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Deep Learning-based Derivatives for Shoreline Change Detection in Cape Town, South Africa

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Abstract

Coastal environments are vital for sustaining key industries, including fisheries, mining, real estate, and tourism, through the provisioning of essential ecosystem services. However, the intricate interplay of bio-chemical and physical processes in these areas is susceptible to disruption by human-driven coastal developments. This disruption has gradually led to adverse consequences such as altered water movement patterns, land quality degradation, habitat loss, pollutant introduction, greenhouse gas emissions, and subsequent sea-level rise. With Cape Town's 240-kilometre coastline serving as a prime example of this complex relationship between coastal processes and livelihoods, this study employs innovative remote sensing and deep learning techniques. We use Sentinel-2 satellite imagery and the Deep Learning-based CoastSat Python toolkit, specifically leveraging the Modified Normalized Difference Water Index (MNDWI) for sub-pixel level shoreline detection. Focusing on four critical Cape Town coastlines - Noordhoek-Kommetjie, Milnerton, Strandfontein-Monwabisi, and Strand, we assess and compare shoreline changes as detected by the CoastSat toolkit. Our findings reveal significant shoreline changes, with Strandfontein-Monwabisi experiencing the most substantial shift, approximately 284 metres. Noordhoek-Kommetjie exhibited a change of 110 metres, while Milnerton and Strand displayed similar changes, with 88 and 91 metres, respectively. This research not only offers valuable insights into Cape Town's dynamic coastlines, but also informs the strategic allocation of coastal management resources. Consistent data collection and analysis hold the potential to foster interactive coastal monitoring tools, enhancing the effectiveness and sustainability of coastal management practices.

Key words: Sentinel-2 satellite imagery, Coastal monitoring, Land quality degradation, Habitat loss, Sea-level rise, Modified Normalized Difference Water Index (MNDWI), Deep Learning, Sustainability

1. Introduction and Background

Coastal sediment movement is a measure of coastal change characterized as either the disintegration and loss of beach sediments by wave action or the restoration of loose sediment to the visible portion of the beach which, in turn, raises the beach level (Roebeling *et al*, 2011). Coastal zones have become a global concern because of their dynamic and unpredictable nature, where the landward retreat of coastlines is also an indicator of sea-level rise because of enhanced climate change (Whittal and Mackie, 2023). This leads to the loss and degradation of land, habitats and ecosystems, as already observed in low-lying places such as the Maldives and Indonesia (Harangozo, 1992; Nurhidayah *et al*, 2022). Anthropogenic activities are a major driver of global warming and the pursuit of socio-economic endeavours derived from the aesthetics and natural resources of coastal zones has exacerbated climate-induced changes along coastlines. Our continual expulsion of greenhouse gases into the atmosphere leads to temperature rises and may exacerbate the increment in the recurrence and intensity of both coastal storms and erosion, which leaves little time for the beach to recover (Rouault *et al*, 2010). The increased frequency of high energy waves along South Africa's coastline has in recent years intensified coastal erosion (Fourie *et al*, 2015). One such example is the Cape storm that occurred in June 2017 that spanned 48 hours and caused records of 11-metre-high waves and collapsed coastal dunes (Barnes *et al*, 2021; Dube *et al*, 2021). The responses to coastal climate change have been slow, particularly in the Global South, and more so in Africa[1]. Coastal climate change is viewed as a remote phenomenon which is not of immediate concern, while issues centred around the economic disparity that exists between Africa and the rest of the world take centre stage. However, climate change has only exposed and exasperated the African vulnerabilities (Department of Environmental Affairs: Climate Change, 2018).[2] There are several attributes and influences of interest along coastlines, such as the underlying geology, biotic factors, and tides, which occur over varying time scales and spatial extents. The response of coastal zones to the combined effect of these influences has thus far not been quantified, and coastal observation is therefore becoming a major research target (Colenbrander and Bavinck, 2017; Mather et al, 2009; Whittal and Mackie, 2023). Despite the growing body of literature that addresses various coastal management aspects, to date, most approaches to coastal observation have been based on numerical modelling which can be inaccessible for people without the appropriate expertise.

