Shoreline extraction and coastal change detection from satellite SAR using thresholding-based methods

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Abstract

Coastal erosion, which is the gradual loss of sediment over time, poses a significant threat to South Africa’s coastline. The monitoring and detection of coastal erosion is essential for the effective management of coastal environments and can be quantified by the delineation of coastal boundaries. Remote sensing techniques such as Synthetic Aperture Radar (SAR) offer an unique opportunity to extract shoreline positions over large areas of the coast. In this study, C-band SAR data was used to derive backscatter coefficients for three different areas of interest in the Eastern Cape province in South Africa over a ten year period. Thresholding and edge detection techniques were used to delineate shoreline positions. The coastal erosion and accretion trends were calculated and the results indicated that the Linear Regression Rate (LRR) for the three different study areas showed various coastal erosion seasonality trends. The shoreline LLR ranged between -0.01 and -3.28 m/year for the Cape Recife area and 0.17 and -4.78 m/year for the Nelson Mandela Bay beach front. The overall pattern was erosion during the winter months and accretion during the summer months. In contrast, for the Kings Beach area, there was a consistent accretion trend where the LRR values ranged between 0.94 and 1.68 m/year. The findings of this study suggest that SAR remote sensing and thresholding-based methods could be a suitable technique for detecting and monitoring coastal erosion seasonality patterns.

1. Introduction

1.1 Importance of monitoring coastal erosion

Coastal environments have ecological, economic and societal importance. South Africa has more than 2850 km of coastline and contributes to 35% of the Gross Domestic Product (GDP). Ecologically, South Africa has been ranked as the third most biodiverse country in the world (Goble et al., 2014). This is attributed to the number of Marine Protected Areas, with 23% of the coastline being formally defined as conservation areas or nature reserves (Griffiths et al., 2010). Furthermore, communities that reside in coastal areas depend on the ocean for their livelihoods (Celliers et al., 2009).

Coastal erosion is the gradual loss of sediment or land from beaches, dune fields or cliffs to the sea over an extended period of time (Prasad and Kumar, 2014). Any changes that occur in the coastal morphology have consequences for the sustainability of coastal communities, structures and ecosystems (Mentaschi et al., 2018). Coastal erosion is induced by both natural phenomena and human activities. Furthermore, climate change effects such as sea level rise and extreme weather events result in significant changes to shoreline dynamics which increase the risk of erosion, inundation and accretion along the coastal environments (Christofi et al., 2025). Understanding and quantifying coastal erosion is essential for effective coastal management and sustainable development (Di Biase and Hanssen, 2024). Coastal erosion seasonality along the South African coastline is characterised by high-energy swells and storms that cause erosion in the winter months (June to October). Calmer conditions of summer months are attributed to accretion (November to February).

One technique used to quantify coastal erosion is to extract coastal shoreline positions. This method involves the delineation of the area between the land and the sea. Shoreline positions can be used as proxy for coastal erosion seasonality. This information is crucial for coastal scientists, and this can provide measures for evaluating coastal vulnerability (Dike et al., 2023). Traditional shoreline extraction methods include ground surveys and aerial photography. Topographic and beach profiles surveys, conducted using theodolites or total stations, measure the elevation and cross-sectional shape of beaches at fixed transects, thereby allowing for the precise calculation of sediment loss or gain. However, these techniques have limitations such as frequency, coverage and robustness in dynamic coastal zones (Christofi et al., 2025). To overcome these limitations, remote sensing can be used to delineate shoreline boundaries and monitor coastal erosion.

A range of remote sensing techniques can be used to derive shoreline boundaries. These include light detection and ranging (LiDAR), optical and multispectral satellite image-based technologies and Synthetic Aperture Radar (SAR). LiDAR is highly accurate however, field campaigns over large areas cannot be repeated frequently (Garrido et al., 2012). Optical remote sensing can be utilised to determine the presence of erosion or accretion by comparing the shoreline position in multi-temporal imagery (Luijendijk et al., 2018). The main limitation of using optical remote sensing is that imagery is affected by cloud cover, therefore it cannot be used to accurately delineate shoreline boundaries. SAR techniques can be used to overcome the limitations associated with LiDAR and optical remote sensing (Zhou et al., 2023).

SAR sensors are active sensors that transmit electromagnetic pulses and measure the backscattered radiation from the target to the ground (Moreia et al., 2013). SAR has all-weather and all-day capability thereby ensuring the continuous monitoring required for consistent temporal analysis of short-term seasonal as well as long-term changes (Ferrentino et al., 2023). SAR backscatter is sensitive to surface roughness and indicates a high contrast between the land and sea, essential for accurately identifying and

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extracting the land-water boundary (Di Biase and Hanssen, 2024).

In this study, the aim was to determine if C-band SAR remote sensing can be used to detect and monitor coastal erosion in the Eastern Cape province of South Africa. The objectives are to apply thresholding and edge detection techniques to delineate shoreline positions in three different dynamic coastal environments. A statistical analysis was conducted to determine the average coastal erosion seasonality trends for the various areas of interest. In Section 2, the related work is presented. Section 3 presents the methodology, which includes the data, study area and methods that will be employed. Thereafter, in Section 4, the results of the statistical analysis are presented Section 5 the results are discussed. Finally, in Section 6, the concluding remarks on the efficacy of the SAR techniques to extract shorelines are presented.

