidal Mediter-

anean beaches, comparing with high-resolution orthomosaics and in-situ GNSS data specified in Section 2.2.3. Second, a tool for megacusp characterization is implemented and subsequently validated with reference data (Section 3.2.3). Section 3.3 collects the results of the validation of the shoreline extraction tool and the megacusp characterization tool. In addition, the methodology is also tested for monitoring the weekly to daily megacusp evolution using various potential metrics, made possible by the combined use of S2 and PLN imagery. Section 3.4 presents a detailed discussion of the characteristics of the tools developed, including their main advantages and shortcomings, and an examination of the sources of errors. The chapter ends with the conclusions drawn from this study (3.5).

3.2 Methodology

3.2.1 Multispectral image preprocessing

S2 products were downloaded using the GEE platform. Initially, three areas of interest were selected, and a filter was applied to limit the number of clouds in the images (0.60). Then, individual bands of interest were downloaded at different resolutions: 10 m for the blue (B02), green (B03), red (B04) and Near-Infrared 1 (NIR 1, B08) bands and 20 m for the Red-Edge 1 (B05), Short-Wave Infrared 1 (SWIR 1, B11) and Short-Wave Infrared 2 (SWIR 2, B12) bands. The bands were later resampled to a final resolution of 10 m, employing a nearest neighbor approach. Additionally, a median filter with a 3×3 pixel kernel size was applied to minimize image noise while maintaining edge detection integrity. Finally, several spectral indices resulting from the combination of the resampled S2 bands were calculated (Table 3.1): the Normalized Difference Water Index (NDWI), Modified Normalized Difference Water Index (MNDWI), Sentinel Water Index (SWI), Water Index (WI), Sentinel Water Map (SWM), and Automated Water Extraction Index (AWEI) in its two formulations suitable for situations with thin clouds (AWEIsh) and without (AWEInosh).

The PLN data were downloaded through the dedicated portal, where it is possible to filter products by cloud coverage and select the area of interest. All the provided bands have a resolution of 3 m, so resampling was unnecessary. The limited number of available bands allowed only the calculation of the NDWI index and the use of the NIR band (Table 3.1).

Table 3.1: Formulations of indices derived from different combinations of spectral bands of the Sentinel-2 and PlanetScope platforms (see the Abbreviations list).

Sentinel-2	
Index	Formula
NDWI	$\frac{\text{GREEN} - \text{NIR}}{\text{GREEN} + \text{NIR}}$
MNDWI	$\frac{\text{GREEN} - \text{SWIR1}}{(\text{GREEN} + \text{SWIR1})}$
SWM	$\frac{\text{BLUE} + \text{GREEN}}{(\text{NIR} + \text{SWIR1})}$
SWI	$\frac{\text{RED EDGE} - \text{SWIR1}}{\text{RED EDGE} + \text{SWIR1}}$
WI	$(1.7204 + 171 \times \text{GREEN} + 3 \times \text{RED} - 70 \times (\text{NIR} - 45 \times \text{SWIR1} - 71 \times \text{SWIR2}))$
AWEINOsh	$(4 \times (\text{BLUE} - \text{SWIR1}) - (0.25 \times \text{NIR}) + 2.75 \times \text{SWIR2})$
AWEIsh	$(\text{BLUE} + 2.5 \times \text{GREEN} - 1.5 \times (\text{NIR} + \text{SWIR1}) - 0.25 \times \text{SWIR2})$
PlanetScope	
Index	Formula
NDWI	$\frac{\text{GREEN} - \text{NIR}}{\text{GREEN} + \text{NIR}}$
NIR	NIR

3.2.2 Shoreline detection tool

The core of the methodology was developed in two separate tools (programmed in Python 3.9), one for shoreline extraction and the other for megacusp characterization (Figure 3.1). The shoreline extraction procedure consisted of the selection of four methods to separate the pixels into land and sea classes automatically using the spectral index raster. Two methods were based on automatic threshold definition, and the other two on unsupervised clustering. The procedures described below were repeated for all the considered spectral indices (Table 3.1).

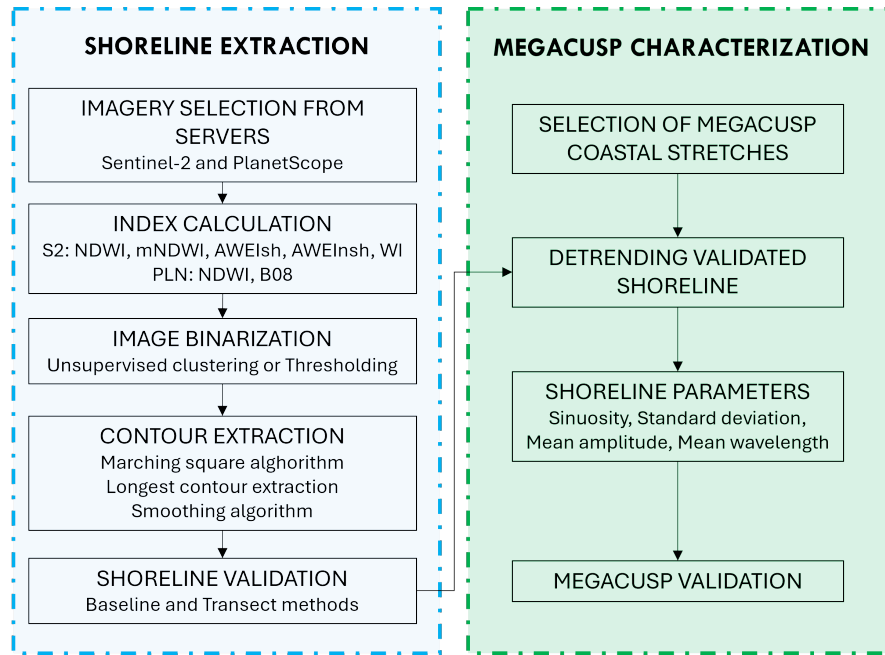


Figure 3.1: Workflow of the shoreline extraction tool and the megacusp characterization tool.

The implemented thresholding methods were Otsu [Liao et al. 2001] and Niblack [Milyaev et al. 2013]. Details regarding thresholding methods are presented in Section 1.2.3. In addition, unsupervised clustering methods, namely K-means [Hartigan and Wong 1979] and GMM [Zhuang et al. 1996], were tested. These methodologies offer a significant advantage in the binarization of raster files compared to conventional thresholding techniques by adapting to the intricate and varied distributions of pixel intensities and providing a more robust approach to image segmentation [Calkoen et al. 2021]. More details about unsupervised clustering are presented in Section 1.2.3. In this chapter, the number of clusters was set to 2 for both classification methods.

Subsequently, the shoreline extraction process from the binarized image consisted of the following three steps:

- The contour was extracted by scanning through the binarized raster data using a Marching Square algorithm with a threshold of 0.5, by passing through the middle of the boundary pixels (Figure 3.2c).
- The longest contour was selected as the shoreline after the evaluation of the lengths of the various contours extracted.

- A Laplacian smoothing algorithm was implemented. Two parameters characterize this algorithm: a smoothing factor (set to 0.2), to adjust each point on the contour line based on neighboring positions, and the number of iterations (set to 10) to refine the line shape gradually.

In addition, shorelines for the same dates, both for FNG beach and the SLD coast, were obtained from the CoastSat tool v.2.3 [Vos et al. 2019] for use as benchmarks. The dates analyzed were the same S2 images visible in Table 2.1. CoastSat was used with the default classification parameters, and the shorelines were extracted by manually adjusting the threshold to maximize accuracy. In the SLD, the threshold was adjusted for each date and site to obtain the most accurate shoreline, following Zollini et al. (2023), while in FNG, a constant threshold of -0.1 was used.

The various cases validation, namely the different combinations of indices and methods for shoreline extraction, was carried out using a “baseline and transect” method. The following steps were executed:

- A reference line (baseline) along and behind the beaches was established.
- Perpendicular lines (transects) to the baseline at 10 m intervals were created.
- Each transect intersected the reference shoreline and the automatically extracted shorelines (Figure 3.2e), and the signs for subsequent calculations were established. By convention, a negative (positive) sign was associated with cases where the extracted shoreline was located landward (seaward) from the reference shoreline.
- Various statistical measures of the distance between the two shorelines were computed to assess the accuracy and reliability of the extracted shoreline data compared to the reference shorelines.

Statistical metrics used to quantify errors were the Mean Absolute Deviation (MAD), the Bias (μ_d), the Root Mean Square Deviation ($RMSD$), and the standard deviation (σ_d):

$$MAD = \frac{1}{N} \sum_{i=1}^N |d_i| \quad (3.1)$$

$$\mu_d = \frac{1}{N} \sum_{i=1}^N d_i \quad (3.2)$$

$$RMSD = \sqrt{\frac{1}{N} \sum_{i=1}^N (d_i)^2} \quad (3.3)$$

$$\sigma_d = \sqrt{\frac{1}{N-1} \sum_{i=1}^N (d_i - \mu_d)^2} \quad (3.4)$$

where N is the total number of observations and d_i represents the value of the distance of the i -th transect.

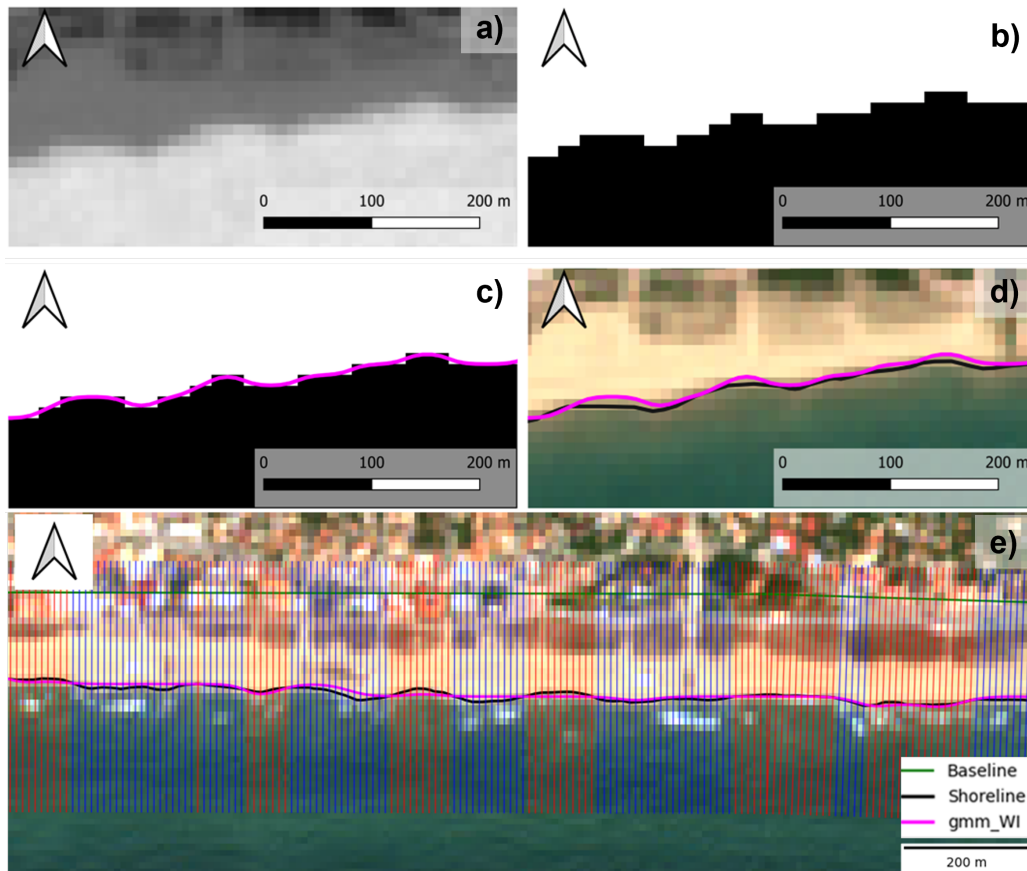


Figure 3.2: Example of the shoreline extraction method with S2 data: (a) raster file of the spectral index (NDWI), (b) binarization of the image with K-means, (c) contour extraction, (d) comparison between the reference shoreline and the detected one, and (e) validation by using the baseline and transect method.

3.2.3 Megacusps detection tool

To validate the identification and characterization of megacusps, only the two available SLD orthomosaics with visible megacusps were considered (Table 2.1). The closest satellite images were used, and the best algorithms in terms of $RMSD$

both from S2 (Table 3.2) and PLN (Table 3.3) data were considered. The CoastSat shorelines were also included in this analysis.

Table 3.2: Shoreline extraction error statistics for the best 3 index–method combinations in each site by using Sentinel-2 imagery along the available reference dates (7 for SLD, 3 for FNG, and 2 for NOD beach). Details are reported in Table 2.1.

Index	Method	<i>MAD</i> (m)	Bias (m)	<i>RMSD</i> (m)	σ_d (m)
SLD (10.12 km—1012 transects)					
NDWI	GMM	3.78	−3.32	4.32	2.48
WI	GMM	4.00	1.33	5.10	4.50
AWEInosh	K-means	4.14	−0.72	5.16	5.01
CoastSat		4.64	3.55	4.57	4.02
FNG (5.82 km—582 transects)					
WI	K-means	3.66	−1.15	4.57	4.01
WI	GMM	4.04	2.96	4.86	3.71
WI	Niblack	4.44	−1.89	6.39	4.95
NOD (4.43 km—443 transects)					
AWEIsh	K-means	4.93	−2.33	6.27	5.81
MNDWI	Otsu	5.04	−0.08	9.73	5.99
SWM	Niblack	5.18	−0.36	9.15	6.03

Table 3.3: Shoreline extraction error statistics for the best three index–method combinations in each site by using PlanetScope imagery along the available reference dates (7 for SLD, 3 for FNG, and 2 for NOD beach). Details are reported in Table 2.1.

Index	Method	MAD (m)	Bias (m)	$RMSE$ (m)	σ_d (m)
SLD (10.12 km—1012 transects)					
NIR	K-means	1.40	−0.19	1.87	1.82
NIR	Otsu	1.43	−0.08	1.89	1.81
NIR	Niblack	4.06	4.04	4.77	2.13
FNG (5.82 km—582 transects)					
NIR	Otsu	1.91	−0.48	2.50	2.39
NIR	Niblack	2.76	2.60	3.17	1.78
NIR	K-means	2.83	1.28	3.24	2.04
NOD (4.43 km—443 transects)					
NDWI	GMM	2.05	−0.47	2.56	2.46
NDWI	K-means	2.28	−1.03	2.66	2.48
NIR	Niblack	3.27	−2.53	8.53	2.68

The megacusp characterization tool (Figure 3.1) consisted of several steps. Before performing the analysis, the coastline was divided into discontinuous segments varying in length between 1.2 km and 1.6 km. There were two with megacusps and three straight for 2017, and three with megacusps and three straight for 2019 (eleven in total). This classification was performed by visual analysis by two experienced users. One of the segments from 2017 was excluded from the analysis because the shoreline exhibited short-wavelength oscillations (10–20 m), corresponding to beach cusps rather than megacusps, which cannot be captured using S2 imagery due to its spatial resolution limitations.

Then, the various shorelines were detrended by fitting a cubic function and subsequently subtracting it from the original signal. Coordinate axes were not previously rotated because the two beaches had a similar orientation, facing south. An initial characterization of potential shoreline oscillations was then carried out in the sections with and without megacusps by computing the sinuosity and standard deviation [Ojeda et al. 2010]. Sinuosity is defined as $s = l_1/l_2$, where l_1 represents the actual measured total length of the shoreline (including the undulations) and l_2 is the length of the straight line between its endpoints. High sinuosity values indicate a shoreline with more pronounced curves. The standard deviation of the shoreline (σ_s) was also evaluated to quantify the variation in or dispersion of shoreline position data from the mean position.

Subsequently, an algorithm to find peaks and valleys was implemented. Various amplitude thresholds (2, 3, 4, and 5 m), to find significant peaks and avoid small oscillations, were tested. Finally, several parameters to characterize the potential megacusps were calculated. The amplitude (a) was defined as half the cross-shore distance between the megacusp horns and the adjacent bays. Mean amplitude ($\bar{a}$) and the standard deviation of the amplitude (σ_a) were considered. The wavelength (λ) was the alongshore distance between successive horns. Mean wavelength ($\bar{\lambda}$) and the standard deviation of the wavelength (σ_λ) were examined.

3.3 Results

3.3.1 Shoreline detection

A total of nine spectral indices derivable from S2 (7) and PLN (2) images (Table 3.1), as well as two automatic thresholding methods and two unsupervised classification methods, were tested, to assess which combination was able to extract more accurate shorelines in each of the three study areas (SLD, FNG, and NOD). The combination of these indices and methods resulted in twenty-eight shorelines extracted from S2 data and eight from PLN data for each of the twelve dates when in situ data or orthomosaics were available (Table 2.1). Results for the S2 data, divided by site, are summarized in Table 3.2, by showing the best three results ordered by *MAD* from the reference shorelines. Bias, *RMSE*, and σ_d are also reported. The result obtained with the benchmark CoastSat tool [Vos et al. 2019] in the SLD coast, with the same S2 images as input, is also shown in this table. The results obtained in the three sites with PLN images are also displayed in Table 3.3. Finally, Figure 3.3 shows examples of the most accurately extracted shoreline from PLN and S2 data for each study site, compared with their respective reference shorelines.

The results for the three sites using S2 data provided very good accuracy in terms of *MAD* and Bias, being less than half a pixel for the best combinations in the SLD and FNG (~ 4 m) and up to ~ 5 m in the NOD. The standard deviation and *RMSE* were also smaller in the SLD and FNG ($\sigma_d \sim 4$ m and *RMSE* = 5 m) than in the NOD ($\sigma_d \sim 6$ m and *RMSE* ~ 6 m). The CoastSat tool yielded results in the SLD comparable with those of the in-house tested combinations. Regarding PLN data, a remarkable subpixel accuracy of about 2 m was also reached in all the used metrics. The level of subpixel accuracy reached was slightly less pronounced for PLN images compared to S2.