Remote sensing (RS) has increasingly become a well-integrated tool for coastal observation, particularly with the availability of freely accessible satellite imagery such as the Landsat or Sentinel constellations which offers continuity of coverage (Acharya *et al*, 2016; European Space Agency, 2021; Gomez *et al*, 2014). The principle of (RS) is based on capturing the spectral response of earth surfaces as they interact with electromagnetic energy that is incident on them and recorded by receiving sensors[3] (Gens, 2010). Geospatial sciences have integrated several measures into the shoreline change matrix, including vegetation lines, coastal landforms, or instantaneous waterline wet/dry boundaries. Furthermore, studies have combined varied approaches, such as using Global Positioning Systems (GPS) or Light Detection and Ranging (LiDAR) surveys and Differential Interferometry Synthetic Aperture Radar (DInSAR), to create robust Digital Elevation Models (DEM's) and to mark the edge of vegetation and infrastructural limits or capture instantaneous shorelines. However, these applications have proved to be labour-intensive and build around optical imagery which, owing to easy accessibility, is not only the earliest form of remote sensing but remains a dominant preference (Grandin, 2015; Lee *et al*, 2016; Pe'eri and Long, 2011). The optical operation attributes a value to every pixel in an image associated with a specific reflectance that allows it then

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[1,2] Department Of Environmental Affairs: Climate Change 2018. South Africa's 3rd Climate Change Report. Pretoria

[3] CCRS 2004. Canada Centre For Remote Sensing. Remote Sensing Tutorial. Fundamentals Of Remote Sensing

to be classified as a particular land cover or theme (Ashraf *et al*, 2011). However, this classification approach struggles in heterogenous spaces, such as coastal regions, where both the spectral and spatial variations present complexities ─ owing to the influence of turbidity, pollutants, plankton, and the bio-chemical composition of coastal waters ─ which alter the optical properties of water bodies (Loubersac, 2003). Figure 1 shows scenes from two beaches in Cape Town.

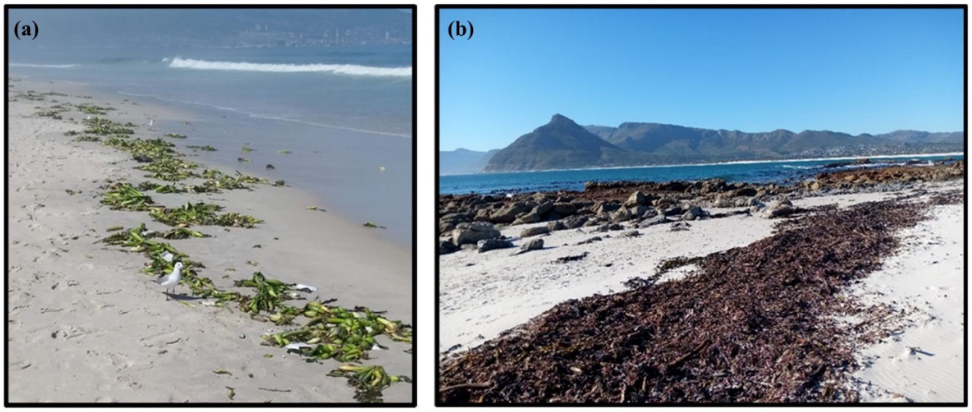

Figure 1. Scene complexity with seaweed flotsam along (a) Milnerton Beach and (b) Kommetjie Beach

This paper aims to employ deep learning strategies on Sentinel-2 data to quantify and compare the coastal change of four (4) beaches under different environmental, geomorphic, and hydrodynamic conditions along the Cape Town coastline. The researchers achieved this by detecting the high-water mark by capturing instantaneous waterlines. Cape Town represents an interesting case in the given context because of its unique geology, thriving coastal tourism industry and the prevailing social inequalities that have led to the growth of informal settlements along its coastlines, intimating poor coastal and town planning (Colenbrander *et al*, 2014; Dube *et al*, 2021; Searson and Brundrit, 1995). The researchers then used a plug-and-play python-coded toolkit called CoastSat to detect the shorelines, which were then used to calculate the cross-shoreline change (Vos *et al*, 2019a).