2. Related Work

Previous research used SAR imagery to delineate water from land through efficient and simple thresholding-based methods. In thresholding-based methods, pixels are divided into different categories by comparing each pixel to a specified threshold value (Sun et al., 2023). A study conducted by Dike et al. (2023) used Sentinel-1 C-band to derive backscatter and perform a simple classification of land and water boundaries. The threshold values were empirically tuned to known local conditions. The results indicated that the thresholding technique delineated shorelines effectively in areas where there was a strong contrast between land and water. However, in tidal zones and wet sandy beaches, there was a reduced accuracy in the classification of the land and water boundaries. This was due to backscatter values that overlapped in these conditions. The study suggested that additional tidal normalisations are needed in these areas to improve the accuracy. Overall, the study highlighted the efficiency of thresholding techniques for operational shoreline delineation.

Shoreline changes were monitored using automated thresholding and multi-temporal backscatter Sentinel-1 SAR images (Isiaka and Tata, 2024). The extracted shorelines were compared and validated against reference datasets and ground observations. The results showed that thresholding produced consistent shoreline maps over time. However, the accuracy of the results was dependent on the choice of the threshold values as well as the effectiveness of post-processing to reduce the speckle noise. Furthermore, the study highlighted that the SAR and thresholding-based techniques can be a reliable and cost-effective alternative for large-scale coastal monitoring, particularly in regions where higher-cost methods are deemed as impractical (Isiaka and Tata, 2024).

In addition to the thresholding-based techniques, the previous studies also applied edge detection methods to extract shoreline boundaries. Edge detection methods are used to identify abrupt changes in backscatter intensity which corresponds to the transition between land and water (Dike et al., 2023). Various edge detection methods have successfully applied to shoreline detection which include Sobel, linear and Canny (Sun et al., 2023). The Canny edge detection has been specifically used to extract edges using SAR data (Zollini et al., 2023). Previous studies have stated that the Canny edge detection method performs best in visual objects with high-signal to noise ratio, high positioning accuracy, strong single-edge response ability and clear continuous edges (Zhou et al., 2023). However, in areas where the coastline image background is complex, the Canny edge detection algorithm is sensitive to noise and manual intervention may be required (Zhou et al.,2023)

In the study conducted by Dike et al. (2023), comparable results were produced by both the thresholding-based and edge detection techniques. The edge detection method performed well in areas where there was a strong backscatter contrast between land and water. The accuracy was reduced in high tide conditions. Similar results found in a previous study concluded that edge detection techniques improved the delineation of shoreline boundaries in complex coastal areas (Isiaka and Tata, 2024). The study also highlighted that edge detection can complement thresholding methods by detecting greater boundary sharpness and improving the accuracy when both methods are combined.

To assess the accuracy, Digital Shoreline Analysis System (DSAS) metrics can be used to statistically quantify shoreline changes (Oyedotun, 2014). These metrics measure the time series changes of extracted shorelines and detect trends of erosion, accretion, or stability over time (Murray et al., 2023). The metrics include Net Shoreline Movement (NSM), End Point Rate (EPR) and Linear Regression Rate (LRR). NSM and EPR are both indicators of net change and short-term rates whereas LRR provides long-term trends and mapping of significant changes. NSM measures the total displacement between the earliest and latest shoreline present in the time series, while EPR determines the average annual rate of change through the end-point shorelines (Kilar, 2023). LRR uses regression on all the extracted shorelines to estimate long-term trends and confidence intervals which reduce its sensitivity to outliers and makes it better suited to significance testing and trend detection (Paz-Delgado et al., 2022). Shoreline change detection used the DSAS technique to automatically quantify erosion and accretion pattens in the North Sinai coast (Nasser et al., 2018). Isiaka and Tata (2024) made use of these three DSAS metrics to quantify the erosion rates along the Lagos lagoon coastline and predict the future shoreline positions, thereby demonstrating how the implementation of these metrics can both be used to identify erosion prone areas and support coastal-risk forecasting.

SAR remote sensing combined with thresholding, edge detection and statistical methods offers an efficient approach to delineate shoreline boundaries. However, the limitations of SAR for shoreline detection are that high wave action can increase the speckle effect and preprocessing may not always be effective. Furthermore, small-scale changes in shoreline features may be misclassified using medium-resolution SAR data (Ferrentino et al., 2023). Despite the inherent limitations of SAR remote sensing, integrating SAR, thresholding, edge detection and DSAS techniques remains a suitable method for accurately delineating shoreline boundaries. However, as evident from previous studies, there is a need for more robust approaches that can be used to accurately delineate the dynamic land-water boundary, as both thresholding and edge detection methods exhibit decreased performance in tidal environments given the dynamic nature of swash zones. This study aims to explore the performance of these existing methods and possible improvements.