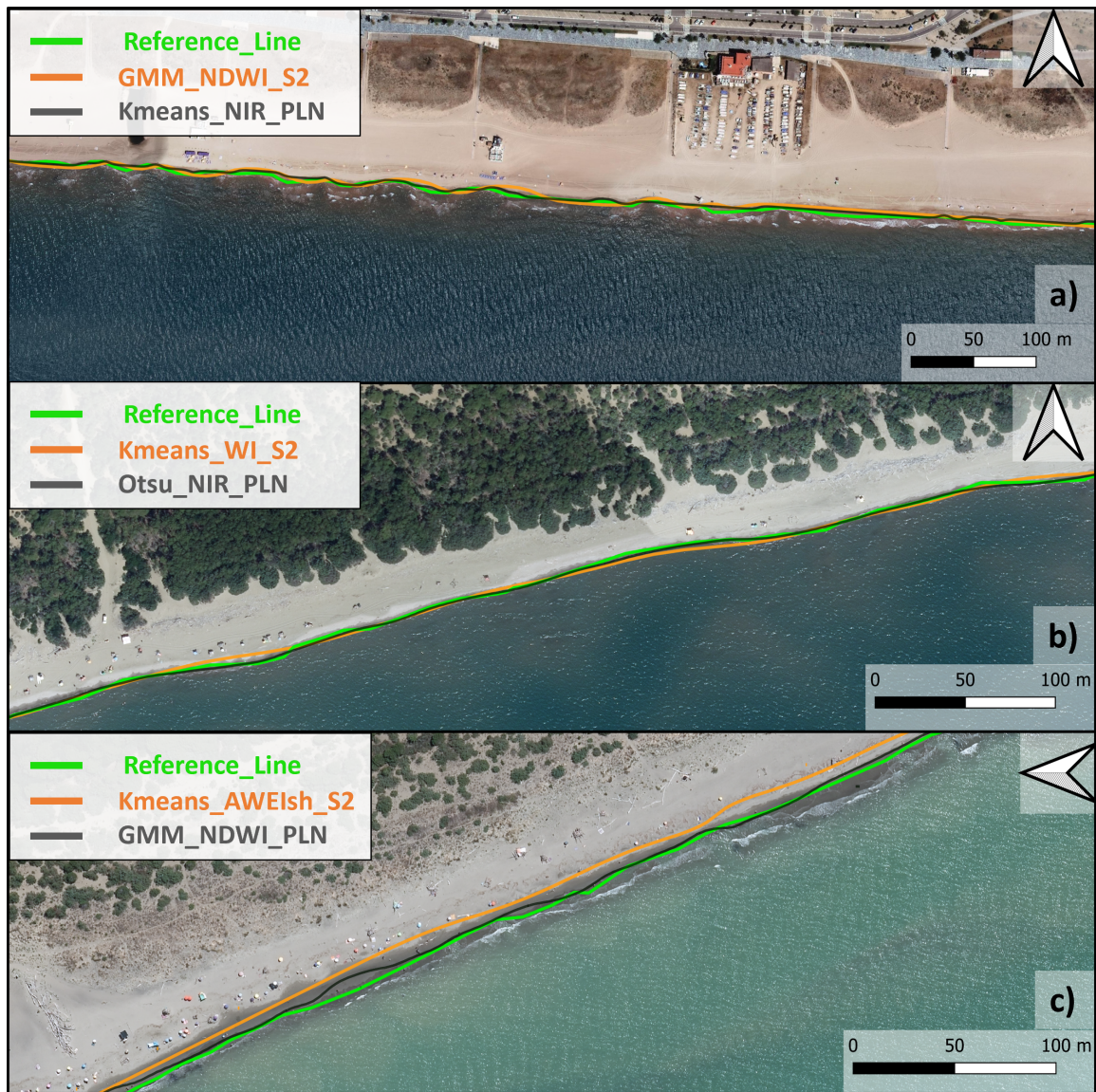


Figure 3.3: Results of the best index–method combination for S2 and PLN compared with the reference, for (a) the SLD coast (23 May 2019) , (b) FNG beach (20 July 2021), and (c) the NOD coast (20 July 2021). In the background, orthomosaics closest to the satellite overpass dates are displayed for each beach.

3.3.2 Megacusps characterization

The feasibility of using the satellite-derived shorelines for identifying megacusps was tested on the two SLD dates with the available orthomosaics showing megacusps (May 2017 and May 2019). The two corresponding manually digitized shorelines derived from them were used as references. Regarding the satellite shorelines, the most accurate result from the shoreline extraction phase (in terms of

MAD and $RMSD$) for both S2 (GMM–NDWI combination in Table 3.2) and PLN (Kmeans-NIR combination in Table 3.3) was considered. The shorelines obtained with the CoastSat tool on these two dates were also tested in this phase.

Table 3.4 displays the shoreline sinuosity, s , and standard deviation, σ_s , obtained in all the shorelines for two segments with megacusps in May 2017 and three in May 2019. Moreover, Table 3.5 shows s and σ_s in the three segments without megacusps for both dates. Sinuosity turned out to be a good indicator of the presence of megacusps in all of the eleven reference shorelines, being $s > 1.010$ in the segments with megacusps and $s < 1.010$ in the segments without megacusps. On the other hand, $\sigma_s > 2.0$ m could also be a way to define megacusp presence in the reference shorelines, but there were two segments in 2017 with megacusps quite close to this threshold and one segment without megacusps (the first in 2017) that exceeded it. Both s and σ_s indicated greater undulations in 2019 compared to 2017, in agreement with the visual observations. The s and σ_s values of the S2– and PLN–derived shorelines with in–house methods were highly coherent with those of the reference case (Tables 3.4 and 3.5) and, therefore, the proposed thresholds could also be applied to define megacusp presence. Contrarily, the shorelines detected with the CoastSat tool in S2 images had values of s and σ_s significantly different from those of the reference shoreline, and the thresholds for megacusp detection did not work. For example, in all segments with megacusps $s < 1.010$ and in two of the six segments without megacusps, $s > 1.010$.

Table 3.4: Results of megacusp validation analysis for May 2017 and May 2019 in SLD coastal segments with megacusps. The sinuosity (s), the standard deviation (σ_s), the megacusp amplitude ($\bar{a}$), and wavelength ($\bar{\lambda}$) for the reference and the S2, PLN, and CoastSat shorelines are shown in the segments with the presence of megacusps.

Data Source	s	σ_s (m)	$\bar{a}$ (m)	$\bar{\lambda}$ (m)
First Segment (1020 m) of May 2017				
Reference	1.016	2.0	5.6	74.7
GMM-NDWI (S2)	1.018	2.9	7.2	80.0
K-means-NIR (PLN)	1.011	1.9	5.5	109.6
Coastsat (S2)	1.004	1.4	4.9	135.2
Second Segment (1217 m) of May 2017				
Reference	1.015	2.1	6.7	90.7
GMM-NDWI (S2)	1.013	2.3	7.8	122.3
K-means-NIR (PLN)	1.017	2.0	6.5	89.3
Coastsat (S2)	1.005	1.2	4.6	244.9
First Segment (1226 m) of May 2019				
Reference	1.022	4.3	9.7	104.9
GMM-NDWI (S2)	1.013	4.6	8.3	131.3
K-means-NIR (PLN)	1.019	3.6	8.4	125.7
Coastsat (S2)	1.004	2.6	6.7	156.4
Second Segment (1115 m) of May 2019				
Reference	1.014	4.3	11.8	140.9
GMM-NDWI (S2)	1.015	4.4	10.6	142.9
K-means-NIR (PLN)	1.015	3.9	11.1	142.9
Coastsat (S2)	1.005	3.1	8.2	172.2
Third Segment (1184 m) of May 2019				
Reference	1.019	6.2	13.4	196.5
GMM-NDWI (S2)	1.022	6.0	13.7	158.1
K-means-NIR (PLN)	1.021	5.8	15.2	190.0
Coastsat (S2)	1.008	5.1	12.9	317.2

The final step was the characterization of the megacusp shape (amplitude and wavelength) using the peak detection algorithm. Several amplitude thresholds were tested, and a value of 3 m was chosen, taking into account that the error of the satellite shorelines was 4 m in S2 and 2 m in PNL images. Results were not

strongly sensitive to this value, with a threshold of 2 m providing similar results. Table 3.4 also displays the obtained megacusp mean amplitudes ($\bar{a}$) and wavelengths ($\bar{\lambda}$). Figure 3.4a shows the first segment of the 2017 orthomosaic with the three extracted shorelines, and the manually digitized one. Figure 3.4b shows the same lines, detrended and with the identified peaks and valleys, with the x -axis zero-aligned to the starting point of the segment under examination. This figure also illustrates that the shorelines detected in both S2 and PLN data were able to capture the oscillations of the coastline, whereas the shoreline extracted with CoastSat tended to smooth the alongshore undulations. A second example (Figure 3.5), in line with the previous representation, shows a segment from May 2019 where the megacusps had a higher amplitude and wavelength than the 2017 one, in agreement with the larger values of s and σ_s . In general, the oscillations of the shoreline varied in amplitude from an average of 7 m in the segments of May 2017 to an average of 11 m for those of May 2019, with a wavelength of approximately 100 m on average in the segments of May 2017 and 150 m for those of May 2019. The results demonstrated good consistency between the megacusp parameters of the in-house-derived satellite shorelines and those from the reference shoreline. As before, CoastSat shorelines showed less similarity with the reference on many more occasions.

Table 3.5: Results of megacusp validation analysis for May 2017 and May 2019 in SLD coastal segments without megacusps. The sinuosity (s) and the standard deviation (σ_s) for the reference and for the S2, PLN, and CoastSat shorelines are shown in the segments without the presence of megacusps.

Data Source	s	σ_s (m)
First Segment (1053 m) of May 2017		
Reference	1.003	2.6
GMM-NDWI (S2)	1.007	2.9
K-means-NIR (PLN)	1.008	2.5
Coastsat (S2)	1.016	3.6
Second Segment (1052 m) of May 2017		
Reference	1.002	1.6
GMM-NDWI (S2)	1.005	2.7
K-means-NIR (PLN)	1.008	2.0
Coastsat (S2)	1.009	3.0
Third Segment (1000 m) of May 2017		
Reference	1.001	1.2
GMM-NDWI (S2)	1.003	1.8
K-means-NIR (PLN)	1.007	1.2
Coastsat (S2)	1.014	1.8
First Segment (1561 m) of May 2019		
Reference	1.002	1.3
GMM-NDWI (S2)	1.005	1.7
K-means-NIR (PLN)	1.006	1.5
Coastsat (S2)	1.004	1.5
Second Segment (940 m) of May 2019		
Reference	1.001	0.8
GMM-NDWI (S2)	1.001	1.9
K-means-NIR (PLN)	1.007	1.2
Coastsat (S2)	1.002	1.3
Third Segment (859 m) of May 2019		
Reference	1.006	1.5
GMM-NDWI (S2)	1.006	1.9
K-means-NIR (PLN)	1.007	1.4
Coastsat (S2)	1.002	1.0

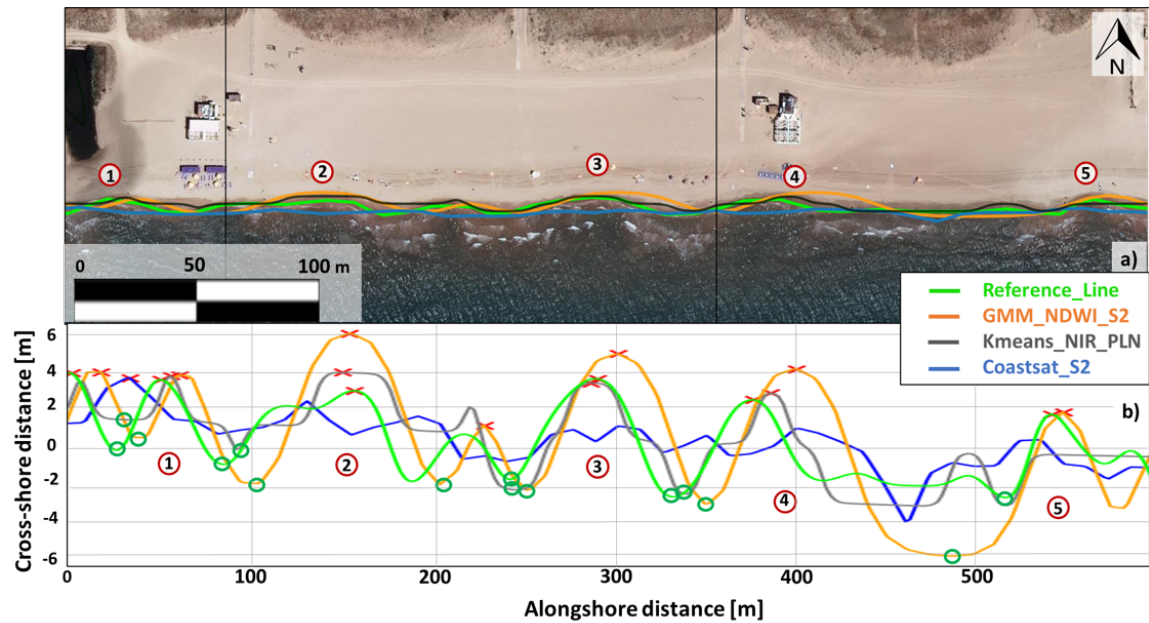


Figure 3.4: First segment of May 2017 used for the validation phase. On top, the four lines correspond to the shorelines of the reference case (green), the best method–index combination in S2 data (GMM–NDWI, orange), the best method–index combination in PLN data (K-means–NIR, grey), and the CoastSat tool (blue). At the bottom, with the same color, the detrended lines show the automatic peaks (red square) and valleys (green dot) for each detected megacusp. The numbers refer to the megacusp embayments that are visible in the orthomosaic. The x -axis is set to zero at the starting point of the segment.

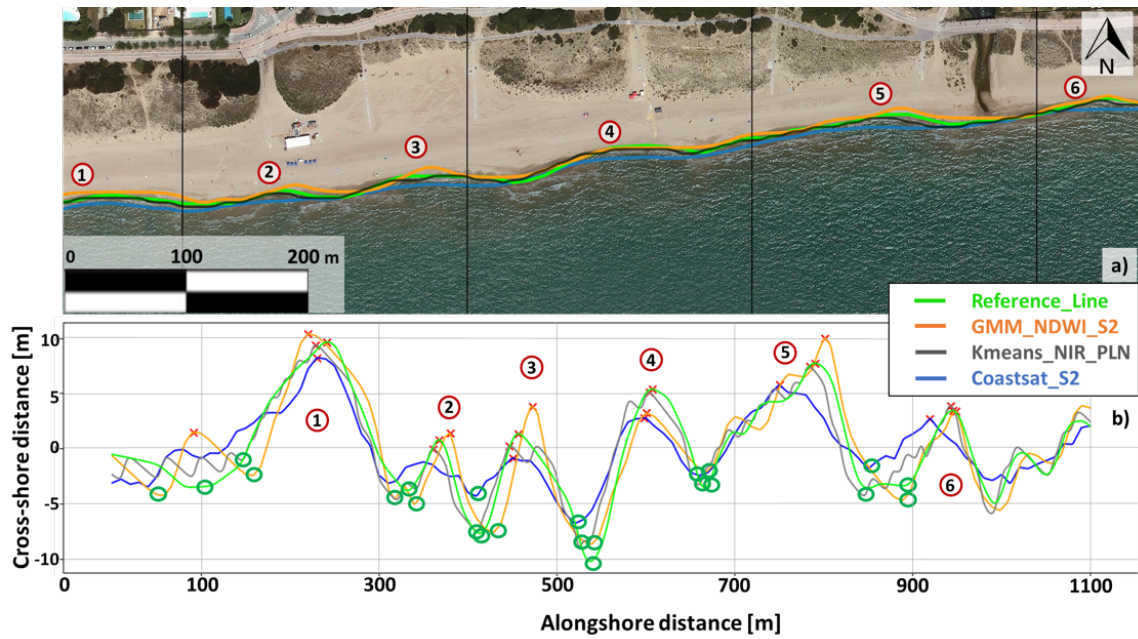


Figure 3.5: Second segment of May 2019 used for the validation phase. On top, the four lines present the shorelines of the reference case (green), the best method–index combination in S2 data (GMM–NDWI, orange), the best method–index combination in PLN data (K–means–NIR, grey), and the CoastSat tool (blue). On the bottom, with the same color, the detrended lines show the automatically detected peaks (red square) and valleys (green dot) for each megacusp. The numbers enumerate the megacusp embayments that are visible in the orthomosaic. The x -axis is set to zero at the starting point of the segment.

3.3.3 Monitoring of Megacusp Development Events

The developed methodology was finally applied to monitor the time evolution of two megacusp events in the SLD in 2023 and in the FNG in 2022. Given the successful identification of megacusps using both satellite sources, S2 data were used for a general view of the events, while PLN data were added to enrich the analysis during the peak periods of these events. The combination of methods used to detect the shorelines was the same as in the megacusp validation phase (Section 3.3.2). The images with clouds were discarded, as well as those with high waves ($H_s > 2$ m) to avoid beach inundation moments that hid megacusps.

The 2023 megacusp event at the SLD coast spanned a significant portion of the beach length. Two contiguous segments were analyzed separately due to their different orientations relative to the north. To characterize the event, a total of twenty S2 images between March and October 2023 and twenty PLN images between May

and June 2023 were used. Figure 3.6 shows key moments in the temporal evolution of the SLD event from March 2023 to October 2023 in the first segment. To numerically characterize the megacusps, all the parameters described in Section 3.3.2 were calculated for each date, as shown in Figure 3.7. The wave conditions (significant height, peak period, and mean direction) over the study period are also shown.

Megacusps of 8–10 m amplitude and 150–200 m wavelength (with $s = 1.0075 - 1.010$ and $\sigma_s = 3-4$ m) were present during the whole study period (Figure 3.7). At the end of May 2023, their amplitude increased up to 15 m (without modifying the wavelength), with $s > 1.010$ and $\sigma_s > 4$ m, after 2 days of 1 m high waves coming from a rather constant SEE direction. The amplitude decreased again in the following weeks, which were characterized by lower wave heights and variable wave directions. At the end of June 2023, a new period of H_s slightly higher than 1 m and constant SEE direction induced a new increase in amplitude up to 15 m, this time with an increase in wavelength up to 400 m (Figure 3.7).

The 2022 FNG beach megacusp event occurred between February and June. For this study, nineteen S2 images and sixteen PLN images from March 2022 were analyzed. Megacusps primarily formed in the central part of FNG beach, so the analysis focused on a 2 km section in this area. Figure 3.8 showcases the highlights of the event, providing a visual representation of the megacusps. The obtained quantitative megacusp characteristics (Figure 3.9) show that small amplitude features were already detectable at the beginning of the study period and remained relatively constant from February to the middle of March ($1.010 < s < 1.020$, $\sigma_s \sim 4-5$ m, $a \sim 10-15$ m, and $\lambda \sim 150-250$ m). At the end of March, the megacusp amplitude increased up to 20 m, with a more regular wavelength of 160–220 m, during a series of minor storms (H_s up to 2 m) from the S. At the beginning of April, a couple of storms with H_s up to 3–4 m coming from the SW had a destructive effect on the megacusps, again diminishing the amplitude to 10 m with the same wavelength. The megacusps maintained these characteristics until the end of the study period, slowly diminishing the amplitude.