2. Associated Theory

Literature posits that clear water has the highest reflection within the blue waveband as opposed to the red band for turbid water, which is unexpected to the inexperienced remote sensing user, thus presenting a non-trivial analysis task (Acharya *et al*, 2016; Xu, 2006). Similarly, beach sand will experience a decrease in reflectance as its water content increases and its spectral signature is dependent on its mineral composition (Xu, 2006). The presence of phytoplankton, for example, will introduce chlorophyll into the system, thus affecting spectral responses and presenting further complexities for analysts (Loubersac, 2003). It is therefore important to have in-depth knowledge on satellite band designations and to optimally extract specific land covers and meet study objectives in a specific environment (Gens, 2010). Shorelines are naturally occurring edges as they are the interface between water and sand; thus their extraction is based on edge detection (Boak and Turner, 2005).

The successful manipulation of earth observation data in shoreline detection lies in how accurate the separation of land and water cover is (Boak and Turner, 2005; Stockdon *et al*, 2002). In low level processing, this can be accomplished through the usual remote sensing prescriptions of image classification, thresholding, or the application of spectral indices (Toure *et al*, 2019). Work derived from Otsu (1979) has seen the use of histogram stretching and thresholding applied to panchromatic images to use specific values to separate image components; however; in the case of multi-spectral imagery, colour, texture, pattern, and the geometry of the land components are used to simplify images into homogenous classes at the pixel level or through object-oriented classification (Acharya *et al*, 2016; Otsu, 1979). The fruits of these studies form the basis of early warning systems for coastal alerts and urgent coastal engineering. For the Global South, data scarcity and capacity to manipulate high-level analytical tools is a major hindrance to the full implementation of coastal alerts (Department of Environmental Affairs: Climate Change, 2018). Advances in research have fast-tracked several aspects of coastal analysis through the development of tools and platforms for coordinated work. Of specific mention is CoastSat, which is quickly becoming an accepted tool for coastal change observations and which is also available on an open-source basis (Vos *et al*, 2019b). It is a python-coded toolbox created by Vos *et al*, 2019b for the measurement of coastal change time series along any beach in the world (Repo and Tool; Vos *et al*, 2019b). Since its inception in 2019, researchers have applied CoastSat globally, especially with the restrictions that the COVID-19 pandemic imposed on fieldwork. However, it is yet to be applied to the Cape Town shores (Curoy *et al*, 2022; Gunasinghe *et al*, 2022; Vos *et al*, 2019a). Several studies have further shown its adaptability across various hydrodynamic and geomorphic conditions, as well as temporal scales. Because CoastSat is a relatively new tool, its efficacy is still under scrutiny and novel study areas for shoreline detection are showing their interest in its outcomes (Curoy *et al.,* 2022; Wei-Hao and Tseng, 2021; Gunasinghe *et al.,* 2022).

3. Materials and methods

1.1 Study area, materials and transects.

Cape Town is world renowned for its beaches and scenic coastal drives. The current study applied remote sensing and more specifically, tested deep learning tools on Sentinel-2 satellite imagery to determine and compare the shoreline changes along four of Cape Town’s coastlines. This detail, depicted in Figure 2, was sourced through the application of the CoastSat Python toolkit for Modified Normalized Difference Water Index (MNDWI)-based shoreline detection at the sub-pixel level. Multi-spectral Sentinel-2 products were used to detect coastlines along the Noordhoek-Kommetjie, Milnerton, Strandfontein-Monwabisi and Strand stretches of beach. Because the entire Cape Town coastline proved to be too long to process in one study and to reduce processing and storage strain, the four (4) regions of interest were separately delineated.