3. Methodology

The methodology developed for this research follows a quantitative approach using SAR remote sensing data and thresholding techniques to detect shoreline changes. The workflow of the methodology is shown in Figure 1. The three different study areas and the data used in the study are presented in Sections 3.1 and 3.2. Thereafter, the pre-processing steps are briefly described in Section 3.3. Sections 3.4 and 3.5 discuss the use of the thresholding-based and edge detection methods. Finally, Section 3.6 presents the morphological filtering and the DSAS evaluation for statistical analysis.

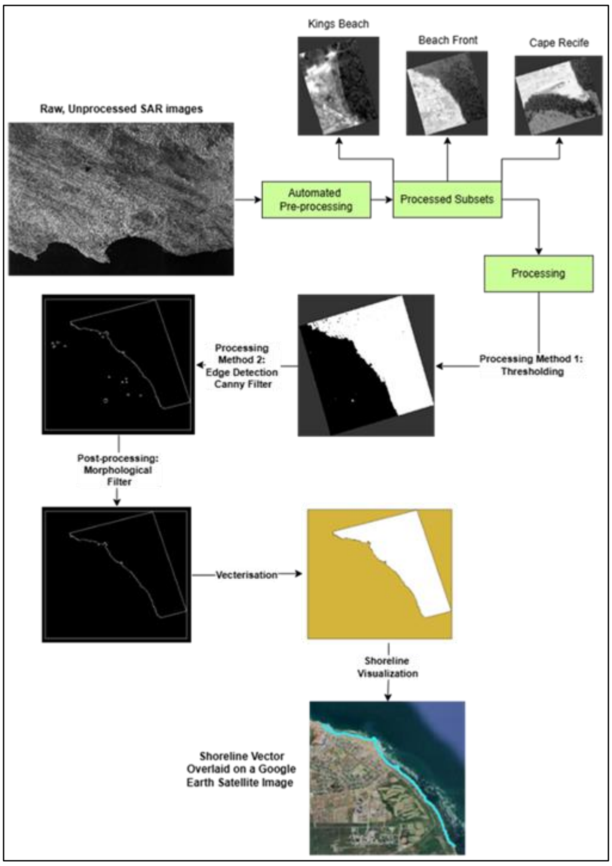

Figure 1. The methodology followed to extract shoreline boundaries from Sentinel-1 SAR imagery.

3.1 Study Areas

Three different coastal areas in Gqeberha, South Africa were used as the areas of interest. The areas are Kings Beach, Nelson Mandela Bay beach front and Cape Recife nature reserve as illustrated in Figure 2 Gqeberha is situated in the Eastern Cape Province of South Africa and is one of five major seaports in the country. The coastal environment of Gqeberha has great variability, with sandy beaches and coastal dunes as well as sheer and rocky shorelines (Lubke and Bruton, 1988). The city of Gqeberha is part of Algoa Bay which is dominated by South-Westerly swells and the occurrence of a longshore current. The longshore current is water that flows parallel to the shoreline; this occurs when the waves approach the shore at an angle, causing the water to break sideways. As the water breaks there is a continuous flow along the shore. The longshore current is therefore a key driver of coastal erosion and accretion, as it creates a mechanism that causes the displacement and deposition of sediment in the bay (Lubke and Bruton, 1988). As a result, the movement of the sediment along the coastline by obliquely breaking waves is known as longshore drift.

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The first area of interest is the Cape Recife Nature Reserve which is an environmental protected area, focused on the preservation of endangered coastal fynbos and marine life. The area consists of unspoilt beaches, natural dune vegetation and rocky outcrops. This area has less human activity than the other two study sites, and this suggests that the shoreline changes that result from human activity are less drastic. The longshore drift along the rocky promontories can cause erosion and accretion processes to occur in this area.

The second study area is the Nelson Mandela Bay beach front which consists of a long stretch of beaches such as Hobie Beach, Bird Rock Beach and Pollock Beach. All three of these areas have a high rate of daily human activity. Furthermore, there are commercial and residential developments along the bay which could contribute to shoreline changes. The area mostly consists of sandy, flat and even shores. The sand can be easily carried away by erosion forces such as wind and waves.

The third area of interest is Kings beach which is a strip of beach area between an industrial area and the Port of Gqeberha harbour. The Port of Gqeberha is one of the biggest exporters of manganese globally. The area of the harbour breakwater has a similar effect to Cape Recife Nature Reserve of the longshore current and rocky outcrops. This suggests that there are increased erosion and accretion processes.

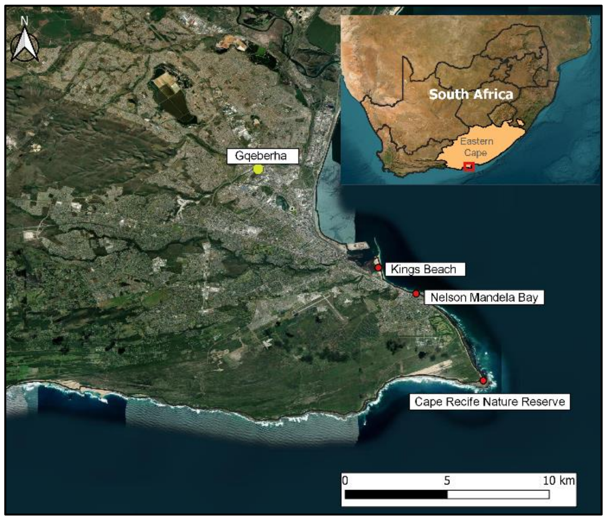

Figure 2. Map showing the locations of the three coastal areas that constitute the study area, these are Kings beach, Nelson Mandela Beach front and Cape Recife nature reserve.