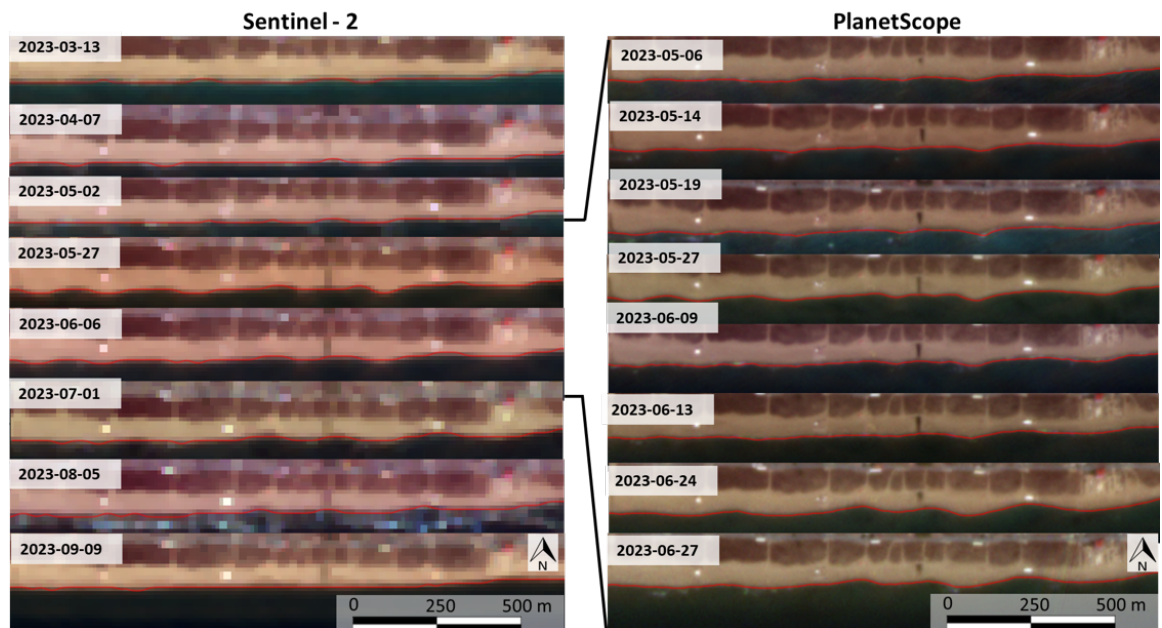


Figure 3.6: Time series of the megacusp event in the SLD coast in 2023. On the left are Sentinel-2 images in the period between March and October 2023. On the right, the time series is enriched by adding PlanetScope images during the peak of the event (May–June 2023).

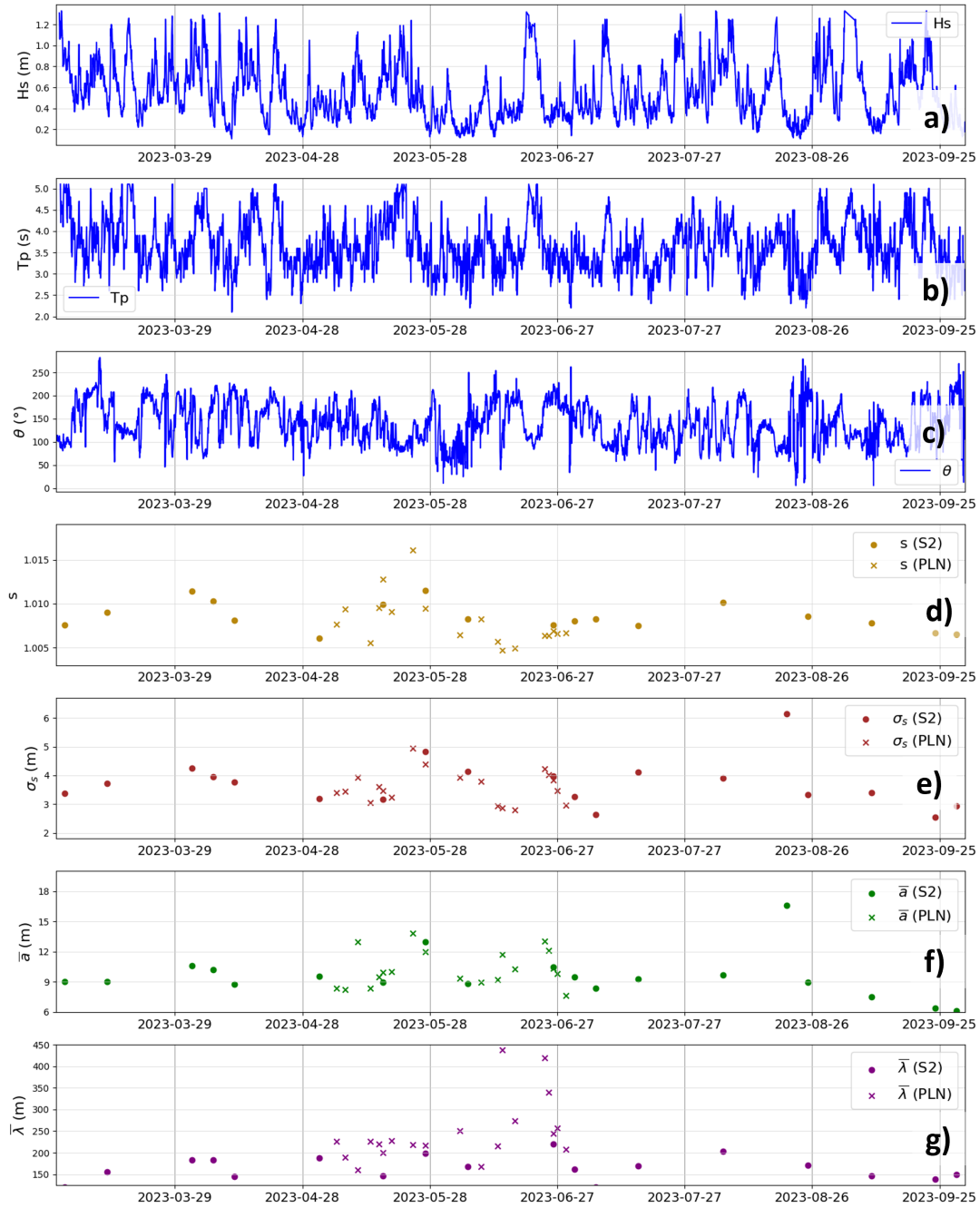


Figure 3.7: Results of the 2023 megacusp event in the SLD coast with the corresponding wave conditions. Time series of (a) significant wave height (H_s), (b) peak wave period (T_p), (c) direction of wave incidence concerning the north (θ), (d) sinuosity (s), (e) shoreline standard deviation (σ_s), (f) mean megacusp amplitude ($\bar{a}$), and (g) mean megacusp wavelength ($\bar{\lambda}$) are shown.

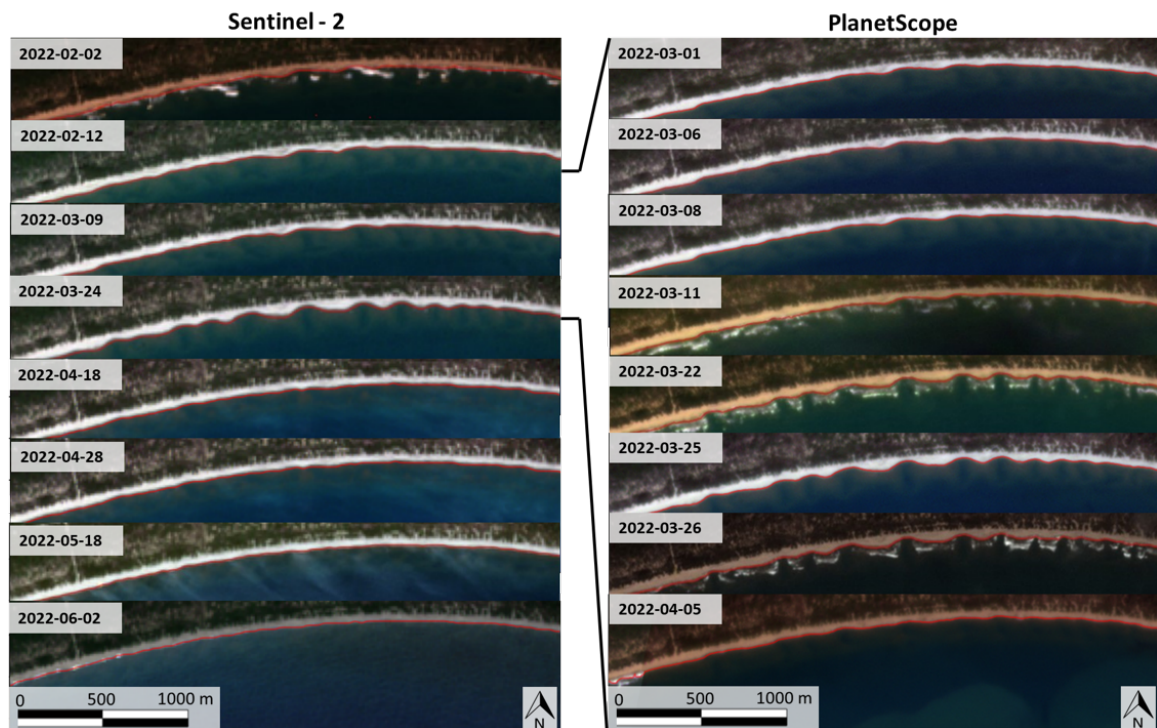


Figure 3.8: Time series of the megacusp event in FNG beach in 2022. On the left are Sentinel-2 images in the period between February and June 2022. On the right, the time series was enriched by adding PlanetScope images at the peak of the event (March 2022).

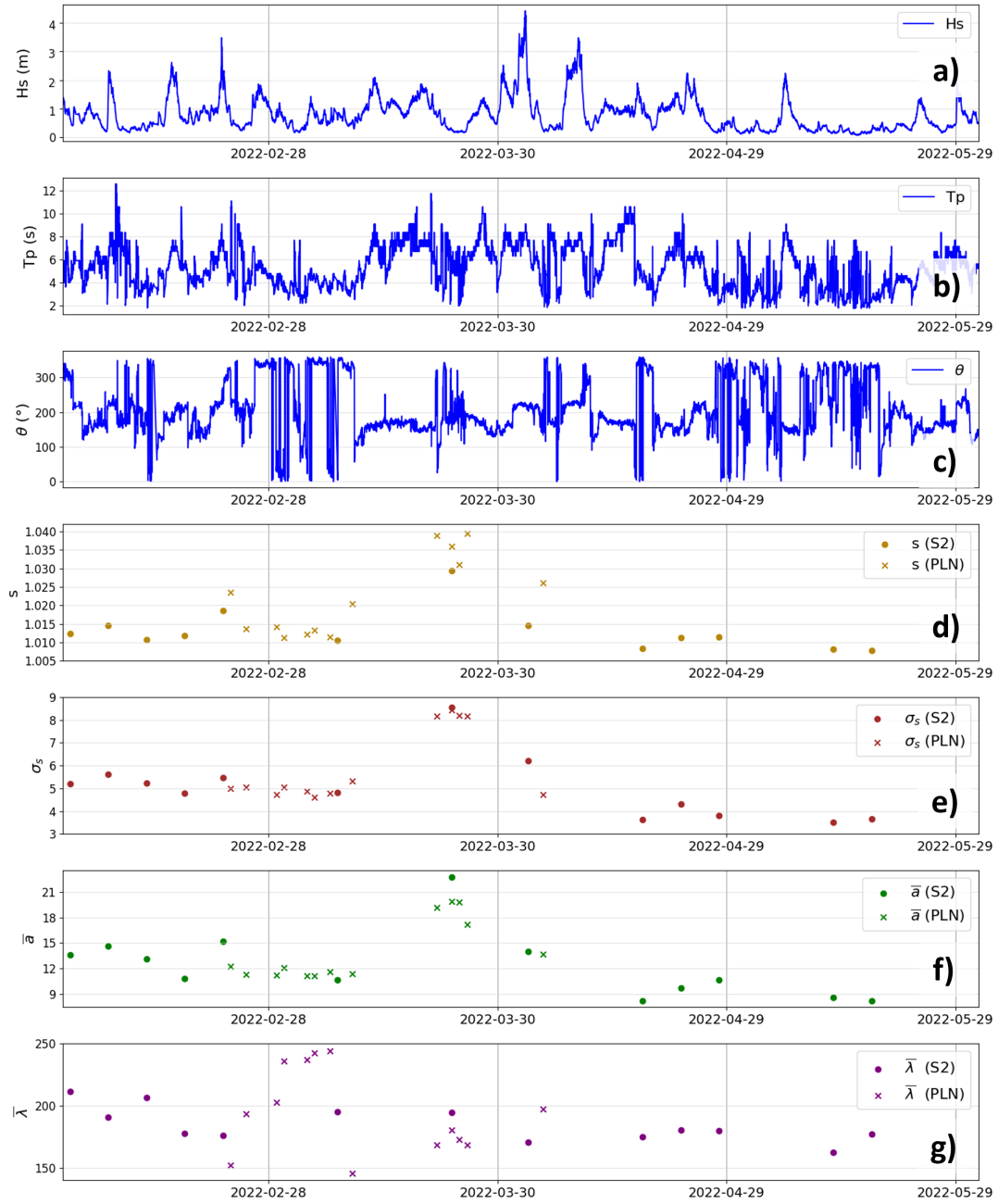


Figure 3.9: Results of the 2022 megacusp event in FNG beach with the corresponding wave conditions. Time series of (a) significant wave height (H_s), (b) peak wave period (T_p), (c) direction of wave incidence to north (θ), (d) sinuosity (s), (e) shore-line standard deviation (σ_s), (f) mean megacusp amplitude ($\bar{a}$), and (g) mean megacusp wavelength ($\bar{\lambda}$) are shown.

3.4 Discussion

3.4.1 Shoreline Detection Tool

In this chapter, various combinations of spectral indices and shoreline extraction algorithms were compared to detect the shoreline in S2 and PLN images, using in situ GNSS RTK measurements and high-resolution orthomosaics as validation data (Table 2.1). To prevent misinterpretations of the results, various metrics were utilized, with an emphasis on *MAD* and *RMSD*, which highlight the error in absolute terms. The best performance in terms of *MAD* when using S2 images (10 m of spatial resolution) was about 4 m at the SLD coast and FNG beach and 5 m at the NOD coast (Table 3.2). For the PLN data (3 m of spatial resolution), the best performance was a *MAD* of about 1.5 m at the SLD coast and of about 2 m at FNG beach and the NOD coast (Table 3.3). These results are consistent with those reported in previous benchmark studies for medium-resolution satellites [Vos et al. 2023b] and in previous PLN results [Darwish and Smith 2021]. The two satellite-derived shorelines exhibited subpixel accuracy, but in PLN, this was slightly less pronounced than in S2 data, in line with Bishop-Taylor et al. (2019).

Previous studies have demonstrated that no single spectral index or methodology performs optimally in all circumstances [Kelly and Gontz 2018, Pucino et al. 2022, Bishop-Taylor et al. 2019]. This was also observed in our results, both for S2 and PLN data. However, certain trends could be identified. The WI index proved to be highly effective in detecting shorelines in SLD and FNG S2 images (Table 3.2). The benefits of using this index were previously identified by Pucino et al. (2022). PLN images in these sites showed maximum accuracy in shoreline detection using the NIR channel directly. The NOD results needed a separate analysis. The stretch of the coast close to the delta suffers from high erosion rates, with the beach almost disappearing and vegetation approaching the water. In such a dynamic scenario, spectral indices that are less sensitive to changes in scene radiance, such as the AWEI [Feyisa et al. 2014, Bishop-Taylor et al. 2019], obtained better results. Finally, the best index for PLN in the NOD was the NDWI.

Regarding the methodology, combinations of index-methods that involve using two unsupervised classification methods, K-means and GMM, generally performed better than combinations that employed thresholding. Unsupervised classification eliminated the need for a training phase, which is required, for example, in the partially supervised classification employed by CoastSat [Vos et al. 2019]. This unsupervised approach also minimizes operator intervention.

3.4.2 Megacusp Monitoring Tool

The initial identification of segments with megacusps in Section 3.3.2 and the identification of the two events analyzed in Section 3.3.3 took place through visual analysis by experienced users, as in previous studies [de Swart et al. 2022a]. The analysis of the results (Tables 3.4 and 3.5) indicated the possibility of automatically identifying the presence of megacusps by using a threshold in the sinuosity parameter of $s = 1.010$. In all the segments of the validation phase, this proposed sinuosity threshold correctly identified segments with and without megacusps. On the other hand, the standard deviation parameter σ_s showed greater variability, and it was impossible to identify a clear threshold, a value of 2 m working well in most but not all the cases. Note also that the obtained values for average wavelength and amplitude were coherent with those measured using a video system by a previous study in the same site but for different years [de Swart et al. 2022a].

Regarding the event-scale analysis of the megacusp evolution presented in Section 3.3.3, the sinuosity parameter performed well in capturing the development of the event in the SLD, but the threshold established during the validation phase seems slightly too selective in comparison with visual analysis. The coastline exhibits undulations even with $s < 1.010$. Conversely, at FNG beach, $s = 1.010$ effectively allowed us to identify the start and end of the event. As for the standard deviation parameter σ_s , the values followed the same trend as s for both sites, but the potential threshold of 2 m established during validation was almost always exceeded during the periods under examination.

This event-scale analysis could represent a significant step forward for coastal planning. The embayments created during the development of large-amplitude megacusps constitute erosive hotspots. Traditionally, the long-term monitoring of megacusp phenomena has been conducted through video monitoring systems [de Swart et al. 2022a], which require operator maintenance and have a limited field of view (approximately 1 km). LiDAR, GNSS, and drone surveys have also been used [Feyssat et al. 2024]; however, the need for repeated measurement campaigns makes them difficult to implement. Only one study [Leuci et al. 2022] observed these phenomena from satellites, but it was based on visual analysis and did not provide a numerical quantification of megacusp characteristics. Therefore, our methodology, by utilizing both medium-spatial-resolution (10 m) and medium-temporal-resolution (5 days) satellites like S2 and high spatial (3 m) and

temporal (about 1 day) resolution satellites like PLN, expands the possibilities for monitoring these phenomena.

Finally, a comparative analysis with the CoastSat tool [Vos et al. 2019] was also conducted in Section 3.3.2. Our results suggest that the CoastSat tool is limited in its ability to detect megacusps across all the analyzed shorelines. This is probably due to its method of applying thresholding to the index values of pixels near the shoreline. Specifically, CoastSat defines shorelines solely based on pixels with index values close to the threshold level. Consequently, this method utilizes only a subset of shoreline pixels for evaluation, incorporating a type of internal “along-shore smoothing”. This approach turned out to limit its capability to detect along-shore oscillations at the spatial scale of megacusps.

3.4.3 Error Sources

The main sources of error affecting shoreline extraction algorithms include georeferencing inaccuracies, the spatial resolution of satellite imagery, and water level variability caused by wave and tidal dynamics. Regarding georeferencing, an accuracy of 11 m has been reported for S2 images until 2021 and an improvement up to 6 m for more recent images [Enache et al. 2022]. Regarding PLN data, the geolocation accuracy varies between 8.5 and 11.7 m up to 2021 [Saunier 2020] and between 3.7 and 7.6 m from then on [Laurentiis 2024]. Without prior information on the direction of this error, its impact on the cross-shore direction and thereby on the total *MAD* and Bias remains unknown, but this could explain the (small) remaining errors in shoreline detection of the present study. In fact, among the tools available for shoreline extraction, only SHOREX provides image coregistration, seeking to enhance the absolute geolocation accuracy by fitting all images to a high-resolution orthomosaic. In a comparison study, Vos et al. (2023b) indeed reported an enhanced accuracy due to SHOREX image coregistration, improving the accuracy of shoreline time series derived from S2.

The resolution of satellite images affects the size of objects recognizable in the scene. Many previous studies using medium-resolution images (10 m) have already demonstrated that it is possible to achieve subpixel resolutions [Almeida et al. 2021, Palomar-Vázquez et al. 2023, Pucino et al. 2022]. The proliferation of high-resolution satellite images (3 m) has not yet allowed for achieving the same level of subpixel accuracy as medium-resolution images [Bishop-Taylor et al. 2019], as occurred in our study. This discrepancy is likely due to the increased contribution of other error sources.