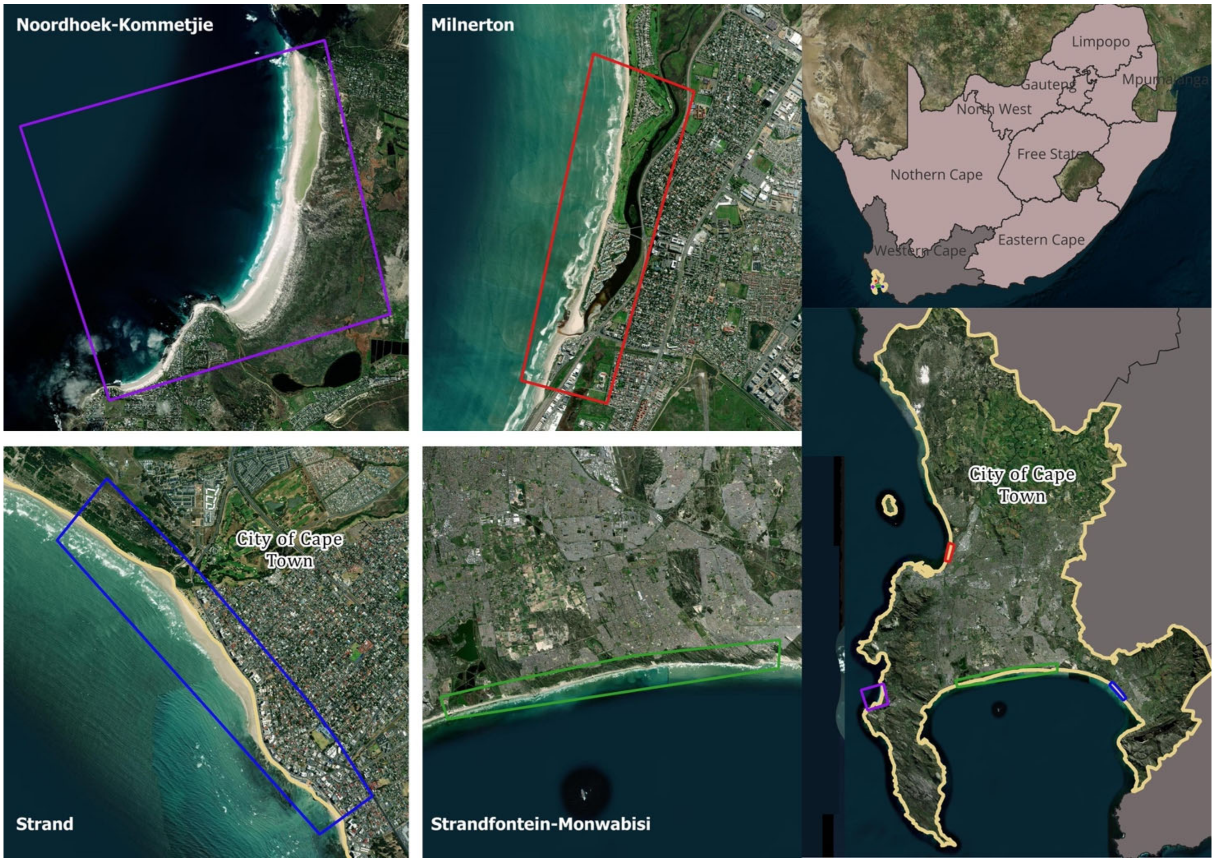

Figure 2. Study areas

Whilst Sentinel-2 has 13 bands, only the near infra - red (NIR), shortwave infra-red (SWIR), red, green, and blue bands were included in the extracted image. These bands were the most effective in the detection and separation of the expected coastal components such as sand, water, and vegetation. Research further filtered images of interest by date to focus only on those that in 2021 presented with a specified cloud cover percentage. Sentinel-2's quality assessment band, which has a pre-calculated by-pixel cloud mask, was used for this purpose (Zhu et al., 2015). The NIR, red, blue, and green bands occurring at a resolution of 10 metres (m) were of interest; however, the SWIR band had a resolution of 20m. To create spatial uniformity, the SWIR band was resampled to 10m using bilinear interpolation. It must be noted that Sentinel-2 can be incorporated into Landsat images, but, as postulated in the work done by Zhu *et al.* (2015), an accuracy of 15m can be achieved by using panchromatic band image sharpening. Past work has also shown that used in isolation, Sentinel-2 can achieve a much higher shoreline extraction accuracy for this very reason (Vos *et al*, 2019b). The number of usable images for the current study varied along the Cape Town coastline. This was due to the filtering of low cloud or the elimination of cloud shadows from the analysis and was based on preferences. The exact number of images, the actual extracted shorelines and the number of transects arelisted in Table 1.