3.2 Data

To extract the shorelines in the study, C-band Sentinel-1 GRDH (Ground Range Detected in High Resolution) data were used to derive the SAR backscatter coefficient. Sentinel-1 is a SAR instrument that operates at C-band at various spatial resolutions and imaging modes. The spatial resolution for the GRDH imaging mode is approximately 14 m. A total of 118 images from 2014 to 2024 were acquired from Alaska Satellite Facility (ASF) Vertex. The subsets of the areas of interest were undertaken, and the final output consisted of 354 images. The images were collected in Interferometric Wide swath mode and in ascending orbit. The temporal resolution ranged between 12 and 36 days. Both the vertical-vertical (VV) and vertical-horizontal (VH) polarisations were used in the analysis.

3.3 Deriving backscatter from the C-band SAR data.

The derivation of SAR backscatter was undertaken using a standard generic methodology described by Filipponi (Filipponi, 2019). The workflow that was applied in ESA's SNAP toolkit included preprocessing steps designed to reduce error propagation. The steps include updating the orbital file, thermal noise removal, border noise removal, radiometric calibration, speckle filtering, terrain correction and a logarithmic transformation to decibels. The first and second steps included updating the orbital information and removal of the thermal noise. This function reduced the noise effects in the inter-sub swath texture and normalised the backscattered signal within the entire Sentinel-1 scene (Filipponi, 2019). The thermal noise removal and border noise removal can be applied as an optional step in areas near the borders of the image that are prone to additional noise. The fourth step included radiometric calibration of the images, which involved converting the raw intensity values into the sigma nought backscatter values. Once the images were radiometrically calibrated, a speckle filter was used to remove the effect of speckle as the fifth step. In this instance, the Refined-Lee filter with a kernel size of 3x3 and a damping factor of 1 was used. The sixth step, terrain correction was performed using the 30 m Copernicus Digital Elevation Model through the Range-Doppler approach on each image to geocode the data from slant range to ground geometry. The last step of the process is converting the unitless backscatter coefficient to decibels (dB) using a logarithmic transformation (Filipponi, 2019). The output backscatter images were used as input for the thresholding-based technique.

3.4 Thresholding SAR backscatter

A histogram-based thresholding method was computed to visualise the backscatter values and determine the appropriate separation point, also known as a threshold value. For each image in the three study areas, the midpoint of the backscatter coefficient was selected as the threshold value illustrated in Figure 3. The threshold values ranged from -19.1 to -25.7. These values were used to separate and classify the pixels into two classes namely, water and land. Smoother surfaces such as bodies of water are known to have lower backscatter values and areas with rougher surfaces such as sandy or gravel beaches have higher backscatter values. Water surfaces will have a peak concentrated on the lower end of the intensity range, while land surfaces are concentrated at the higher end of the intensity range. This creates a distinct bimodal distribution on the histogram. The output was a land-sea segmentation map which was visually inspected and used as input for the edge-detection method.

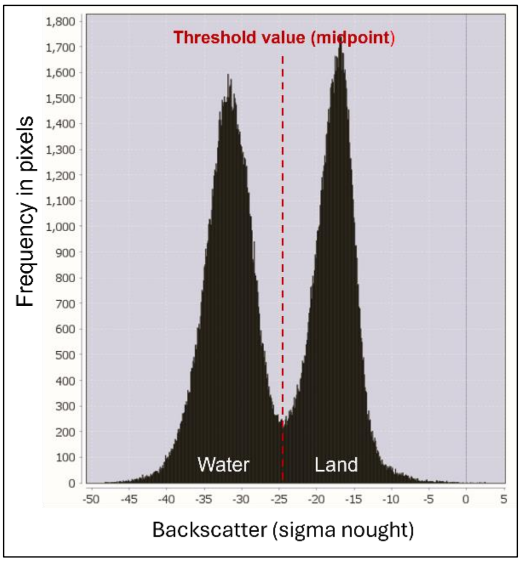

Figure 3. Example of a bimodal histogram distribution of the backscatter coefficient showing the separation between water and land.

3.5 Edge detection techniques used to delineate shoreline boundaries

As discussed in literature, thresholding-based methods can misclassify waves, wet sand and certain urban areas as applicable to the study area defined in this paper. Edge detection techniques are thus used complementary to the defined thresholding method to extract boundaries from the land-water threshold maps. An adaptive Canny filter edge detection technique was applied to the land-sea segmentation maps that were created from the thresholding method in section 3.4.