To achieve accurate shoreline detection, even in microtidal environments, it is necessary to integrate satellite-derived shorelines with in situ wave and tide data collected at the time of image acquisition. There is no one-size-fits-all solution, and more research is needed to identify how to optimally apply wave corrections across different coastal environments and beach morphologies [Vos et al. 2023b]. Here, the wave and tide effects were checked ex-post. For both contributions, the differences between the water level values at the time of the satellite images and those at the time of the references (Table 2.1) were first evaluated. Subsequently, the apparent total shoreline distances due to waves and tides were calculated by considering the swash slope in each site (details in Section 2.4.1). The results showed maximum apparent distance values of approximately 2 m in only two cases, the rest being smaller than 1.5 m (Table 3.6). The fact that the sites have small tidal ranges (<0.5 m) and low-energy waves most of the time explains why their effect plays a minor role, being smaller than the average deviations (e.g., *MAD* in Tables 3.2 and 3.3). However, they are among the factors contributing to the errors obtained. Thereby, in Appendix A a quantification of the potential error reduction obtained when correcting for the tide and wave induced movements is presented. The most important outcome is that a small reduction in *MAD* and *Bias* is obtained (but not in all studied dates). Despite the reduction is not significant, it is still useful to incorporate these corrections into the shoreline extraction tools even for Mediterranean tideless beaches since it allows to rule out these effects as potential error sources.

Table 3.6: Planimetric shoreline displacements due to both tidal and wave setup contributions. The apparent total distances are between the S2– and PLN–derived shorelines and the reference ones. The positions of the tide gauges/buoys used for the analyses are reported in Section 2.4.1 for the three coastal areas. The difference in days between PLN and S2 and the reference is shown in Table 2.1.

Reference Shoreline Date	Total Distance (m) S2–Reference	Total Distance (m) PLN–Reference
SLD		
25 May 2017	0.4	1.4
31 May 2017	−1.2	−0.5
20 November 2017	0.5	0.2
18 January 2018	−0.8	−0.2
14 March 2018	−0.2	1.9
23 May 2019	0.4	0.5
09 June 2021	0.1	0.3
FNG		
19 July 2019	−2.2	0.1
20 July 2021	0.6	0.6
05 April 2023	1.5	1.3
NOD		
19 July 2019	0.3	1.5
20 July 2021	1.0	0.2

It is important to note that the megacusp monitoring tool is not significantly affected by the potential sources of error previously discussed for shoreline detection. The georeferencing errors do not affect megacusp characteristics because, at this spatial scale, they only imply a positional shift and not a distortion. The same applies to the effect of tides and waves, which produce changes only in the direction orthogonal to the shoreline, so without any impact on the undulation parameters. Finally, it is noticeable that the increase in the resolution, from 10 m of S2 to 3 m for PLN, does not have a major impact on the accuracy in megacusp characterization.

3.4.4 Strengths and Limitations of the Applied Methodologies

The shoreline extraction methodology developed has provided excellent results, in line with the most recent tools [Vos et al. 2023b, Palomar-Vázquez et al. 2023].

However, it is important to highlight some weaknesses and other areas that have not yet been explored. First, this study considered micro-tidal sandy areas, the scenario where shoreline extraction tools perform best. In mesotidal environments, there can be more difficulties due to the identification of the transition area [Almeida et al. 2021], and the large number of indices offered by our tool could partially solve this problem.

Other issues arose in the analysis of images with wave conditions that created foam. This problem can be solved in the way employed by the CoastSat tool [Vos et al. 2019], i.e., by performing a previous supervised selection. Depending on the objectives and the level of automation desired, it is possible to set a wave height threshold and avoid analyzing specific images. This would be an additional restriction, similar to what already occurs during the preprocessing phase of satellite images when a threshold for cloud cover in the image is applied. However, this would come at the cost of reducing the number of images available for analysis. The CASSIE tool [Almeida et al. 2021] attempts to eliminate the effect of the intertidal zone by performing a multi-threshold Otsu and excluding this area in the final division between land and water. In the present work, an attempt to mitigate the effect of foam is made by exploring the use of unsupervised classification techniques. However, a remaining open issue is applying an automatic methodology to determine the optimal number of clusters into which the image should be divided.

Further improvements could include incorporating tidal correction and wave motion adjustments into the workflow for the extracted shorelines. Several studies [Pucino et al. 2022] have investigated the differences in using offshore buoys or modeling, and others have successfully integrated them into their tools [Vos et al. 2023b]. Similarly, the inclusion of image coregistration, which can be implemented through high-resolution orthomosaics [Sánchez-García et al. 2020], could enhance the accuracy and usability of the results. However, these latter potential corrections do not affect megacusp characterization, so they were not considered necessary in the present study.

Regarding the megacusp tool, the results obtained suggest the difficulty in finding fixed thresholds in the parameters to detect megacusp presence. Different coastal contexts (FNG and SLD) in terms of orientation, wave exposure, and coastal morphology lead to slightly different success rates when applying the threshold values selected during the validation phase. Future developments of this work

should involve attempting to find a more robust indicator of megacusp presence suitable for different scenarios and events.

3.5 Conclusions

In this chapter, a methodology for shoreline detection in Sentinel-2 and PlanetScope satellite images was developed, achieving a good global accuracy compared with reference shorelines, analogous to the current state-of-the-art methods. It was found that a mean absolute error of approximately half a pixel could be consistently achieved in the three tested Mediterranean micro-tidal coasts. This detection accuracy was achievable with both types of satellite images, requiring only minor adjustments in the preprocessing steps. Specifically, mean absolute distances of 4–5 m for S2 and 1.5–2 m for PLN were achieved. The research revealed that the efficacy of index–method combinations changed across the different beach environments and occasionally varied from day to day on the same beach. This fact highlighted the dynamic nature of coastal environments and the requirement for adaptable monitoring techniques.

The shorelines extracted with these methodologies were the starting point for developing a semi-automatic approach for identifying and characterizing megacusps, which are shoreline undulations with wavelengths of a few hundred meters and amplitudes of several meters. This novel approach achieved excellent results in terms of megacusp characterization in the satellite images, compared with those in the reference shorelines. Including the ability to modify the level of smoothing, the shoreline extraction method was found to better catch the alongshore variations as opposed to other tools such as CoastSat, which tends to smooth the alongshore undulations. Notably, the methodology was able to determine megacusp presence (using sinuosity as an indicator) and capture the spatial characteristics of the megacusps (wavelength and amplitude). Their temporal evolution, at scales ranging from days to weeks, was also captured, enabling the possibility of establishing correlations with wave forcing and enhancing the understanding of megacusp dynamics. To achieve this level of temporal resolution, the integration of S2 images with PLN images proved essential.

The use of satellite imagery in the monitoring of megacusps demonstrated the potential for characterizing large geographical areas, presenting an advantage over traditional video monitoring systems (which otherwise remain fundamental in ensuring a higher temporal resolution and avoiding the issue of cloudiness during storms). These outcomes emphasized the importance of using shoreline extraction tools capable of monitoring not just long-term erosion but also rapid changes

in beach width, such as those induced by megacusps. This capability is deemed critical for the advancement of beach management strategies.

Chapter 4

SAR-Based shoreline extraction

4.1 Introduction

Among satellite-based techniques, MSI has been extensively employed for shore-line detection, leveraging the broad range of spatial resolutions and the inherent spectral contrast between land and water in the visible and near-infrared regions. The tool developed in Chapter 3 and refined in Appendix A falls within this context by integrating medium-resolution S2 constellation and high-resolution PLN images. In contrast, Synthetic Aperture Radar (SAR) imagery has emerged as a powerful alternative for environmental applications, overcoming several limitations inherent to optical sensors. SAR systems operate in the microwave spectrum, actively transmitting signals and recording the energy backscattered by the Earth's surface (see the details in Section 1.2.2). This allows for observations that are independent of weather conditions and solar illumination. Due to its sensitivity to surface roughness, dielectric properties, and target geometry, SAR imagery is particularly suited to delineating the land-water interface.

However, despite the many advancements in SAR-based shoreline extraction, the extent to which the backscatter signal from the sea surface differs from that of the adjacent land remains only partially understood [Kim et al. 2007, Mann et al. 2024]. This contrast is essential for accurate shoreline delineation and is affected by several parameters, including polarization mode, terrain morphology, and sea surface state. Polarization affects the strength and clarity of the backscatter signal, while features such as dunes or cliffs can generate shadows or specular reflections. Meteorological conditions, including wind and waves, may induce undulating patterns on the sea surface, affecting the backscatter and thereby reducing the contrast between land and water. Moreover, SAR imagery is inherently affected by speckle phenomenon, which imparts a granular appearance and complicates image interpretation when compared to optical data (see more details in Section 1.2.5). Although shoreline detection from SAR imagery can achieve an accuracy between 10 and 15 m [Wu et al. 2024], such precision remains insufficient for monitoring subtle shoreline changes in many coastal settings.

In this chapter, the objective is to develop and validate a robust methodology for automatic shoreline detection using SAR data from S1 and TSX satellites, acquired over four microtidal Mediterranean sandy and gravel beaches (details on the dataset and study sites are in Chapter 2). Another key aim of this chapter is to enhance the precision of SAR-derived shorelines by investigating the factors limiting shoreline extraction methodologies. SAR images are processed using a

multi-step workflow that includes preprocessing, noise reduction, land-sea segmentation by clustering or thresholding methods, shoreline extraction, and outlier detection techniques. The accuracy of the SAR-derived shorelines is evaluated against reference ones obtained from high-resolution aerial orthomosaics or PLN imagery (Section 4.2). The results of the S1 and TSX analyses are presented in Section 4.3. The focus of the discussion is placed on analysing key variables that influence the contrast in SAR backscatter responses between land and sea pixels (Section 4.4) and can limit or enhance shoreline detection accuracy. Finally, Section 4.5 summarizes the main implications of the chapter.

4.2 Methodology

The proposed methodology is structured according to the workflow shown in Figure 4.2. This workflow is based on the processing of satellite images acquired either from S1 (in both ASC and DESC mode) or from TSX, through a series of steps including preprocessing (4.2.1), followed by the selection of one image band, one denoising method (4.2.2), one classification method among those considered (4.2.3), and finishing with the selection of one of the outlier detection techniques investigated (4.2.4). In Figure 4.2, parallel boxes represent alternative options. Each step of the workflow is described in detail in the following subsections.

4.2.1 Preprocessing SAR images

The preprocessing of SAR images was performed using the Sentinel Application Platform (SNAP) version 8.0 [Veci et al. 2014], distributed by ESA, and applied to datasets from both S1 and TSX satellite data (workflow shown in Figure 4.2). A fundamental difference between these datasets lies in their available polarimetric channels, with TSX data relying solely on HH polarization, while S1 imagery includes both VV and VH polarizations. The S1 VV polarization has been used together with the SAR Water Index (SARWI), an index proposed by Tian et al. (2017), that combines VV, $VH \times VV$, VV^2 , and VH^2 in a weighted-linear relationship.

The first step of the process was the implementation of precise orbit files to refine the satellite's position and improve geolocation accuracy. Following this, thermal noise removal was applied to mitigate the additive background energy characteristic of radar systems, particularly in the cross-polarization channels, thereby enhancing the quality of the backscatter signal. Subsequently, radiometric calibration was used, transforming raw pixel values into normalized backscatter coefficients, a step essential for ensuring comparability across multiple acquisitions and enabling quantitative interpretation. To address the speckle noise inherent to SAR imagery, a Lee filter [Lee et al. 2009] was employed with the lowest possible filtering intensity to preserve the spatial resolution and the sharpness of image features. Terrain correction was then performed using the Range-Doppler terrain correction algorithm, incorporating a digital elevation model (DEM) to correct geometric distortion such as foreshortening and layover, although these effects are not expected with the almost planar topography of the observed areas. After these preprocessing steps, the obtained images were square grids of 10 m and 3 m spatial resolution

in the S1 and TerraSAR cases, respectively. All data were projected into the Universal Transverse Mercator (UTM) coordinate system specific to each area of interest. A geographic subset was extracted to focus the analysis on the coastal regions, optimizing computational efficiency while retaining all relevant spatial information for the subsequent steps of shoreline extraction. Finally, the decibel (DB) scale was used for radar indices.

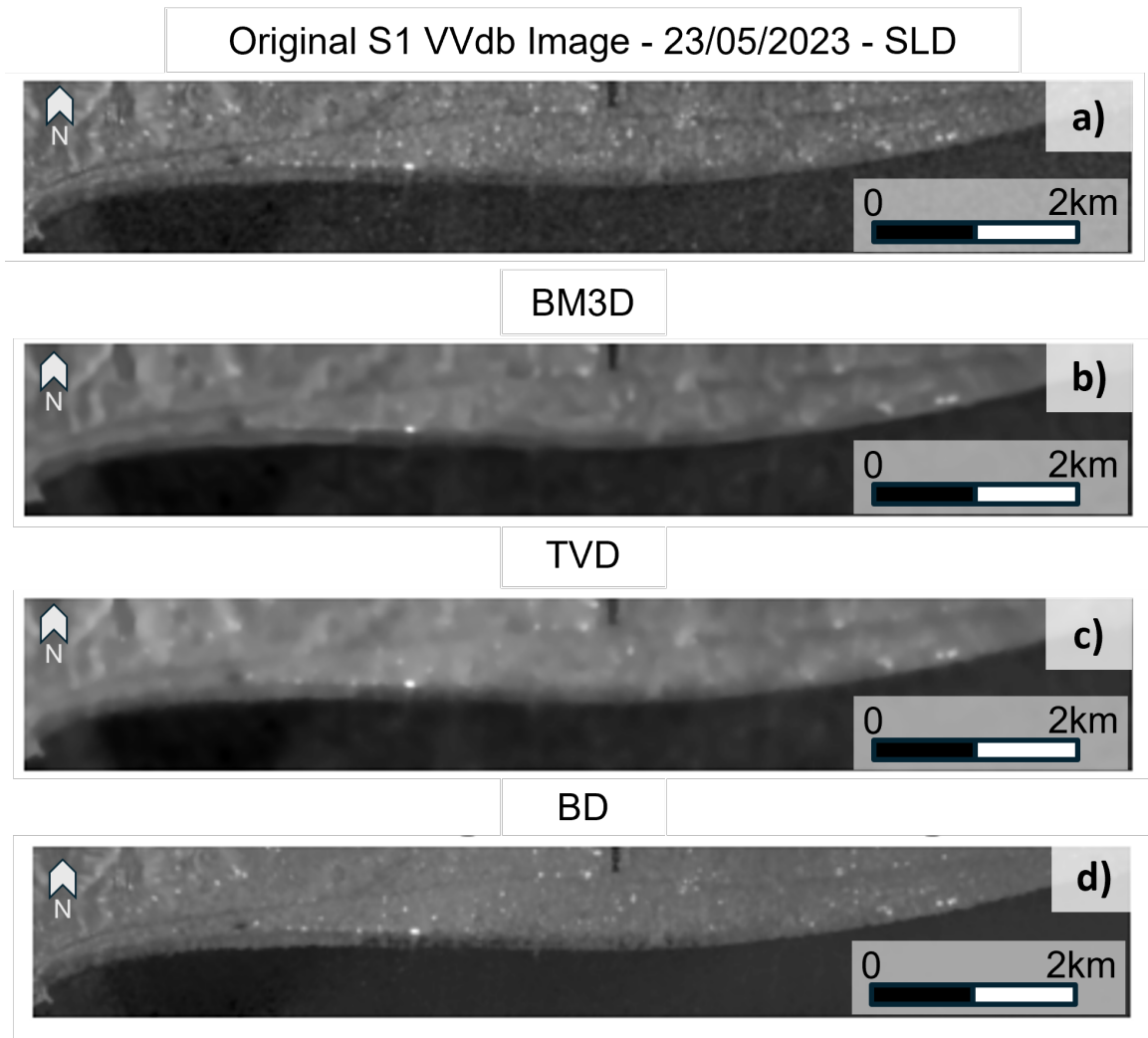


Figure 4.1: Application of different denoising techniques on the original VVdb image along SLD coast(a): BM3D (b), TVD (c), and BD (d).

4.2.2 Denoising techniques

In this chapter, advanced denoising methodologies were applied to radar images (4.2). Three methods were considered: Matching and 3D Filtering (BM3D, Fig-

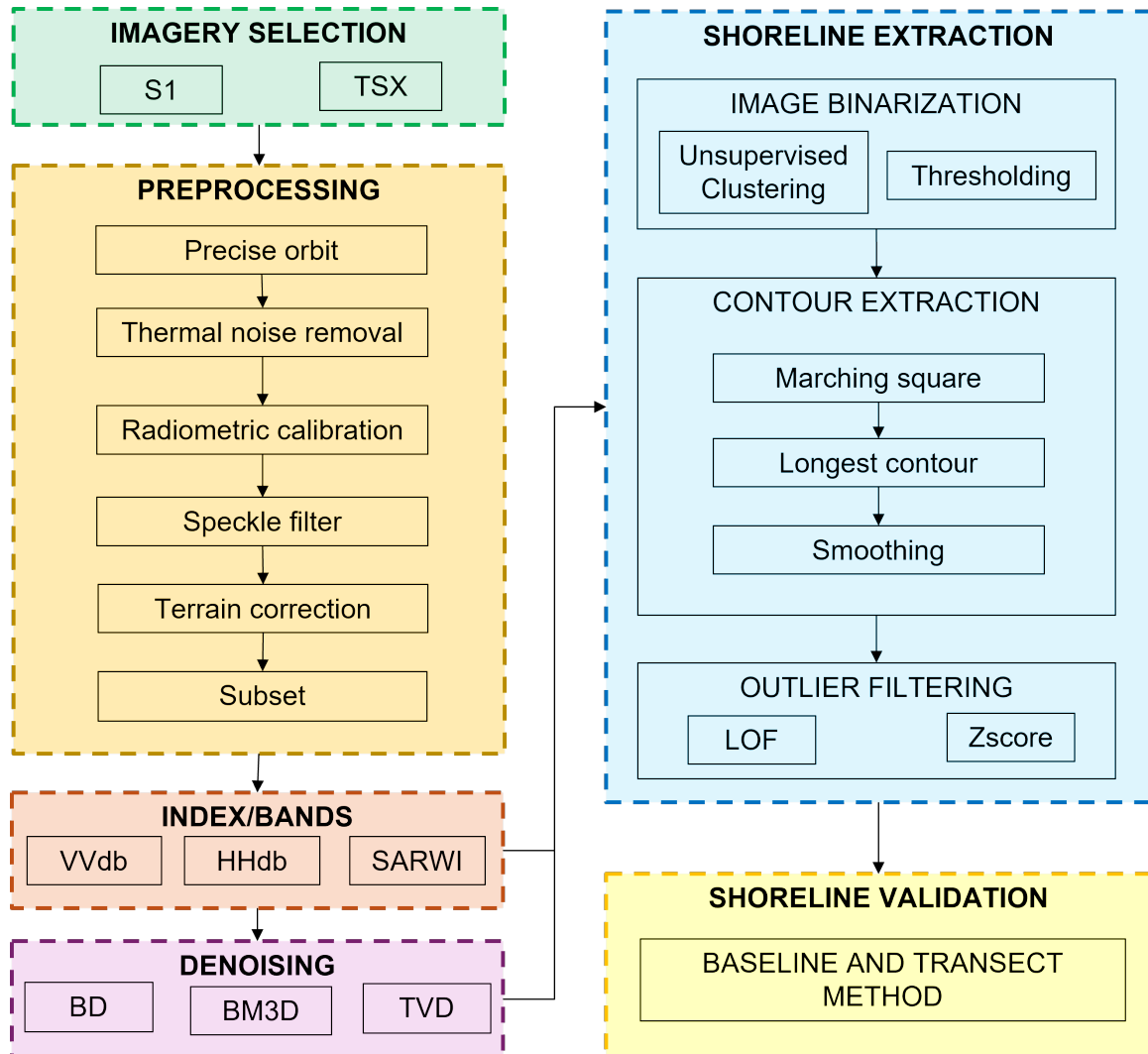


Figure 4.2: Workflow of the SAR shoreline extraction tool. Parallel boxes indicate alternative options.

ure 4.1b), Total Variation Denoising (TVD, Figure 4.1c), and Bilateral Denoising (BD, Figure 4.1d). BM3D operates by grouping similar image blocks into three-dimensional arrays and applying collaborative filtering in the transform domain. This method excels at denoising by leveraging non-local self-similarity [Dabov et al. 2007]. TVD is based on the principle of minimizing the total variation of an image, promoting sparsity in the gradient domain. By penalizing large variations in pixel intensity, this method effectively reduces noise while preserving edges and fine details [Rudin et al. 1992]. BD is a non-linear filtering approach that combines spatial proximity and pixel intensity similarity to smooth images while preserving edges. This dual criterion allows BD to suppress high-frequency noise without compromising the integrity of sharp transitions between regions [Tomasi

and Manduchi 1998].