Table 1. Summary of CoastSat shoreline extraction process

	Kommetjie	Strandfontein-Monwabisi	Milnerton	Strand
Total number of images	134	63	62	131
Number of usable shorelines	18	24	27	23
Number of Transects	26	30	22	21
Length of shoreline (km)	6	18.5	3.5	4

1.2 Shoreline extraction strategy and processing.

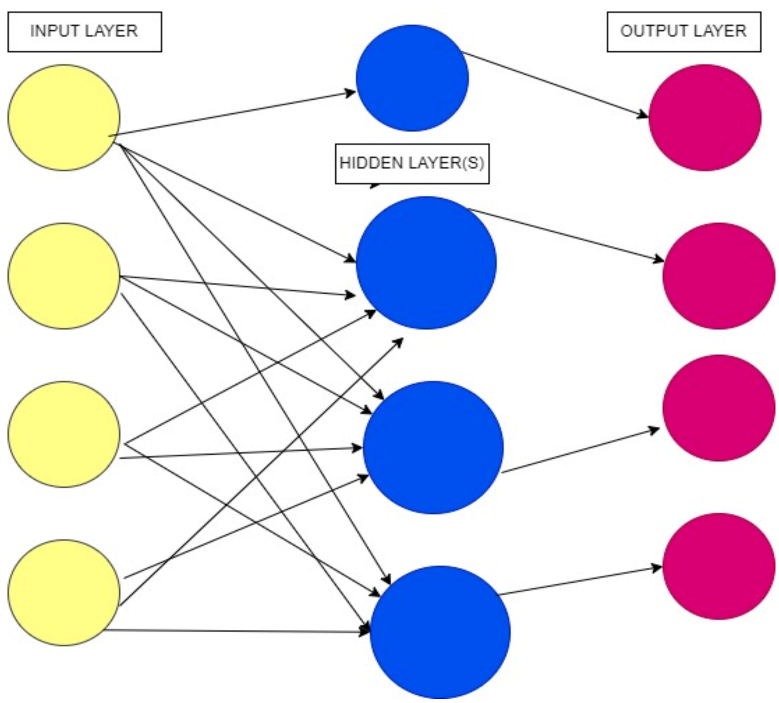

Figure 3. Layered illustration of the architecture of a neural network

The main processing for the study hinged on the following two prongs: extracting shorelines based on a deep learning classifier and quantifying shoreline change along cross-shore transects. Google Earth Engine (GEE) allows researchers to access at least 30 years of satellite data through the GEE Application Programming Interface (GEE API) using Jupyter notebook to access Top of Atmosphere (TOA) reflectance images (Chander et al., 2009). Research has shown that optimum shoreline detection is dependent on the spatial resolution of the images (Gens, 2010). To investigate CoastSat's ability to classify images, researchers have investigated its merits and losses. Ultimately, applying a deep learning Artificial Neural Network (ANN) classifier[4] on the backdrop of a water index-run image cluster has proven to be most effective, as originally proposed by Vos *et al.* (2019b) (Wei-Hao and Tseng, 2021). The ANN classifier, with its layered architecture (see Figure 3) and application of learning algorithms that can independently adjust as they learn, is used for the optimal prediction of shoreline position.

It was noted that image classification and spectral rationing were to be applied for edge detection in line with the findings of Vos *et al.* (2019b). This ANN classifier uses 20-pixel intensity explanatory variables, including the five (5) specified bands on top of or after the application of the spectral indices. These include the Modified Normalized Difference Water Index (MNDWI) or Normalized Difference Vegetation Index (NDVI), along with their variance, to separate land cover classes into sand, water, white water, and other land features and to achieve an accuracy of 99% - pixel classification of their pre-computed classifier (Vos *et al*, 2019b).

Equation 1 shows the computational metrics for the MNDWI, where the labels SWIR1 and GREEN refer to band values.

$$MNDWI = \frac{SWIR1-GREEN}{SWIR1-GREEN} \text{..................Equation 1}$$

Finally, a Marching Squares algorithm was used to determine the sub-pixel position of the shoreline as an iso-valued contour which is represented as a 2-D vector (Vos *et al*, 2019b). CoastSat has the optional function of taking tidal correction into consideration when using tides and beach slope. Tidal datum correction is introduced because the high-water mark moves over time owing to littoral processes, lunar influences and variable hydrodynamics, thus marking the seaward or landward edge of the coastline (Whittal and Mackie, 2023). Tidal datum is calculated on the basis of long-term tidal data for which the South African Navy Hydrographic office is the custodian (Mather et al, 2009). However, because in this instance, the study sites were gently sloping, ranging between 0.8° and 3.12° , the tidal correction, based on the SRTM slope calculations, would not have altered the results significantly and was thus not included in this analysis.