The Canny edge detection method was applied using OpenCV software. The algorithm consists of four stages which are: 1) noise reduction by applying a Gaussian filter, 2) the gradient magnitude and angle is computed, 3) non-maximum suppression and 4) hysteresis thresholding (Hu and Xiao, 2013). Due to the variability of the three study areas, an adaptive approach was selected for the hysteresis thresholding stage. The following equations were used to extract the boundary pixels:

$$\text{Lower threshold} = \sigma \times \text{median(land\_sea mask)} \quad (1)$$
$$\text{Upper threshold} = (1+ \sigma) \times \text{median(land\_sea mask)} \quad (2)$$

where $\sigma = 0.33$

The lower threshold (Equation 1) filtered the weak edges, and the upper threshold (Equation 2) identified the strong and defined edges. The default value for sigma of 0.33 was used. The median value of the land-sea masks was used because the median value is better at preserving edges between two different features (Qui et al., 2013). The result is a continuous boundary. The shoreline boundaries were then used in a sensitivity analysis to evaluate erosion and accretion patterns.

3.6 Sensitivity Analysis

To assess the accuracy of the shoreline boundary, two processes were evaluated. Firstly, morphological filtering was used to refine the edges and reduce the noise by using smoothing techniques. This process reduces the noise by eliminating isolated or misclassified pixels. The shorelines derived were then

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converted from raster to vector. Thereafter, a statistical analysis DSAS was used to quantify erosion and accretion rates in the three areas of interest and to evaluate the long-term trends over the ten-year period. The metrics were calculated for each month for each study area from August to December.

Secondly, various statistical metrics were generated using the baseline and the transects of each extracted boundary. This was conducted in QSCAT plugin in QGIS. The method starts by selecting a baseline layer and a shoreline vector for each year. It should be noted that Eastern Cape provincial boundary was provided by the South African Environmental Ocean Network (SEAON) and was used as the baseline for the position of the shoreline. A spacing of 25 m was chosen to determine the number of measurement locations, the transect length was set to 2000 m to ensure that all the shorelines were intersected. The shoreline changes metrics between all the shoreline vectors and the baseline layer was calculated. Four statistical metrics were calculated which included the Linear Regression Rate (LRR), Standard error (LR^2), Standard error of estimate (LSE) and Lower confidence interval (LCI). The LRR (m/year) represents the slope of the linear regression line and is a measure the average long-term change that occurs in the area of interest. Positive LRR values indicates that the shoreline is moving seaward and suggest accretion has occurred. In contrast, negative LRR values indicate that the shoreline is moving landward and suggest that there is erosion taking place. When the LRR value is zero there are no long-term erosion or accretion trends that can be observed. Other metrics were also calculated, namely the standard error (LR^2) associated with the LRR estimate. The LR^2 measures how much uncertainty there is in the slope estimate. The LSE regression is the measure of the spread of the data points relative to the regression line. The LCI was used to represent where the lowest possible erosion or accretion rate will be statistically supported. The metrics were evaluated for each study area, and the erosion and accretion patterns were discussed.

4. Results

After the preprocessing, processing and post processing of the SAR images, 144 shorelines were extracted, 48 for each of the 3 study sites. These shoreline vectors visualised how the shorelines changes from 2014 to 2024. Coastal erosion and accretion processes shows seasonality along the Gqeberha coastline. Therefore, erosion and accretion patterns were assessed during the August to December period. A total of 144 (48 for each area of interest was extracted from all the SAR images. The results for the Cape Recife, Nelson Mandela Bay beach front and the Kings beach area are discussed in Sections 3.1, 3.2 and 3.3 respectively.

4.1 Cape Recife

The extracted shorelines were derived from Sentinel-1A SAR data from 2014 to 2024. An example of the extracted shorelines is shown in Figure 4 for the year 2024.

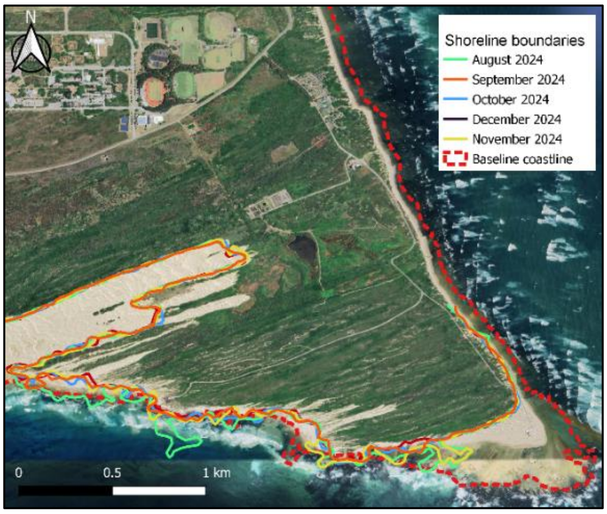

Figure 4. Shorelines derived from Sentinel-1 data in the Cape Recife area showing the changes between August 2024 and December 2024.

The statistical analysis of the Cape Recife shorelines from 2014-2024 shows that this study site aligns with the erosion seasonality, as can be seen by the results in Table 1.

Month	LRR (m/year)	LR^2	LSE	LCI
August	-0.01	0.23	93.92	95.72
September	-1.54	0.23	8.49	6.34
October	-3.28	0.14	41.73	24.05
November	0.61	0.12	28.49	13.18
December	3.36	0.09	73.02	33.34

Table 1. The statistical analysis of the shorelines extracted for the Cape Recife areas from August to December (2014 to 2024).