These techniques were systematically applied and compared with the outcome of raw SAR imagery to assess their effectiveness in reducing noise, enhancing image interpretability, and improving shoreline detection. The analysis focused on whether the application of these methods could produce a balance between noise reduction and preservation of essential image features, such as the shoreline.

4.2.3 Shoreline detection algorithm

The methodology for shoreline detection from preprocessed and denoised images (Figure 4.2) was developed as a Python tool, adapting the one developed in Chapter 3. The procedure started with two raster sources, the preprocessed bands and indices (VVdb and SARWI for S1 and HHdb for TSX). To separate pixels into land and sea classes, three alternative methods were used: one based on automatic threshold definition and the other two on unsupervised machine learning. These methods were applied independently to the images processed by the three denoising techniques, as well as to the original images, resulting in 24 combinations for S1 and 12 combinations for TSX.

The thresholding method applied in this study was the multi-threshold Otsu algorithm [Liao et al. 2001], an extension of the classic Otsu method.

Two unsupervised clustering methods, K-means [Hartigan and Wong 1979] or GMM [Zhuang et al. 1996] were employed.

The classification methods were tested by defining a region of interest around the coastline to exclude non-relevant parts of the image, such as the anthropic settlements behind the beach. Classification was performed using either two or three classes. When three classes were used, the classified image was semi-automatically reduced to a binarized form. For sandy beaches, the three classes are assumed to represent the water, the dry sand, and the dune/vegetation. Following this rationale, the two classes with the highest average pixel values were merged into one. On the contrary, for gravel beaches, the three clusters are assumed as water, an area of backscattering transition into the sea, and a dry beach. To support this choice, the two classes with the lower average pixel values were merged into one.

The shoreline extraction process from the binarized image was carried out in three different steps. Initially, contours were identified by analyzing the raster data with a Marching Square algorithm, which applied a threshold of 0.5 to ensure that the extracted line passed centrally through the boundary pixels. Among the generated contours, the one with the longest length was selected to represent the

shoreline, as this typically corresponded to the main land-water interface. To enhance the accuracy and smoothness of the resulting line, a Laplacian smoothing algorithm was then employed. This smoothing process relied on two parameters: a smoothing factor of 0.2, which influenced how each point was adjusted based on its neighboring points, and the number of iterations (set to 10), which were used to progressively refine the line shape. The implementation of this smoothing methodology was maintained to ensure consistency with the approach previously developed for MSI in Chapter 3. However, we previously confirmed that the parameters selected for this first smoothing algorithm did not produce any strong effects capable of altering the subsequent outlier detection phase.

4.2.4 Outlier detection and validation process

The nature of radar data entails the presence of Gaussian noise. Despite partially reducing it during the preprocessing and denoising stages, detected shorelines can show errors, sometimes in the form of outliers. To further refine the analysis, two outlier detection filters were tested on the extracted shorelines. The LOF [Breunig et al. 2000] algorithm evaluates the local density of each data point relative to its neighbors, identifying points as outliers when their density is significantly lower than that of the surrounding data. The Z-score approach [Zar 1999] computes the standard deviation of individual data points from the mean of the dataset, flagging those that exceed a predetermined threshold as outliers.

The specific algorithm employed for outlier detection started with the definition of a mean shoreline, a strongly smoothed version of the detected shoreline. It was retrieved from interpolated points along each shoreline at an interval of 10 m, accordingly with the grid spacing of the images, by applying a moving-window smoothing technique with a window size of 750 m. The window size was selected based on the coastal characteristics of the study sites, as it effectively filters out alongshore shoreline undulations while preserving overall beach curvature. Central finite differences were subsequently used to calculate tangent vectors between the points on the interpolated line. From these, a set of perpendicular transects was generated based on the identified direction. The distance along these directions between the mean line and the extracted shoreline points was used to define LOF and z-score. For the LOF-based outlier detection, we used a number of nearest neighbors equal to 20 and a threshold of 1.5. The first parameter specifies that, for each data point, the local density is estimated by considering its 20 nearest neighbors, and a threshold equal to 1.5 indicates that any data point with an LOF

score greater than 1.5 is considered an outlier. These values were chosen to achieve a balance between sensitivity to outliers and robustness to false positives. On the other hand, for the Z-score-based method, a threshold of Z-score equal to 3 was employed, meaning that any observation with a value exceeding 3 standard deviations from the local mean is flagged as an anomaly to exclude only the most extreme anomalies relative to the local shoreline trend.

Validation of the different cases examined, namely the various combinations of indices and methods for shoreline extraction, was performed using the baseline and transect method. For this purpose, a baseline was established along and behind the beaches, and perpendicular lines (transects) were drawn at 10 m intervals relative to the baseline. Each transect intersected both the reference shoreline and the automatically extracted shorelines, thus determining the signs used in subsequent calculations. By convention, a negative (positive) sign was assigned when the extracted shoreline laid landward (seaward) of the reference shoreline. Lastly, several statistical indicators of the distance between the two shorelines were computed to assess accuracy and robustness: the Mean Absolute Deviation (*MAD*) and the Bias (or Mean, μ_d):

$$MAD = \frac{1}{N} \sum_{i=1}^N |d_i| \quad (4.1)$$

$$\mu_d = \frac{1}{N} \sum_{i=1}^N d_i \quad (4.2)$$

where N is the total number of observations and d_i is the distance for the i -th transect.

4.3 Results

4.3.1 Main results for Sentinel-1 images

A total of two indices, VVdb and SARWI, with three denoising methods (BM3D, TVD, and BD) and the original data (RAW), were tested separately using 2 unsupervised clustering methods (K-means and GMM) and one thresholding method (Otsu), on 20 S1 images (Table 2.1). One automatic thresholding method and two unsupervised classification methods were also employed. The combination of these indices, denoising, and clustering methods resulted in 20 shorelines extracted from S1 data for each of the 10 reference images. The obtained results, separated by site, are summarized in Figure 4.3 in terms of MAD and in Figure 4.4 in terms of bias. These MAD and bias correspond to all the transects of all the images of each site, so they allow assessing which combination of methods was able to extract more accurate shorelines in each of the four study areas (SLD, FNG, MRJ, and RDC).

The average results for each site showed a strong regularity in gravel beaches: both MRJ and RDC display the majority of the method combinations below the S1 pixel size threshold in terms of MAD (the light yellow area in Figure 4.3 and 4.4). In particular, the BM3D denoising method proves to be highly effective, pushing accuracy to around 6 m. The bias (Figure 4.4) showed, on average, positive values (seaward) or values close to zero in the gravel beaches. It is worth noting that, in general, the RAW data exhibits higher bias values.

For sandy beaches, however, results were different in the two sites. In FNG, a very good accuracy was obtained, with best MAD values slightly below 5 m (i.e., half of S1 pixel, Figure 4.3). At SLD, on the other hand, the shoreline extraction process was more challenging, and the results showed higher variability in terms of MAD and Bias, which will be discussed in Section 4.4.2. Note that the coastal extension was larger in SLD (10 km), and there were more dates tested, some of them with challenging weather conditions. Nevertheless, with the VVdb index, the TVD denoising methodology, and the GMM classification method, it was possible to achieve an accuracy of slightly less than 1 px (10 m) in terms of MAD (Figure 4.3). It is important to note here that the original images collected by S1 have a resolution of ~ 20 m, making the results obtained even better. In both sandy beaches, the bias generally showed negative values (landward), especially in SLD (Figure 4.4).

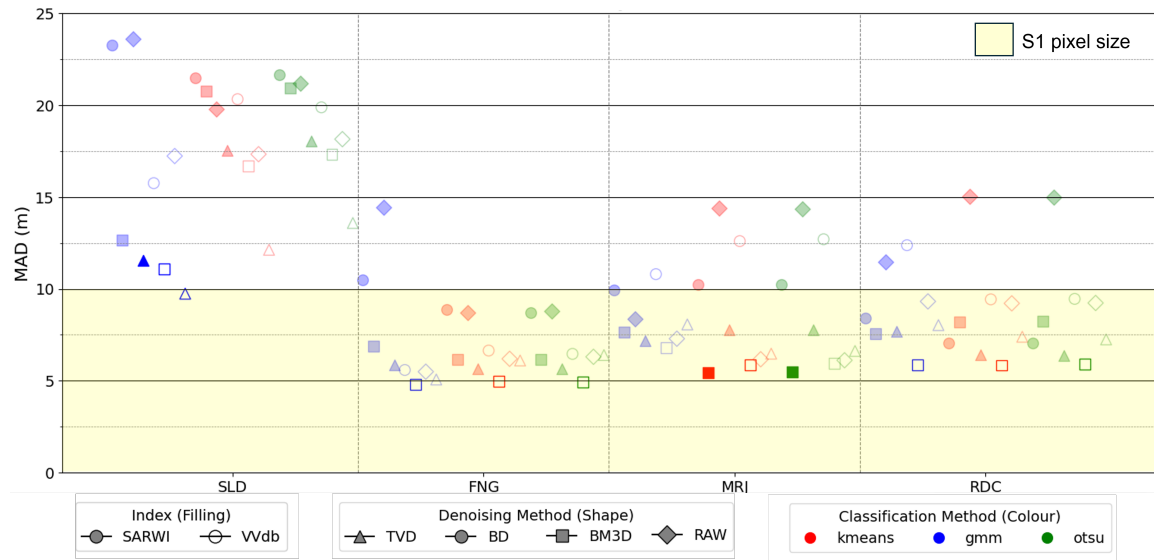


Figure 4.3: MAD obtained for the 24 combinations of index, denoising technique, and classification method at each site (averaged across all dates) for the S1 platform. The three best-performing combinations in terms of MAD are highlighted. The yellow shaded area indicates the pixel size of S1 (10 m). For illustrative purposes, the configuration combining the VVdb index (empty filling), TVD denoising (triangle shape), and GMM classification method (blue color) is shown as the best-performing setup in terms of MAD value at the SLD site.

4.3.2 Main results for TerraSAR-X images

Only two TSX images for SLD beach were available (bold dates in Table 2.1). For TSX, the combinations of HHdb polarization with three denoising methods (BM3D, TVD, and BD) and the original data (RAW) were tested on these two images. Since the three automatic classification methods were also tested, 12 shorelines were detected in each image. The results for the TSX data are summarized in Figure 4.5 in terms of MAD and in Figure 4.6 in terms of bias.

The results on the two dates showed significant differences in accuracy. The 2017 data obtained a best MAD value of approximately 7.5 m, likely due to the associated meteorological conditions (details in Section 4.4.2). In contrast, the 2018 data achieved very high accuracy levels, with the smaller MAD values being of 2.5 m, roughly corresponding to the TSX pixel size (3 m) (Figure 4.5 a). On that specific date, with S1 data, an accuracy of 6.5 m was achieved. An example of the two SAR images and the corresponding derived shorelines for the 2018 date is shown in Figure 4.7. A test was also conducted on the same two TSX images but resampling them to the S1 pixel size (10 m) (Figure 4.5 b). The best results obtained

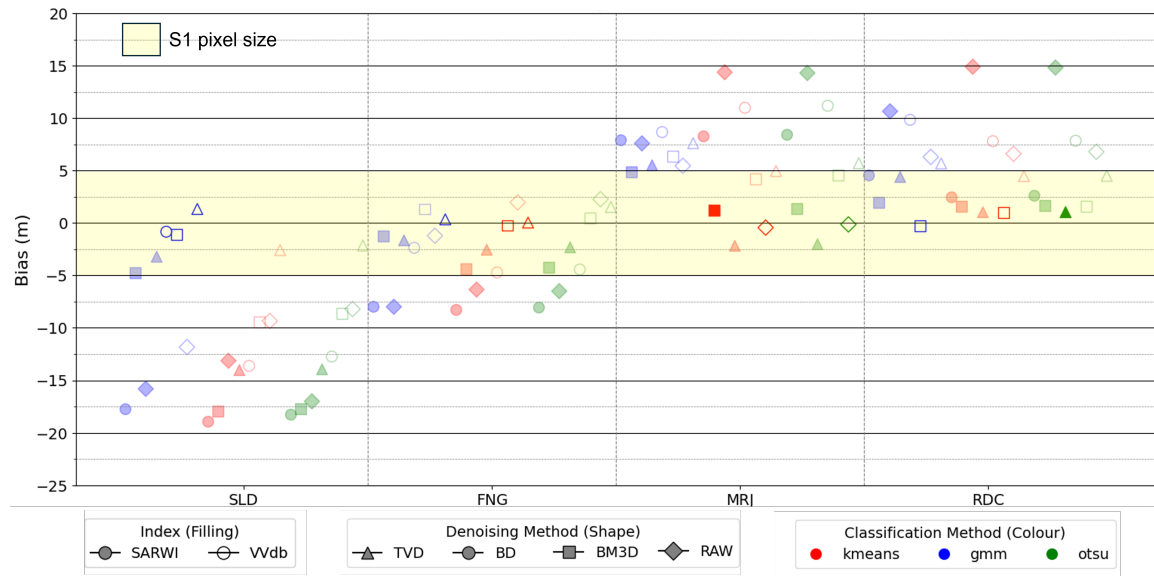


Figure 4.4: Bias obtained for the 24 combinations of index, denoising technique, and classification method at each site (averaged across all dates) for the S1 platform. The three best-performing combinations in terms of bias are highlighted. The yellow shaded area indicates the pixel size of S1 (10 m). For illustrative purposes, the configuration combining the VVdb index (empty filling), TVD denoising (triangle shape), and K-means classification method (red color) is shown as the one achieving the bias value closest to zero at the FNG site.

after resampling were comparable to those using the original resolution TSX images, reaching an accuracy of 2.5 m in terms of MAD, but some combinations gave significantly larger errors.

4.3.3 Sensitivity of shoreline extraction to several methodological aspects

Among the implemented classification and thresholding methods, no significant sensitivity was observed under favorable weather conditions (cases of FNG, MRJ, and RDC). In contrast, in more variable situations, such as those observed on SLD beach, GMM and (to a lesser extent) K-means clustering methods outperformed Otsu (smaller MAD in Figures 4.3 and 4.5).

Denoising techniques have shown to always improve the performance compared to the use of raw data (Figures 4.3 and 4.5), especially on dates characterized by unfavorable weather and sea conditions in SLD (more details in 4.4.2). In particular, in three out of the four examined sites, combinations that incorporate BM3D denoising techniques demonstrated superior performance compared to the

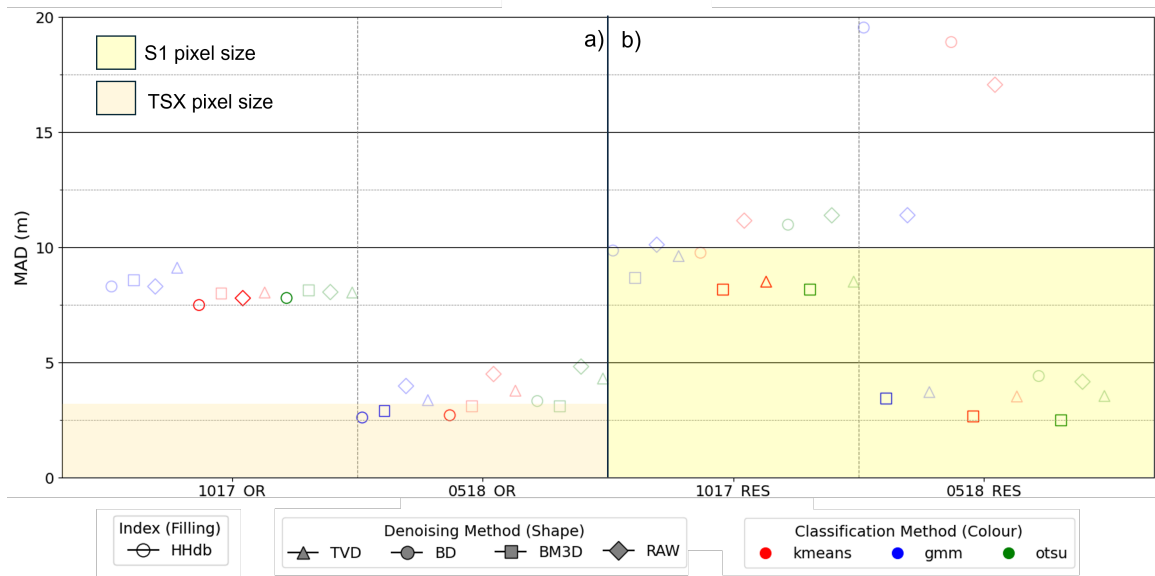


Figure 4.5: MAD obtained for the 12 combinations of index, denoising technique, and classification method in the SLD site for each of the two dates for the TSX platform. The three best combinations in terms of MAD are highlighted. Panel a) shows the results obtained along the two dates with the original pixel size (OR) (3 m) represented by the orange-shaded area. Panel b) shows the results obtained along the two dates with resampled TSX data to S1 data pixel size (RES)(10 m). For illustrative purposes: The configuration combining index HHdb (empty filling), BD denoising (circle shape), and K-means classification method (red colour) is shown as the best-performing setup in terms of MAD value on 1017 OR.

other denoising methods. In SLD, results were more variable, and any of the three denoising techniques could give the best result. The implemented denoising techniques play an important role in enhancing the ability to distinguish the boundary between the backscatter values of water and sand.