4. Results and discussion

Based on visual inspection, the lines of the detected shoreline clearly follow the natural curvature of the study sites. Figure 4 presents examples of the ANN image processing and MNDWI thresholding.

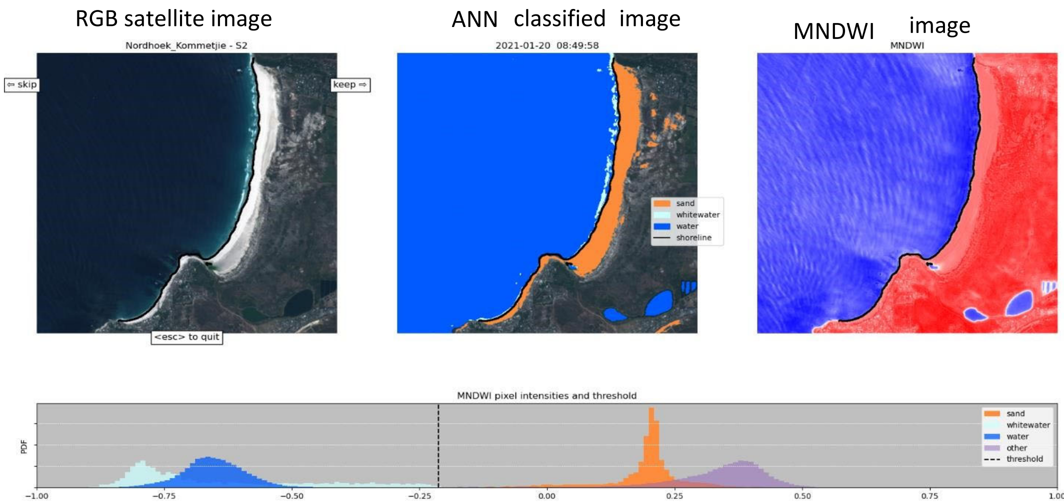

Figure 4. CoastSat automated shoreline extraction along Noordhoek-Kommetjie beach and the associated MNDWI histogram

The vectorized, instantaneous shorelines were intersected by digitized transects to deduce the cross-shoreline change, as shown in Figure 5 below.

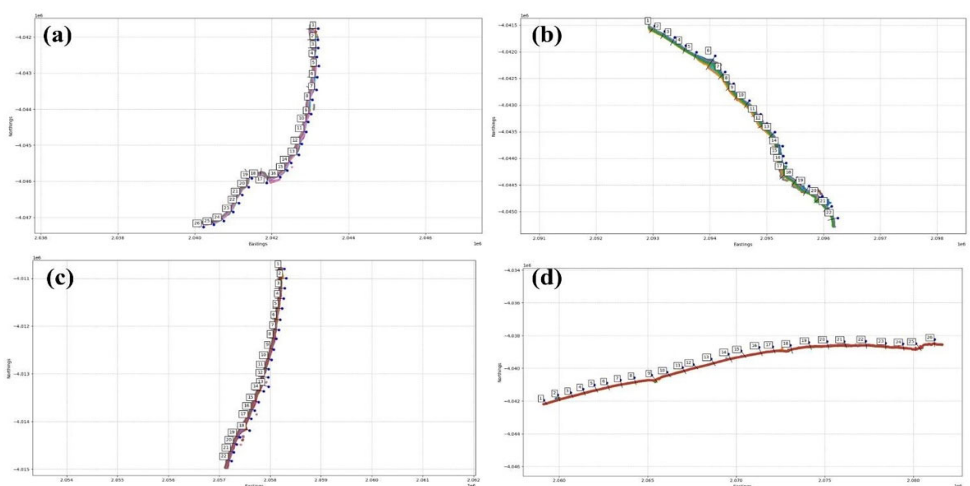

Figure 5. Plot of transects along the CoastSat-extracted shorelines (a) Noordhoek-Kommetjie (b)Strand (c) Milnerton (d) Strandfontein-Monwabisi

The shoreline movement along the transects was averaged and is depicted in the graph below. The Strandfontein-Monwabisi stretch of coastline experienced the greatest change with 284 metres (m) of lateral displacement in the position of its shoreline, followed by the Noordhoek-Kommetjie beach with 110m displacement. Interestingly, the Strand and Milnerton beaches experienced almost equal shoreline changes of 91m and 88m, respectively. This can beattributed to the fact that Strandfontein-Monwabisi is the longest analysed shoreline.