The months of August to October experience erosion, with the LRR values being predominantly between -0.01 and -3.28 m/year, with October experiencing the peak erosion phenomena. The LRR values for November and December indicate accretion, with 3.36 m/year of accretion. This is expected as seasonal recovery occurs during the December period. The LR^2 values range from 0.09 to 0.23, which indicates that the slope estimations are moderately reliable. The LSE values are varied, ranging from 8.49 to 93.92, indicating that the shoreline positions fluctuate around the regression line. The LCI values range from 6.34 to 95.72. This implies that there is high natural variability, which could most likely be due to storm events.

4.2 Nelson Mandela Bay beach front

The extracted shorelines for this area of interest were assessed from 2014 to 2024. The shorelines that were extracted from 2024 are shown in Figure 5. The derived statistical metrics are shown in Table 2.

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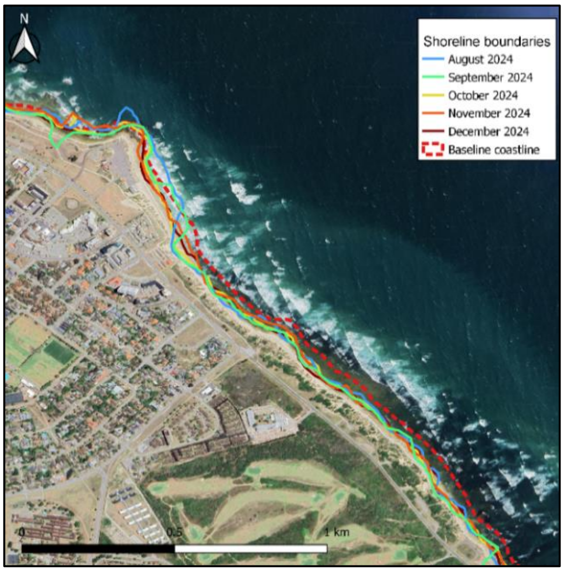

Figure 5. Shorelines derived from Sentinel-1 data for the Nelson Mandela Bay Beach Front area from August 2024 to December 2024.

Month	LRR (m/year)	LR^2	LSE	LCI
August	-0.17	0.14	19.04	9.71
September	-4.45	0.28	24.26	17.96
October	-4.78	0.30	37.15	16.37
November	-1.90	0.12	36.58	16.85
December	2.69	0.12	38.09	14.57

Table 2. The statistical analysis of the shorelines extracted for the Nelson Mandela Bay beach front areas from August to December (2014 to 2024).

The LRR values indicate that erosion occurred between August and October, where the maximum erosion was -4.78 m/year. An expected erosion seasonality can be seen from October to December, which suggests that there was accretion due to the calmer summer conditions. The LR^2 ranged between 0.12 to 0.3, and the LSE values ranged between 19.04 and 38.09. The LCI suggests there was high variability which could be attributed to anomalies in the shoreline extraction.

4.3 Kings beach

The third study area that was evaluated was Kings beach. The shoreline delineation was extracted from August to December from 2014 to 2024. The results for the shoreline extraction for the year 2023 are indicated in Figure 6. The statistical analysis is presented in Table 3.

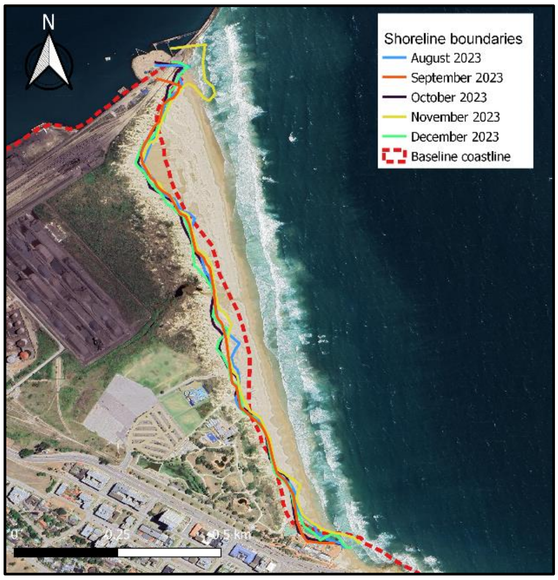

Figure 6. Shorelines derived from Sentinel-1 data for the Kings beach area showing the shoreline boundaries from August to December 2023.

Month	LRR (m/year)	LR^2	LSE	LCI
August	0.94	0.18	9.73	4.97
September	0.96	0.28	7.73	7.82
October	1.26	0.29	7.95	5.87
November	1.55	0.34	8.39	3.89
December	1.68	0.38	7.89	4.26

Table 3. The statistical analysis of the shorelines extracted for the King Beach area from August to December (2014 to 2024).

For the Kings beach areas, the results show that accretion occurred between August and December for each year. The LRR values indicate consistent accretion from August to December, with the LRR values intensifying from October to December, which indicates strong sediment deposition heading into the summer months. In contrast to the results for the previous two areas of interest the erosion seasonality is not observed for this area. The LR^2 values range from 0.18 to 0.38, indicating low uncertainty in the estimated LRR values. The LSE values are low and stable, with a range of 7.73 and 9.73 indicating that the regression line fits the shoreline data well, with very little variation present. The LCI ranged between 3.89 and 7.84.