Regarding the application of outlier detection methods, both tested approaches identified a small percentage of outliers on the SLD coast. On the other hand, in the other coastal stretch, due to the regularity of the extracted lines, the percentage of outliers detected results in zero. On average, the Local Outlier Factor (LOF) detected 1% of outliers, and the z-score method gave 2% of outliers. Excluding these outliers led to a modest increase in accuracy, with MAD improving by approximately 0.4 m on the 2017 TSX date and 0.5 m on the 2018 TSX date (5 % and 15 % improvement, respectively). For the S1 analysis, the mean improvement was 0.4 m, corresponding to 4 %. This means that on many occasions, the errors on the detected shoreline were not in the form of outliers.

The use of two versus three classes in image classification was also tested in the

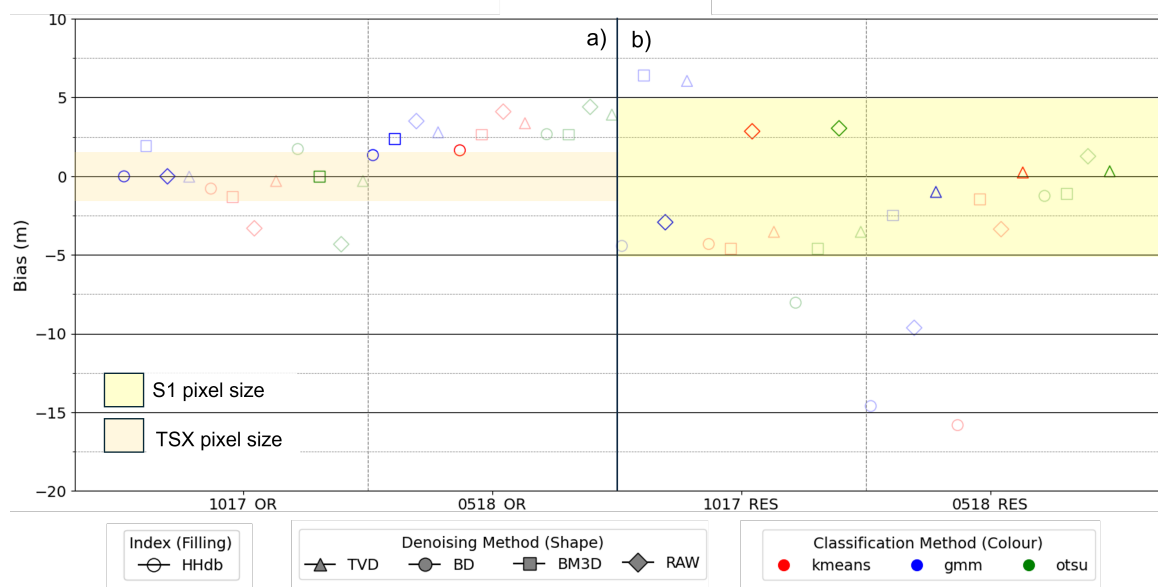


Figure 4.6: Bias obtained for the 12 combinations of index, denoising technique, and classification method in the SLD site for each of the two dates for the TSX platform. The three best combinations in terms of Bias are highlighted. Panel a) shows the results obtained along the two dates with the original pixel size (OR) (3 m) represented by the orange-shaded area. Panel b) shows the results obtained along the two dates with resampled TSX data to S1 data pixel size (RES) (10 m). For illustrative purposes: The configuration combining index HHdb (empty filling), BD denoising (circle shape), and GMM classification method (blue color) is shown as the one achieving the bias value closest to zero on 1017 OR.

four beaches. Employing three classes instead of two proved advantageous across all examined cases studied (results with two classes are not shown). The third class in the sandy beaches allowed for better identification of the dry beach by reducing the negative bias when merging the two classes with the higher average backscatter. For gravel beaches in contrast, merging the two classes with the lowest backscatter reduced the positive bias. MAD experienced a more marked reduction in gravel beaches, approximately 5 m (50 % improvement), and around 5 m in the more variable context of SLD (33 % improvement). In FNG, where the results were already very satisfactory with two classes, the reduction was about 1.5 m (23 % improvement). This analysis was also conducted for the two available dates of TSX. On the 2017 date, which presented the worst conditions, the improvement was approximately 1 m (12 % improvement). Conversely, on the 2018 date, the improvement was about 0.5 m (16 % improvement). Similar trends were recorded for both the original and resampled data.

Finally, the applied methodology did not account for a shoreline correction re-

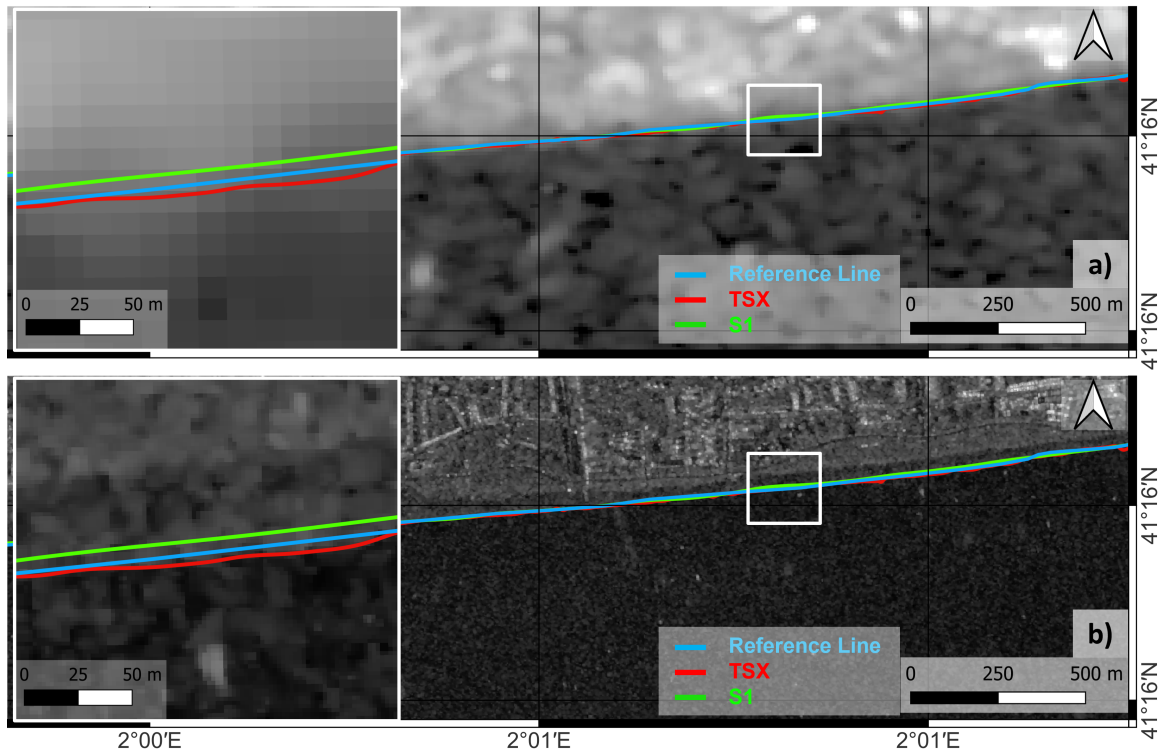


Figure 4.7: Examples of SAR-derived shorelines from S1 (DESC) (green line) and TSX (red line), compared to the reference one (blue line) on SLD stretch of coast in 2018. Panel a) shows the extracted shorelines with S1 image in the background. Panel b) shows them with the TSX image in the background.

lated to sea level differences due to tides and wave setup between the image and the reference dates. These displacements were assumed to be small because our research focused on four micro tidal beaches where tidal oscillation is below 20 cm. Additionally, two of these are gravel beaches with a large swash slope that results in an even more limited planimetric displacement of the instantaneous shoreline related to differences in sea level. To confirm this hypothesis, the sea level and wave setup contributions to potential shoreline displacements were assessed for the two sandy beaches analyzed, FNG and SLD. Since they show a milder swash slope, only in these two cases this contribution could be significant in relation to pixel size and the accuracy obtained in terms of MAD. The apparent total shoreline displacements due to waves and tides were calculated as described in Section 2.4.1). As shown in Table 4.1, displacements were typically below 2 m in the S1 cases and below 1 m for TSX, so they were significantly smaller than the obtained accuracy.

Table 4.1: Planimetric shoreline displacements due to both tidal and wave setup contributions. The apparent total distances are between the S1 (both ASC and DESC images) and TSX-derived shorelines and the reference ones. The positions of the tide gauges/buoys used for the analyses are reported in Section 2.4.1 for the three coastal areas. The details of the difference in days between S1 and TSX to the Reference are shown in Tab. 2.1

Reference Shoreline date	Total distance (m) S1 (ASC)-Reference	Total distance (m) S1 (DESC)-Reference	Total distance (m) TSX-Reference
SLD (Barcellona 2 tide gauge/ Barcellona buoy II)			
26/10/2017	0.8	-1.5	-0.8
19/05/2018	-0.1	-0.5	0.4
24/05/2023	0.1	0.8	–
04/06/2023	1.3	1.2	–
FNG (Civitavecchia harbor/Giannutri buoy)			
19/07/2019	-1.4	-0.3	–
20/07/2021	1.7	2.1	–

4.4 Discussion

4.4.1 Role of grain size and radar wavelength on backscattering

Radar backscattering is strongly influenced by grain size and SAR wavelength. When the particles are small concerning the wavelength, the so-called Rayleigh regime, the intensity of the backscattered energy is proportional to the ratio between d^6 and λ^4 where d is the grain size and λ is the SAR wavelength [Ulaby F. T. 1987]. This condition applies to the two studied sandy beaches, with $d = 0.27$ mm in SLD and $d = 1$ mm at most in FNG (no measurements are available there), considering both the S1 (center in 5.5 cm) and the TSX (center in 3.1 cm) wavelengths. We do not know the pebble size of two gravel beaches, but the order of magnitude ranges between 1 – 10 cm. In these cases where the grain size is comparable to or larger than the SAR wavelength, the response moves to the Mie and optical regime, resulting in a more complex response.

The S1 results obtained in our study were generally better for the gravel beaches, which showed a very good accuracy of half a pixel and a small dispersion of MAD values across different methods. A possible explanation is the higher backscatter from the exposed gravel beach with larger grain sizes compared to the sandy beach for the same wavelength. In Figure 4.8, the backscatter intensity (in dB) of the VV polarization of S1 and for HH polarization of TSX, averaged over all dates for each site, is shown. To collect the backscatter data from the emerged part of the beach (LAND in the Figure 4.8), an appropriate mask was created based on the reference line of each date for each site, ensuring that no other landward features were included. A mirrored mask was created to collect an equal number of backscatter values seaward (SEA in the Figure 4.8). The test shows that, in general, sandy beaches (SLD and FNG) tend to exhibit lower land backscatter values on average. Gravel beaches (MRJ and RDC), on the other hand, show higher land backscatter responses, which also influence the data collected in the sea portion. This also explains the slight seaward bias observed in the results. In general, a greater separation between sea and land backscatter is observed on the gravel beaches and in FNG compared to SLD (S1), where more acquisition dates were available, some of which were affected by unfavorable weather conditions (see the next section).

Several studies have investigated the effects of using different SAR platforms with varying wavelengths for shoreline detection. For example, [Wu et al. 2019] showed that X-band SAR may be preferred over L-band SAR (peak wavelength in 20 cm) for shoreline detection, especially in areas where the beach material consists

of finer grains. In our study, the TSX satellite platform operating in the X-band (peak wavelength in 3.1 cm) was compared with the S1 platform in the C-band (peak in 5.5 cm) in SLD. The comparison was conducted on the two available dates for TSX, selecting the closest S1 images, both close to the reference (2.1). Additionally, both the original data at a 3 m per pixel resolution and a resampled version at 10 m per pixel, matching the S1 resolution, were considered in the analysis to separate the effect of the better spatial resolution of the X-band platform from that of the smaller wavelength (4.5). The comparison in SLD, characterized by fine sand, revealed an advantage in utilizing TSX over S1, with errors decreasing from 6.5 m in the former (best method combination) to 2.5 m in 2018. This is coherent with Figure 9, showing that, in SLD, TSX data shows a greater difference in backscatter values between the land and sea pixels than S1 data. In 2017, the improvement was not relevant, probably due to the occurrence of other sources of error (4.4.2). The use of TSX images resampled to S1's resolution also demonstrated the potential to achieve an accuracy comparable to that one with the original TSX spatial resolution on the two available dates 4.3.2. This indicates that accuracy is more influenced by the wavelength relative to surface roughness rather than by spatial resolution. Further investigations are warranted, primarily by employing a greater number of dates.

4.4.2 Role of meteorological conditions on backscattering

Meteorological conditions (waves and wind) can not only produce an apparent migration of the instantaneous shoreline (see Section 4.3.3), but also contribute to increasing the sea clutter signal in SAR imagery and can potentially impact the four sites. The conditions providing the highest contrast between land and water in SAR backscattering are generally accepted to be a smooth sea surface (relative to the wavelength corresponding to the radar frequency), in which case pixels associated with the sea are black (corresponding to the minimum value of the radar signal, i.e. only noise). In such ideal conditions, pixels around the beach border are stable and the boundary results more discernible, due to the high contrast between pixels associated with land and sea. When the sea surface becomes rough due to waves and wind, its backscattering response increases, reducing the contrast between sand and water pixels. The sea can even reach high values when the Bragg scattering conditions are related to sea surface undulations, wavelength, and incidence angle of the radar signal. The role of the interference of radar signal with wavelength and height of sea waves can even introduce a bias in coastline retrieval

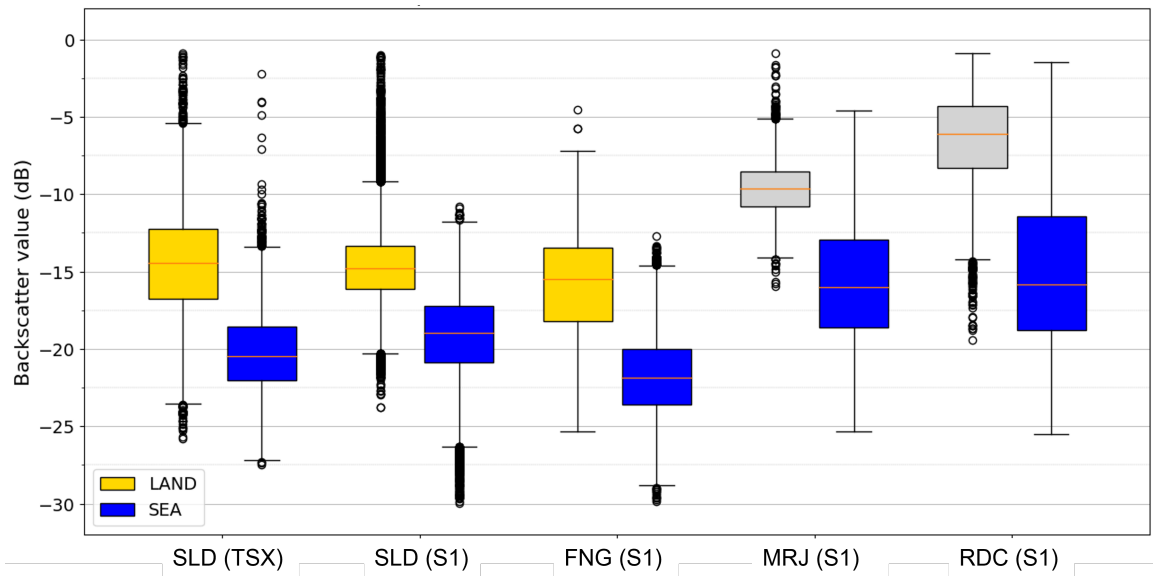


Figure 4.8: Box plots of the backscatter values of land and sea averaged over the available dates, for each site and platform. A mask around the reference line was used to select pixel values on the exposed beach portion (LAND) and the equivalent number of pixels in the sea (SEA). SLD and FNG are sandy beaches (gold color), while MRJ and RDC are gravel beaches (light grey).

as discussed in [Sletten and Hwang \(2011b\)](#). Many researchers have investigated how wind, waves, and tides influence the increase of speckle noise in radar data. For example, [Wu et al. \(2019\)](#) showed how backscattering was affected by wave heights greater than 0.5 m. Local winds, such as breezes, can also generate local waves of a wavelength that can obscure shoreline detection [[Sletten and Hwang 2011a](#)].

A quantification of this aspect was conducted for the SLD beach for the S1 images, given the variability of conditions experienced across the larger number of dates considered (Table 2.1). The correlation coefficient between the MAD of each date with the wind speed and wave data was evaluated with Pearson's coefficient first using the raw images and then the denoised images. A significant correlation between MAD and wind speed for RAW images ($r=0.64$) was found while wave height appeared less correlated with MAD ($r=0.34$), as shown in Figure 4.9a. A significant error reduction was observed with the use of denoising techniques, particularly on dates most affected by adverse meteorological and marine conditions (Figure 4.9b). Denoised data showed a low correlation between MAD and both wind ($r=0.16$) and waves ($r=0.4$) on the same dates.

Regarding the TSX–S1 comparison in SLD, the TSX data from 2017 was ac-

quired under more unfavorable wind conditions (5 m/s) compared to the S1 data (3.2 m/s). This may justify the lack of improvement in terms of MAD results. By contrast, in the 2018 dates, under similar wind conditions — 2.6 m/s for the TSX acquisition and 2.9 m/s for the S1 image — the shoreline extraction accuracy, in terms of MAD, was 2.5 m for TSX and 6.5 m for S1.

Finally, beaches with a wide intertidal zone are additionally affected by changes in soil moisture. The episodic beach inundation can drastically vary the dielectric properties of the sand, and SAR backscattering could likely experience a more significant change in the wet-dry sand transition rather than in the sea-wet beach boundary [Savastano et al. 2024]. In the present study, this might explain why the bias was slightly negative for FNG and strongly negative for SLD (Figure 4.4), meaning that the detected shorelines were located landward with respect to the reference ones. In particular, the latter site experienced worse meteorological conditions on some of the examined dates, which might create more beach inundation moments that accentuate this effect. Contrarily, in gravel beaches, the strong backscattering produced by the pebbles, together with the lack of wet sand, shifted the boundary of the land class toward the sea (Figure 4.4). This phenomenon was particularly evident in the results of the RAW data.

4.4.3 Influence of orbits on shoreline detection

According to previous studies, the direction of observation (sea-shore or land-sea) can significantly influence the quality of shoreline extraction. Ascending and descending orbits determine different observation geometries, which in turn influence SAR backscatter and shoreline delineation [Wu et al. 2019]. In our study, we calculated the angles formed between the average orientation of the examined beaches and the direction of the different ascending or descending orbit line of sight. SLD and FNG, with similar E-W orientations (85° and 111° relative to the North, respectively), exhibited little distinction between ascending and descending orbits in terms of beach perspective. The situation was slightly different for MRJ and RDC (61° and 35° relative to the North, respectively). However, no patterns were observed in the results concerning the orbit either.

Another investigated factor is the incidence angle between the sensor's outgoing signal and the terrain, but no influence was found on the results. The examined beaches all fell within a range of incidence angles between 30° and 50° , which is optimal for avoiding negative effects in shoreline detection, according to Wu et al. (2019).