5. Discussion

Coastal erosion and accretion can be quantified by measuring the rate of shoreline movement over time which can be expressed as metres per year. The research aimed to determine if medium resolution SAR data can be used to quantify coastal change. For the Cape Recife area of interest, the results aligned with the expected erosion seasonality, with periods of erosion occurring between winter (August to October) and accretion in the summer months (November to December). The headland in the area is comprised of resistant rock which is subjected to volatile wave action and currents and caused a swash zone. It should be noted that for the Cape Recife area of interest the derived land-sea boundary classification was not accurate. SAR backscatter is influenced by the moisture content of the ground. In this specific area, there are swash zones (areas where the waves run up and down the beach), and high moisture content is expected. This can lead to the misclassification of the land-sea boundary of the shoreline (Dike et al., 2023). The high LSE and LCI values suggest that there is significant natural variability that could be due to high wave action and storm surges.

The shorelines that were derived in the Nelson Mandela Bay beach front area deviated from the erosion seasonality, and a continuous erosion trend was observed. The highest LRR values was in October 2024 which is not expected. The deviations from the expected erosion seasonality can be attributed to human-induced factors (Christofi et al., 2025). The area is in proximity to both commercial and residential areas, which can influence the sediment dynamics. The third area of interest was Kings beach and the results indicated that a consistent accretion trend occurred. The accretion trend from August to December did not follow erosion seasonality trends that were expected. This could be attributed to the Port of Gqeberha’s Harbour wall which barricades the sediment that is transported via the longshore drift phenomena. This leads to the sediment being deposited on or adjacent to the Kings beach area. The low LSE, LCI also suggests that there were low deviations from August to December for the period from 2014 to 2024.

The erosion and accretion patterns were detected by leveraging the contrast that exists between the SAR backscatter intensities of the water and the land boundaries. However, there were some limitations to the study. Firstly, the baseline shoreline boundary was a generalised provincial shoreline boundary. A more precise baseline extracted from LiDAR or high-resolution optical imagery is recommended for further research. Secondly, in areas where dynamic tidal and wave action is expected, integrating tidal correction would be beneficial. Lastly, further research into the variation of the beach types and SAR backscatter can be undertaken. Overall, the resulting variation in the occurrence of the erosion and accretion patterns across the three study sites indicate how dynamic and complex the interaction is between the natural and anthropogenic drivers

6. Concluding remarks

The aim of the research was to determine if SAR remote sensing techniques could be used to derive shorelines to quantify coastal change. The shorelines were derived from three different areas of interest in the Eastern Cape province of South Africa from 2014 to 2024. The findings confirm that SAR remote sensing is suitable for detecting and monitoring coastal changes in three different coastal environments. There were limitations specifically in areas where high moisture content levels were experienced which led to misclassifications of the land-sea boundary. The resulting areas influence the scattering mechanisms that can be observed from the SAR backscatter. Despite these limitations, the use of SAR remote sensing techniques can be used to evaluate coastal change in areas that are predisposed to inclement weather due to the all-weather capabilities.

All three of the study sites used in this research were different types of beaches. Further research can expand upon how the variation of beach types affect SAR’s ability to detect land-sea boundaries. This can be carried out by comparing SAR’s performance across sandy beaches, rocky beaches, wet and dry beaches, any manner of beach variation can be used. This approach can also be used to evaluate the ability to which SAR can detect human interventions for coastal erosion and quantify their effectiveness. Furthermore, a temporal analysis of the research can be expanded to full years instead of a few months, to isolate the long-term trends of erosion and accretion from episodic weather occurrences or short seasonal variations. The findings can contribute to effective coastal management of coastal environments.

References

Christofi, D., Mettas, C., Evagorou, E., Stylianou, N., Eliades, M., Theocharidis, C., Chatzipavlis, A., Hasiotis, T., Hadjimitsis, D., 2025. A Review of Open Remote Sensing Data with GIS, AI, and UAV Support for Shoreline Detection and Coastal Erosion Monitoring., *Appl. Sci*. 15, 477, 11–43.

Celliers, L., Breetzke, T., Moore, L., Malan, D., 2009. A User-friendly guide to South Africa’s Coastal Management Act. The Department of Environmental Affairs and SSI Engineers and Environmental Consultants. Cape Town, South Africa.

Di Biase, V., Hanssen, R.F., 2024. Analyzing coastal erosion and sedimentation using Sentinel-1 SAR change detection: An application on the Volta Delta, Ghana. *Egypt. J. Remote Sens. Sp. Sci*. 27, 137–145. https://doi.org/10.1016/j.ejrs.2024.02.003.

Dike, E.C., Oyetunji, A.K., 2023. Shoreline Delineation from Synthetic Aperture Radar (SAR) Imagery for High and Low Tidal States in Data-Deficient Niger Delta Region*. J. Mar. Sci*. Eng. 11, 1528.

Ferrentino, E., Famiglietti, N.A., Nunziata, F., Inserra, G., Buono, A., Moschillo, R., Memmolo, A., Colangelo, G., Vicari, A., Migliaccio, M., 2023. The Use of Satellite Synthetic Aperture Radar Imagery to Assist in the Monitoring of the Time Evolution of Challenging Coastal Environments: A Case Study of the Basilicata Coast. *Environments.* 10, 212.

Filipponi, F., 2019. Sentinel-1 GRD Preprocessing Workflow. *Proceedings*, 18, 11. https://doi.org/10.3390/ECRS-3-06201

Garrido, M.S, Gimenez, M.I., Gil, A.J., 2012. A high spatio-temporal methodology for monitoring dunes morphology based on precise GPS-NRTK profiles: Test-case of Dune of Monsul on the south-east Spanish coastline. *Aeo. Res.* 8, 75-84.

Goble, B.J., Lewis, M., Hill, T.R., Phillips, M.R., 2014. Coastal management in South Africa: Historical perspectives and setting the stage of a new era. *Ocean Coast. Manag*, 91 32–40.

Griffiths, C.L., Robinson, T.B., Lange, L., Mead, A., 2010. Marine Biodiversity in South Africa: An evaluation of current states of knowledge. *PLOS ONE,* 5(8), e12008. https://doi.org/10.1371/journal.pone.0012008

Hu, G., Xiao, X., 2013. Edge detection of oil spill using SAR image. Cross Strait Quad-Regional Radio Science and Wireless Technology Conference, Chengdu, China, 2013, 466-469. doi: 10.1109/CSQRWC.2013.6657456.

Isiaka, I.O., Tata, H., 2024. Futuristic prediction of the lagoon coast shorelines using spaceborne Synthetic Aperture Radar (SAR) imagery. *Nova Geodesia* 4(2): 184.

Kilar, H., 2023. Shoreline change assessment using DSAS technique: A case study of Meric Delta. *Heliyon*, 9(2), e13124.

Lubke, R., Bruton, M., 1988. A field guide to the Eastern Cape coast. Grahamstown: Wildlife Society of Southern Africa.

Luijendijk, A., Hagenaars, G., Ranasinghe, R., Baart, F., Donchyts, G., Aarninkhof, S., 2018. The State of the World’s Beaches. *Nat. Sci. Rep*.–11. https://doi.org/10.1038/s41598-018-24630-6.

Mentaschi, L., Vousdoukas, M.I., Pekel, J., Voukouvalas, E., Feyen, L., 2018. Global long-term observations of coastal erosion and accretion. *Sci Rep,* 8. https://doi.org/10.1038/s41598-018-30904-w.

Moreira, A., Pratsiraola, P., Younis, M., Krieger, G., Hajnsek, I., Papathanassiou, K.P., 2013. A tutorial on synthetic aperture radar. *IEEE Geosci. Remote Sens. Mag*. 1, 6–43. https://doi.org/10.1109/MGRS.2013.2248301.

Murray, J., Adam, E., Woodburne, S., Miller, D., Xulu, S., Evans, M., 2022. Monitoring Shoreline Changes along the Southwestern Coast of South Africa from 1937 to 2020 Using Varied Remote Sensing Data and Approaches. *Remote Sens,* 15(2), 317.

Nasser, K., Mahmod, W. E., Fath, H., Masria, A., Nadaoka, K., Negm, A., 2019. Shoreline change detection using DSAS technique: Case of North Sinai coast, Egypt. *Mar. Georesour. Geotechnol,* 37(1),81-95.

Oyedotun, T. D. T., 2014. Shoreline Geometry: DSAS as a tool for Historical Trend Analysis. *Geomorphological Techniques*. British Society of Geomorphology.

Paz-Delgado, M.V., Payo. A., Gomez-Pazo, A., Beck, A.L., Savastano, S., 2022. Shoreline change from optical and SAR satellite imagery at macro-tidal Estuarine, Cliffed Open-Coast and Gravel Pocket-Beach Environments. *J. Mar. Sci. Eng*, 10(5), 561. https://doi.org/10.3390/jmse10050561

Prasad, D. H., Kumar, N. D., 2014. Coastal Erosion Studies – A Review. *Int. J. Geosci.,* 5, 341-345.

Qui, F., Berglund, J., Jensen, J. R., Thakkar, P., Ren, D., 2004. Speckly noise reduction in SAR imagery using a local adaptive median filter. *GIScience & Remote Sensing*, 41(3), 244-266, doi: 10.2747/1548-1603.41.3.244.

Sun, W., Chen, C., Lui, W., Yang, G., Meng, X., Wang, L., Ren, K., 2023. Coastline extraction using remote sensing: a review. *GIScience & Remote Sensing,* 60(1), 2243671.

Zhou, X., Wang, J., Zheng, F., Wang, H., Yang., 2023. An Overview of Coastline Extraction from Remote Sensing. *Remote Sens,* 15. https://doi.org/10.3390/rs15194865

Zollini, S., Dominici, D., Alicandro, M., Cuevas-Gonzalez, M., Angelats, E., Ribas, F., Simarro, G., 2023. New Methodology for Shoreline Extraction Using Optical and Radar (SAR) Satellite Imagery. *J. Mar. Sci. Eng.,* 11, 627. https://doi.org/10.3390/jmse11030627