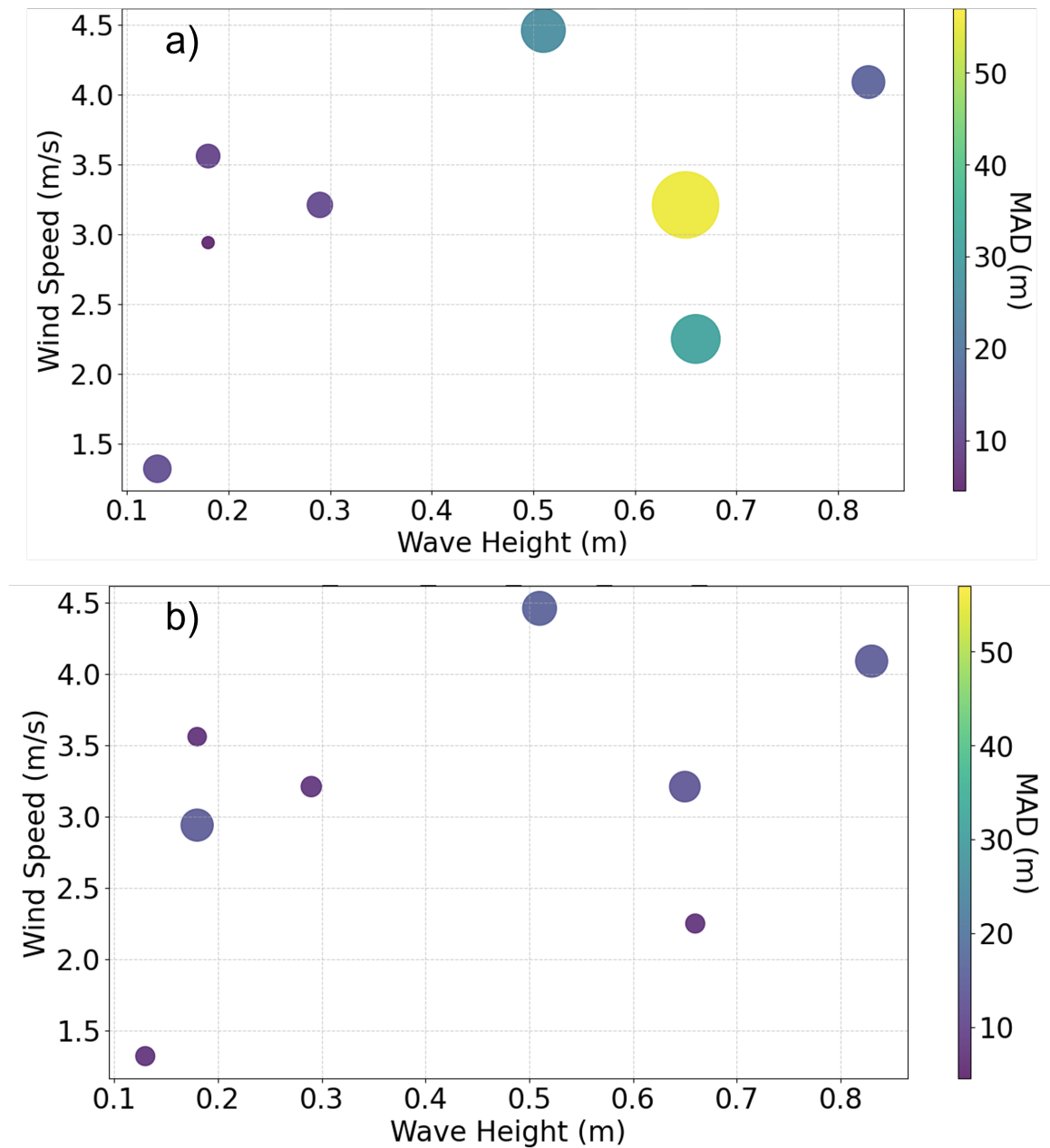


Figure 4.9: Relationship between MAD, wind speed, and wave height. a) Result of combining GMM clustering on VVdb polarization using RAW data (i.e. without denoising). b) Result of combining GMM clustering on VVdb polarization using TVD denoising. The size of the circles increases with the MAD, following the color scale from purple to yellow.

4.4.4 Strengths and limitations of the applied methodologies

Previous studies on shoreline extraction from SAR images had employed both probabilistic validation approaches [Wu et al. 2019, Savastano et al. 2024] and

methods utilizing in-situ data [Zollini et al. 2023, Tajima et al. 2021], achieving accuracies ranging between 10 and 15 m (larger than the S1 pixel size). By employing denoising methodologies, various clustering techniques, and outlier filters, our work has advanced the reliability and accuracy of shorelines extracted from SAR imagery, with unprecedented accuracies up to 5 m (half of S1 pixel size).

Compared to some probabilistic approaches, our methodology is limited by the reduced number of images utilized. The number of S1 images tested was large enough to produce a robust outcome, but the obtained TSX results should be confirmed by testing on more images. In addition, the methodology was tested on beaches with different geomorphological characteristics, but all located within the Mediterranean basin under microtidal conditions and on dates with near-ideal weather conditions. The methodology could be applied globally, testing it in the future in beaches with significant tides, especially because the results obtained in this study using clustering methods with multiple classes in sandy beaches suggest the possibility of identifying the intertidal zone in tidal environments, based on the varying backscattering on the water, the wet low-lying sand area, and the dry sand area.

In instances of adverse meteorological conditions and in environments characterized by fine, flood-prone sands (SLD site), the accuracies achieved have been variable, but they represent an improvement on previous studies. Restricting the use of SAR data to favorable weather conditions (e.g., wave height < 0.5 m and wind speed < 3 m/s) would provide more accurate results (of 5 m in this study), but this would diminish its advantages over optical data, particularly regarding nocturnal operability. The application of denoising techniques appears to partially decouple accuracy from meteorological conditions (Figure 4.9), thereby increasing usability.

A potential limitation arises from the use of PlanetScope (PLN) data as a reference in the case of SLD. Given the availability of TSX data on only two specific dates, the authors were compelled to use a manually digitized reference from PLN, which provides near-daily imagery. Considering that manual digitization entails an error comparable to the PLN pixel size (3 m), the accuracy is close to the MAD values found for the TSX images in the best case.

A notable strength of our approach is that it did not require substantial efforts to transition from the methodology developed in Chapter 4 for MSI to that for SAR images. The only changes made were in the preprocessing module and the identification of outliers. Compared to shoreline extraction results obtained from optical

data, which typically report accuracies of around 4–5 m using 10 m resolution imagery in microtidal environments [Vos et al. 2023b, Angelini et al. 2024], shoreline detection from radar data generally achieves slightly lower accuracy. The methodology developed in this study helps narrow this gap, facilitating a potential fusion of SAR and multispectral images in subsequent works.

The successful application of the X-band SAR images (TSX) in sandy beach areas, particularly challenging from a conservation perspective, suggests the potential of using other X-band platforms, such as the Spanish PAZ or the Italian COSMO-SkyMed. Future work should involve expanding the available X-band image dataset.

4.5 Conclusions

In this chapter, the potential of SAR imagery for automatic shoreline detection has been evaluated by applying a combination of SAR polarizations, denoising techniques, clustering or thresholding methods, and outlier detection filters. Shorelines extracted from 20 Sentinel-1 and 2 TerraSAR-X images have been validated against high-resolution reference datasets obtained from aerial orthomosaics and PLN imagery. Four Mediterranean beaches characterized by different grain sizes and geomorphological settings have been studied.

SAR-based shoreline extraction significantly improves when applying denoising techniques, particularly the BM3D filter, which consistently reduces noise and enhances the clarity of the land-sea boundary. The use of three clusters (instead of two) in the classification algorithm also improves the results, but the addition of an outlier detection method only implies a marginal decrease in errors. With all these improvements, an unprecedented sub-pixel accuracy is achieved in terms of Mean Absolute Distance (MAD), both in gravel (6 m) and in sandy (7 m) beaches (significantly below the pixel size of S1). At one of the sandy coasts, both S1 and TSX images have been used on two dates. On one date, the best-performing configurations provide a MAD of approximately 6.5 m for S1 and around 2.5 m for TSX, demonstrating that X-band data can yield higher accuracy than C-band data, especially in environments with fine sand. However, further investigation should be performed because S1 and TSX give similar accuracies (7 m) on the other date, probably due to worse conditions on the TSX image time acquisition.

In general, errors in shoreline detection are smaller if backscatter values between land and sea differ more, which happens for gravel beaches and the sandy site with better accuracy. The influence of meteorological conditions has also been analyzed, and a significant negative correlation between wind speed and shoreline accuracy is observed, whilst wave height seems to have a smaller impact. Denoising filters are effective in mitigating these meteorological effects, particularly for S1 data. Contrarily, the comparison between ascending and descending orbits does not reveal systematic differences in shoreline accuracy across the study sites, although previous studies suggested that the geometry of SAR acquisition can affect detection performance.

This chapter highlights the strengths and limitations of SAR-based shoreline detection. In general, the methodology proves effective in extracting accurate and reliable shorelines, particularly in the two gravel beaches and one of the sandy

sites. Thereby, SAR imagery could indeed serve as a viable alternative to optical data, especially under cloudy conditions or during night-time acquisitions. However, its performance can be affected by surface roughness and environmental conditions. Future research should focus on extending this analysis to a broader range of coastal environments, including meso and macro-tidal areas, to further refine the methodology and assess its applicability under more variable meteorological conditions.

Chapter 5

Synthesis

5.1 Key findings

This thesis has contributed to advancing the use of remote sensing for monitoring coastal morphology through satellite imagery by employing both multispectral data (Sentinel-2 and PlanetScope) and SAR data (Sentinel-1 and TerraSAR-X), achieving high accuracy in shoreline extraction with both satellite sensors and also allowing the characterization of megacusp undulations. The five specific objectives defined in Section 1.3 have been addressed, and the main findings related to each of them are:

- **Develop a semi-automatic shoreline extraction methodology for multispectral imagery** (Chapter 3)

A semi-automatic tool was implemented, capable of processing both Sentinel-2 (S2) and PlanetScope (PLN) data, with flexibility in selecting spectral indices and classification techniques. This tool, incorporating a wider range of spectral indices and classification techniques, including both global and local thresholding, K-means, and GMM, when using the most appropriate choice of methods and parameters, is capable of catching the shoreline features in different contexts. The accuracy achieved is analogous to the current better-performing state-of-the-art tools. The developed methodology demonstrated high accuracy, achieving average shoreline positional errors of half a pixel in all three micro-tidal Mediterranean beaches tested. Specifically, mean absolute distances of 4–5 m for S2 and 1.5–2 m for PLN were achieved.

- **Detect and characterize megacusps using multispectral data** (Chapter 3)

The implemented tool successfully identified megacusp undulations using the sinuosity indicator, when compared with the same undulations in the reference line, manually digitized from orthomosaics. Moreover, the tool was able to quantify in a precise way their wavelength and amplitude. Including the ability to modify the level of smoothing, the shoreline extraction method was found to better catch the alongshore variations compared to other tools such as CoastSat, which tends to smooth the alongshore undulations. Thanks to PLN's high temporal resolution and the flexibility of the developed algorithms, the tool allowed for the monitoring of megacusp dynamics at weekly timescales, confirming the high temporal variability of these morphological features. This achievement adds valuable insight into short-term beach morphology patterns, offering meaningful implications for erosional spot identification and coastal planning.

- **Quantify and account for shoreline detection errors caused by wave and tide variability** (Chapter 3 and 4, and Appendix A)

By integrating tide gauge and buoys, in addition to beach slope data, shoreline displacement was estimated based on tidal and setup components at the moment of satellite image acquisition. While the displacement values found are modest in absolute terms, they are comparable to the observed MAD and thus can represent a non-negligible component of the total shoreline positioning error. The integration of these corrections into the tool workflow led to slight improvements in accuracy, typically at the decimeter scale, but it allowed for eliminating one of the sources of error inside an automatic shoreline extraction process. This step would be essential in potential extensions for high-precision shoreline mapping in meso- and macro-tidal beaches.

- **Adapt and refine the automated shoreline extraction methodology for SAR imagery** (Chapter 4)

The MSI-Python tool was refined, integrating advanced preprocessing methods like BM3D speckle filtering, as well as the application of Otsu multi-thresholding and unsupervised clustering methods tailored for radar backscatter data. The results demonstrated that SAR-derived shorelines could achieve sub-pixel accuracies with a MAD of approximately 6 m on average on gravel beaches and 7 m on average on sandy beaches tested, for Sentinel-1 (S1). TerraSAR-X (TSX) was tested only on the SLD sandy beach, and it reached 2.5 m of MAD under favorable environmental conditions compared to the 5 m obtained by S1 for the same date. Therefore, the results showed that X-band SAR data (TSX) provided higher shoreline detection accuracy than C-band data (S1), particularly for fine-grained sandy environments, although this advantage diminished under unfavorable meteorological conditions.

- **Investigate key factors affecting land–sea backscatter contrast in SAR** (Chapter 4)

The accuracy of shoreline extraction was strongly dependent on the difference in backscatter values between land and sea. This contrast was enhanced in gravel beaches (with higher land backscatter) and under no-wind conditions (with lower sea backscatter). The presence of wind and wave activity increased the roughness of the sea surface, degrading backscatter contrast and increasing the errors in shoreline detection. Contrarily, the comparison

between ascending and descending orbits does not reveal systematic differences in shoreline accuracy across the study sites. Additionally, the analysis confirmed that the application of advanced denoising filters, in particular the BM3D filter, played a critical role in mitigating these effects.

5.2 Future perspectives

The work presented in this thesis implemented a set of innovative satellite-based methodologies and tools for shoreline extraction and megacusp monitoring that demonstrated an improvement over the current state of the art. However, several future developments can be expected to further enhance their accuracy, robustness, and applicability across different coastal settings.

A key direction concerns the extension of the validated methodologies to meso- and macro-tidal environments, beyond the micro-tidal Mediterranean sites explored here. The classification approaches, particularly the use of unsupervised clustering into multiple classes, showed promising results that may allow for distinguishing between water, wet sand, and dry sand pixels that are particularly relevant in environments with a broader tidal range. The potential use of more recently developed classification methods, based on deep learning and neural networks, could represent a foreseeable advancement. Conducting systematic tests on beaches with different tidal regimes and sedimentological characteristics would help assess the potential generalization of the proposed workflows and calibrate the parameters accordingly, potentially leading to a fully automatic procedure for meso- and macro-tidal beaches.

Regarding megacusp monitoring, while the tool developed here has successfully identified and characterized megacusp features using satellite imagery, its current reliance on fixed sinuosity and amplitude thresholds limits its adaptability to diverse geomorphological settings. Future developments should pursue the definition of adaptive or data-driven indicators of megacusp presence, possibly leveraging machine learning techniques trained on larger datasets across different coastal types. The potential to integrate geomorphological indices, wave energy proxies, or morphological forecasting models could significantly increase the predictive power of the tool.

Another relevant avenue is the automatization of event-scale analysis for megacusp evolution. The current approach involved partial visual interpretation. Developing a fully automatic tracking system for megacusp dynamics could greatly

benefit coastal managers by providing early warning signals for these events that can cause erosional hotspots along sandy coasts. It could be based on time series clustering or shape detection techniques such as wavelet analysis, which has already been successfully tested in the past, and also using the satellite shorelines of the present study.

Another crucial aspect is the integration of dynamic corrections for tidal and wave influences. While this work has tested the inclusion of a simplified Stockdon's formula for run-up estimation in microtidal contexts, future efforts should aim to refine this component, particularly by adapting it to dissipative beaches and more energetic wave climates. The use of synthetic data, such as modeled wave and tide estimates, could offer a feasible alternative in regions lacking dense in-situ instrumentation.

In terms of SAR-based applications, additional effort is needed to quantify the influence of meteorological variables, especially wind and wave conditions, on the accuracy of shoreline extraction. This study demonstrated that denoising techniques, in particular the BM3D filter, effectively mitigate the impact of adverse conditions; however, refining these techniques or incorporating real-time meteorological data into the processing chain could further enhance performance. Moreover, the expansion of the use of SAR images coming from different platforms using different wavelengths could expand the applicability of our shoreline extraction tool to different coastal environments. In particular, using X-band sensors such as COSMO-SkyMed or PAZ would allow refining the analysis in terms of accuracy along the fine-sandy and low-slope beaches, which represent one of the more fragile coastal environments. In addition, the availability of more satellites will help increase the temporal resolution to be used in the analysis.

Finally, the fusion of SAR and MSI datasets represents an especially promising line of research. The distinct advantages of SAR, its non-sensitivity to cloud cover and its ability to acquire data at night, could complement the richness in terms of spectral bands of MSI sensors. Although this thesis independently developed and validated methodologies for each satellite type, future work should explore data fusion strategies, for example, by co-registering SAR and MSI images to enhance shoreline detection robustness in challenging environmental conditions.

5.3 Broader remarks

The methodologies developed in this thesis have proven effective in advancing the semi-automatic detection of shorelines and the monitoring of large-scale morphological features such as megacusps. While much of the discussion has focused on their performance in scientific and operational contexts, their potential extends well beyond the scope of coastal geomorphology or remote sensing research.

First, these methodologies, particularly those based on open-access satellite platforms and open-source processing tools, offer a solid foundation for building public-facing applications and services, such as interactive WebGIS platforms. These could provide near-real-time shoreline evolution maps, serving as accessible tools for both citizens and local governments. Integrating these systems with participatory data (e.g., crowdsourced observations, mobile phone images, or citizen science initiatives) could enhance monitoring accuracy while fostering awareness and engagement around coastal change and vulnerability. This is critical in the face of climate change and the adaptation measures that will be needed, as emphasized in all the Reports of the Intergovernmental Panel on Climate Change.

Moreover, other possible outcomes of the methodology developed could involve different domains. In particular, the image segmentation techniques, initially designed for land-water boundary delineation, can be readily transferred to other contexts. For instance, hydrological applications such as flood extent mapping or the detection of dry riverbeds during drought events could benefit from the developed algorithms and the future perspective of the fusion of SAR and multispectral imagery. In particular, the SAR-based methodologies, which are resilient to cloud cover and low illumination, offer critical advantages for flood mapping during extreme weather events, when optical sensors are often ineffective. In a broader perspective, these segmentation tools could also support wetland management, irrigation monitoring, or water quality assessment, especially when integrated with ancillary data layers and hydrodynamic models.

Another promising avenue lies in the intersection of environmental policy and territorial planning. The ability to monitor shoreline evolution or megacusp formation with high frequency and spatial coverage makes these tools ideal for long-term planning of setback zones, erosion mitigation strategies, or coastal infrastructure design. By translating scientific data into decision-ready products, they can help bridge the gap between academia and policy-making.

Finally, this thesis contributes to the growing trend of democratization of Earth Observation. The use of freely available Copernicus and PlanetScope data, processed through customizable algorithms, underscores a paradigm shift in how geospatial data are produced, interpreted, and disseminated. Encouraging open access not only accelerates innovation but also promotes equity in data availability, particularly for regions or institutions with limited technical or economic resources.

In conclusion, while this thesis has advanced the state of the art in remote sensing-based shoreline analysis, the complexity and variability of coastal systems continue to pose new challenges. Addressing these will require multi-disciplinary approaches combining remote sensing, geomorphology, hydrodynamics, and data science—thereby transforming satellite data into actionable knowledge for sustainable coastal management.

5.4 Research outputs: publications and tool availability

Chapter 3 is based on the following journal article:

- Angelini, R., Angelats, E., Luzi, G., Masiero, A., Simarro, G., & Ribas, F. (2024). *Development of Methods for Satellite Shoreline Detection and Monitoring of Megacusp Undulations*. *Remote Sensing*, 16(23), 4553. DOI: 10.3390/rs16234553

Chapter 4 is based on the following journal article:

- Angelini, R., Angelats, E., Ribas, F., Luzi, G., Di Ciaccio, F., Mugnai, F., & Masiero, A. (submitted). *Enhanced SAR-Based Shoreline Extraction in Microtidal Beaches Through Improved Preprocessing of Sentinel-1 and TerraSAR-X Data*. Submitted to *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, DOI: 10.1109/JSTARS.2025.3604869.

The methodology described in Appendix A derives from this international conference paper:

- Angelini, R., Di Ciaccio, F., Angelats, E., Ribas, F., Luzi, G., & Masiero, A. (2024, October). *Evaluating Tidal and Wave Corrections on Shoreline Extraction from Satellite Imagery in Mediterranean Microtidal Beaches*. In *IEEE International Workshop on Metrology for the Sea (MetroSea)*. DOI: 10.1109/MetroSea62823.2024.10765685

The following international conference paper, although not directly included in the thesis, may serve as a foundation for future research directions focusing on supervised classification techniques:

- Angelini, R., Angelats, E., Luzi, G., Ribas, F., Masiero, A., & Mugnai, F. (2023). *A Review and Test of Shoreline Extraction Techniques. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLVIII-1/W1-2023, 17–24. DOI: 10.5194/isprs-archives-XLVIII-1-W1-2023-17-2023

The following international conference paper included preliminary work that supported the development of the megacusp methodology described in Chapter 3:

- Angelini, R., Angelats, E., Ribas, F., Masiero, A. (2025, May). *Shoreline Extraction Methods and Megacusps Identification from Sentinel-2 Images. Coastal Engineering Proceedings*, 38, management.156. DOI: 10.9753/icce.v38.management.156

Another international conference paper with a preliminary study related to the contents of Chapter 3 is:

- Angelini, R., Angelats, E., Luzi, G., Ribas, F., Masiero, A. (2024, May). *Shoreline Extraction Methods from Sentinel-2 and PlanetScope Images. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLVIII-1-2024. DOI: 10.5194/isprs-archives-XLVIII-1-2024-1-2024

The following Spanish conference paper contains a first attempt at extending the megacusp detection tool (Chapter 3) to perform automatic features recognition:

- Angelats, E., Angelini, R., De Urmenta Rubira, F., Ribas, F. (2024, September). *Detección y caracterización de megacúspides a partir de líneas de costa derivadas de sensores remotos. XII Jornadas de Geomorfología Litoral, València (Spain)*. DOI: 10.4995/GEOLIT24.2024.18720

Finally, this other conference proceeding, used part of the development tool (Chapter 3) to advance in the creation of a WebGIS service for megacusps detection:

- Zhao, Y. and Núñez-Andrés, M.A. and Angelats, E. and Angelini, R. (2024, November). *Geo-herramientas para el seguimiento de la línea de costa y megacúspides a nivel regional mediante Sentinel-2 y datos abiertos. Un caso de estudio en Cataluña: la bahía de Pals. Jornadas Ibéricas de Infraestructuras de Datos Espaciales*. URL: <https://www.idee.es/resources/presentaciones/JIIDE24-IIIgeoEuskadi/Resumenes/80.pdf>

The tool developed and described in Chapter 3 for the shoreline extraction from MSI, which forms the basis for the radar implementation in Chapter 4 and was further refined in Appendix A to incorporate tidal and wave corrections, will be released as open-source. The semi-automatic tool to characterize megacusps (Chapter 3) will be implemented and also made available. Specifically, the complete Python code, including all preprocessing, analysis, and correction modules, will be publicly available on GitHub at:

`https://github.com/riccardoangelini88/MegaShore`

By hosting the software on GitHub, it becomes more accessible, reproducible, and extensible, enabling external researchers to validate and extend the work presented in this thesis.

Abbreviations

The following abbreviations are used in this manuscript:

ASC	Ascending mode orbit
AWEI	Automated Water Extraction Index
CNN	Convolutional Neural Network
DESC	Descending mode orbit
dGNSS	Differential Global Navigation Satellite System
DSM	Digital Surface Model
FNG	Feniglia beach
GEE	Google Earth Engine
GMM	Gaussian Mixture Model
GNSS	Global Navigation Satellite System
GRD	Ground Range Detected
<i>MAD</i>	Mean absolute deviation
ML	Machine Learning
MNDWI	Modified Normalized Water Index
MSI	Multispectral Instrument
NDWI	Normalized Difference Water Index
NIR	Near-infrared
NOD	Northern Ombrone Delta beach
PLN	PlanetScope
<i>RMSE</i>	Root Mean Square Deviation
RTK	Real-Time Kinematic
SAR	Synthetic Aperture Radar
SLD	Southern Llobregat Delta beach
SWI	Sentinel Water Index
SWIR	Short-Wave Infrared
SWM	Sentinel Water Map
S1	Sentinel-1
S2	Sentinel-2
WI	Water Index
TSX	TerraSAR-X

Appendix A

Evaluating tidal and wave corrections for shoreline extraction process

A.1 Introduction

Accurate monitoring of shoreline variations is essential for effective coastal management and determining the consequent mitigation strategies, accounting for the critical effect of coastal erosion (details in Section 1.2.1). Remote sensing technology has greatly enhanced the capability to analyze these dynamic environments, especially in the last years, thanks to the high resolutions of the recent sensing instruments. However, the accuracy of shoreline extraction methodologies from satellite can be influenced by natural phenomena such as tides and wave action, because the shoreline identified by the images is the instantaneous one (see a review of different shoreline definitions in Section 1.2.1). These factors can lead to discrepancies in shoreline data, if not properly accounted, resulting in misleading interpretations of coastal changes. Therefore, incorporating tidal and wave corrections is crucial to refining the automated outputs of the shoreline extraction process from satellite images, ensuring that the extracted shorelines reflect as much as possible the true position.

Many previous studies of shoreline detection in sites with significant tides have described these effects and have proposed methods to correct them [Chen and Chang 2009, Chang et al. 2015, Vos et al. 2023b]. Contrarily, as shown in Chapter 3, the role of waves and tides in tideless Mediterranean beaches is small, producing cross-shore motion of the shoreline from 0 to 2 m at most (effect checked ex post). However, the errors in satellite-derived shorelines in these tideless environments are of 4-5 m in S2 or 1.5-2 m in PLN (see also Chapter 3), significantly smaller than in sites with tides. Given that the displacements produced by differences in

tides and waves are of the same order of magnitude as the errors, and thereby accounting for tidal and wave corrections might diminish them.

This chapter aims firstly to evaluate the impact of tidal and wave corrections on the accuracy of the shoreline extracted in tideless Mediterranean beaches through the automated tool presented in Chapter 3. Another objective is to provide additional evidence of the effectiveness of the methodology proposed in Chapter 3, extending the validation to a temporally larger dataset of the same tideless Mediterranean beaches. More details about the study sites and dataset used are provided in Section 2.2.3. The proposed methodology, which involves the integration of the tidal correction and the wave run-up correction, is presented in Section A.2. Section A.3 proposes an examination and critical analysis of the main results obtained. Finally, the Section A.5 includes the concluding remarks.

A.2 Methodology

This chapter is based on the shoreline extraction methodology developed in Chapter 3, extended to provide planimetric correction of tidal and wave run-up contributions. The tool was developed in Python, and the QGIS software was also used for additional graphical outputs and validation. Such methodology foresees an initial preprocessing phase of satellite imagery by calculating various spectral indices (NDWI, MNDWI, WI, AWEIshadow, and AWEI no-shadow for S2 and NDWI and NIR band for PLN). Two unsupervised classifications, the Gaussian Mixture Model (GMM) and K-means, are then run to binarize the rasters into water and land and extract the contours. These steps followed the methodology described in Section 3.2. The novelty of this chapter was the correction of the extracted shorelines based on tide and wave conditions. The water levels and the waves at the time of the satellite pass and those at the time of the reference shoreline were considered to calculate the difference. The contribution of the run-up was calculated using Stockdon's formula [Stockdon et al. 2006]:

$$z_{\text{runup}} = 0.35 \cdot \tan(\beta) \cdot \sqrt{H_s \cdot L_0} \quad (\text{A.1})$$

where H_s is the significant wave height, L_0 is the deep-water wavelength, and β is the beach slope. L_0 is defined as:

$$L_0 = \frac{g \cdot T^2}{2\pi} \quad (\text{A.2})$$

where T represents the wave period. The beach slopes were calculated for each beach, considering only the swash zone using DSM data. The obtained values are 0.061 rad for NOD, 0.071 rad for FNG, and 0.078 rad for SLD.

The difference between the reference shorelines and those extracted from the satellite data was calculated to adjust the latter to the time of the reference ones. The two components of displacement were calculated using

$$d_{\text{tide}} = \frac{z_{\text{tide-sat}} - z_{\text{tide-ref}}}{\tan(\beta)} \quad (\text{A.3})$$

for the tidal induced movement, with $z_{\text{tide-sat}}$ representing the tidal level at satellite time and $z_{\text{tide-ref}}$ the tidal level at reference time, and

$$d_{\text{runup}} = \frac{z_{\text{runup-sat}} - z_{\text{runup-ref}}}{\tan(\beta)} \quad (\text{A.4})$$

for the wave runup induced movement, with $z_{\text{runup-sat}}$ representing the runup level at satellite time and $z_{\text{runup-ref}}$ the runup level at reference time. Then, they were added to obtain the final displacement.

To finally correct the extracted shorelines, the same transects from the validation phase were used. The original shorelines were sampled every meter, and the points were shifted towards the baseline: a negative displacement value means landward movement, and a positive value means seaward shift. The connecting line across the new points needed to be smoothed at the same level as the raw shorelines.

The accuracy of S2 and PLN-derived shorelines, both before and after correction, was evaluated by comparing them with the reference shorelines obtained through a manual digitalization from high-resolution aerial orthomosaics. The comparison involved computing various metrics using cross-shore transects spaced at 10-meter intervals. This systematic approach is known as “baseline and transect” [Apostolopoulos and Nikolakopoulos 2021a].

A.3 Results

The calculation of the total displacement value, given by the sum of the tidal and run-up contributions, yielded values exceeding one meter in four out of six cases (Table A.1). All values were positive, indicating a landward displacement of the satellite-extracted shorelines relative to the reference shorelines. A displacement of 1.4 m was observed for the PLN data on the SLD beach, while for the FNG beach, a

1.5 m shift and 1.3 m shift were observed for the S2 and the PLN data, respectively. A displacement of 1.5 m was observed for the PLN data on the NOD coast.

Table A.1: Date of reference orthomosaics and total displacement between S2 and PLN data and reference shoreline.

Site	Reference Date	S2 - Reference Total Distance (m)	PLN - Reference Total Distance (m)
SLD	25 May 2017	0.4	1.4
FNG	05 April 2023	1.5	1.3
NOD	20 July 2019	0.3	1.5

The Mean Absolute Deviation (MAD), Bias, and Root Mean Square Distance (RMSD) of the shoreline position error for each case study are reported in Table A.2. All possible combinations were tested, but only the best combination method-index is shown in the two versions, without correction (raw) and with the total contribution of tidal and run-up corrections (transl) (Table A.2).

The results show a high level of accuracy for both versions. Fig. A.1 shows a visual example of the obtained results. S2 data exhibit an accuracy of approximately one-third of a pixel in terms of MAD for SLD (≤ 2 m) and FNG (≤ 3.5 m) and around half a pixel for NOD (≈ 5 m). The PLN results show slightly lower accuracy in terms of MAD but still lower than the pixel size. In general, the best results are obtained for the beaches of SLD and FNG (~ 2 m). Impact of correcting into MAD and RMSD has been reported to have a small (decimetric) and variable effect. In fact, 4 times it slightly improves and 2 times it worsens. The Impact of correcting for Bias has resulted in more significant (0.5 to 1.5 m) and variable effects. Regarding the frequency, the same 4 times it improves and the same 2 times it worsens.

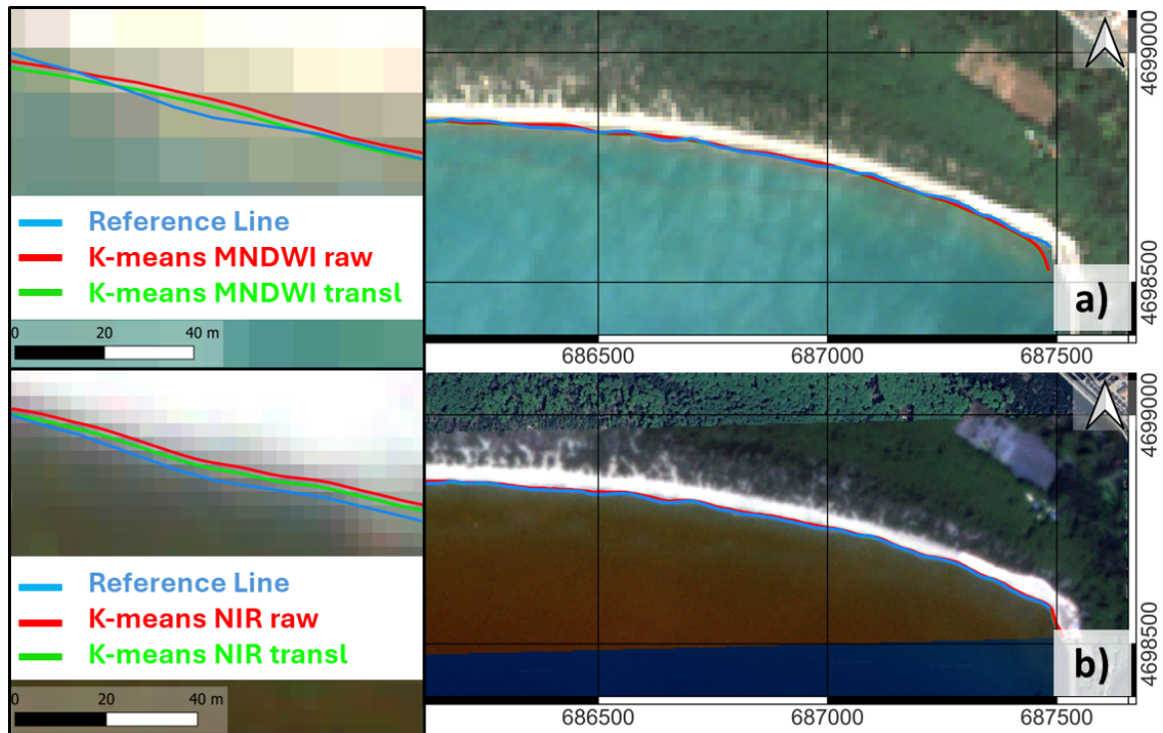


Figure A.1: Visual results with and without the wave and tide corrections on the extracted shorelines in FNG beach: a) shows a general view and a zoom of the best method-index combination for S2 data, b) shows a general view and a zoom of the best method-index combination for PLN data.

Table A.2: Statistical characterization of the shoreline position error: results are reported for the best methodologies (index and method) for each date and site, distinguishing original (raw) shorelines and those with tidal and wave corrections (transl).

Site	Type	Index	Method	MAD (m)	Bias (m)	RMSD (m)
Sentinel-2						
SLD	raw	NDWI	GMM	1.9	-0.9	2.5
	transl	NDWI	GMM	1.8	-0.5	2.4
FNG	raw	MNDWI	K-means	3.2	0.2	4.2
	transl	MNDWI	K-means	3.5	1.7	4.5
NOD	raw	AWEIsh	K-means	5.1	-1.9	6.1
	transl	AWEIsh	K-means	4.9	-1.4	5.9
PlanetScope						
SLD	raw	NIR	K-means	1.3	-0.7	1.7
	transl	NIR	K-means	1.9	1.5	2.9
FNG	raw	NIR	K-means	2.0	-1.4	2.4
	transl	NIR	K-means	1.7	-0.1	2.0
NOD	raw	NDWI	GMM	2.4	-1.0	2.8
	transl	NDWI	GMM	2.1	0.4	2.4

A.4 Discussion

The obtained results are in line with the previous study conducted for the same sites but on different dates described in Chapter 3. The same pattern emerges, with the best performance observed for the beaches of SLD and FNG and the worst performance for NOD. This coastal stretch represents a more complex environment, where it will be necessary in the future to implement differentiated strategies for different sections of the beach with varying contexts. As it specifically relates to the PLN data, the best performance was achieved in two out of the three sites using the same index-method combination (NIR-K-means). For the S2 data, it was not possible to define one-index method fitting the different beaches. This suggests that it is not possible to establish the same index-method combination in every case, in line with the conclusions drawn in previous studies [Pucino et al. 2022]. Moreover, the accuracies are consistent with other studies [Vos et al. 2023a] concerning shoreline extraction from satellite images in tideless and Mediterranean environments.

Tidal and wave correction resulted in changes in the computed MAD statistics at the decimeter level, leading often, but not always, to a slight error reduction, in agreement with the findings of previous works [Vos et al. 2023a]. In tideless environments, it seems that including tidal and wave corrections is especially useful to rule out these as potential sources of bias. This is more noticeable when both components contribute to the displacement in the same direction. This necessity is underscored by the continuous improvement in satellite spatial resolution, from 10 m for S2 to 3 m for PLN. However, the error reduction has been small, and the need to analyze other site-specific sources of error related to morphological characteristics at the beach level or to the coregistration of satellite images is clear.

In this work, a simplified version of Stockdon's formula [Stockdon et al. 2006] was used to calculate the run-up. A matter of discussion is the fact that we used a single slope value instead of the local value in each transect. Moreover, this value can change in time, and we did not take this into account either. Another possible implementation may include the use of synthetic data when in-situ data from buoys and tide gauges are too distant. Current models allow for resolutions up to 200 m along the coast and exhibit a bias of approximately 0.5 m compared to in situ data [Sun et al. 2024].

A.5 Conclusions

The use of high-resolution satellite imagery from S2 and PLN offers substantial benefits for coastal monitoring: in fact, their combination allows for a comprehensive and timely data elaboration, which is essential for capturing the dynamic nature of shorelines. Moreover, automated shoreline extraction tools need some refinement to consider effects such as tidal and wave actions that can cause temporal variations in shoreline positions. In this context, this work demonstrates that the integration of Stockdon's formula in the shoreline extraction process generates more robust results, thus helping in the normalization of the shoreline positions.

Further improvement will focus on validating the results using multi-temporal high-resolution orthomosaics and extracted shorelines to further verify the correlation after computing their linear regression rate. This will allow for the quantification of the improvements achieved through the correction methods.

Future research will further explore the integration of diverse data sources and correction techniques to enhance existing shoreline extraction methods. Moreover, applying these methodologies across a range of coastal environments will support the validation of their generalization and effectiveness, thereby contributing to global efforts in coastal preservation and management.

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