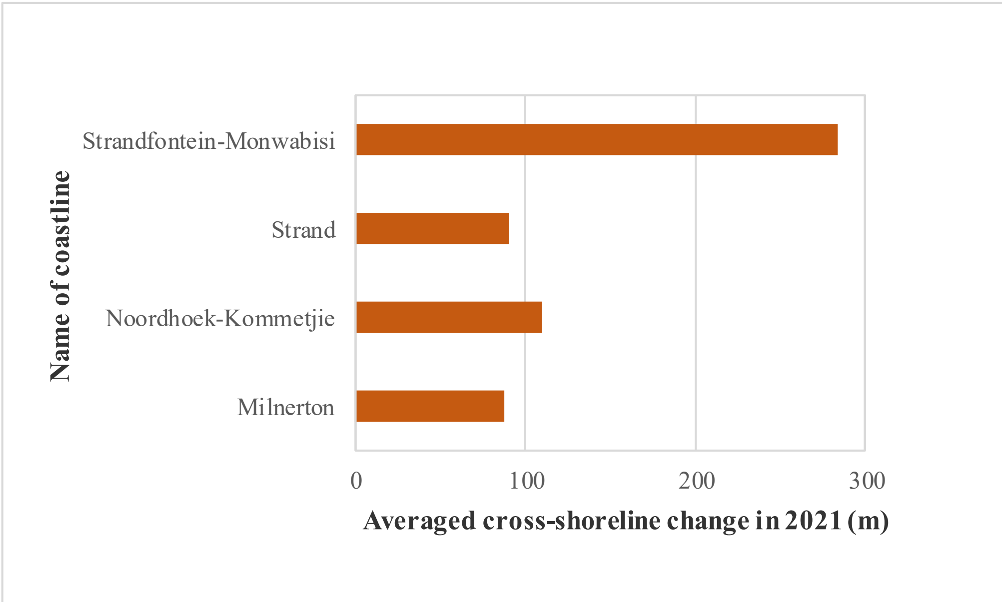

Figure 6. Cross-shoreline change

Worthy of emphasis again is the fact that the analysis of coastlines should be in a localized context. CoastSat is clearly effective on any length of beach; however, it is limited in that it is not yet equipped to quantify coastal erosion rates and to determine whether a shoreline is advancing or retreating. Thus, in accordance with the findings of Curoy *et al* (2022), a further step would be to incorporate DSAS for this purpose (Murray *et al*, 2023). That, however, is beyond the objectives of this study and would, therefore, be a recommendation for future research.

To motivate the observations of the obtained results, a discussion that may shed further light on the context is helpful. South Africa's shoreline boasts numerous sand beaches that are exposed to semi-diurnal tides within a micro-tidal range of two metres (2m) and are wave-dominated (Cartwright, 2011).

Weather patterns determine wave direction and cold fronts occur along the southernmost tip of Africa (MacHutchon, 2015). Waves often move in a south-westerly or north-westerly direction, while the coastal morphology affects the refraction pattern of the waves. The Mediterranean climate and hilly topography that typify Cape Town mean that cyclone-induced, orographic rainfall is prevalent in the winter, whereas the anticyclonic winds in summer result in a rainless (dry) summer season (MacHutchon, 2015). Whilst the coastline is affected by the interaction between the Benguela and Agulhas currents, increased sea surface temperatures from global warming will certainly alter the ocean circulation patterns and thus influence those areas along the shoreline that are particularly exposed to coastal erosion (Theron and Rossouw, 2008).

Understanding the geographical influences and locale of the study areas specific to Cape Town is pertinent to understanding sediment movement (Eliot, 2016). For example, whilst Milnerton and Kommetjie are adjacent to the Atlantic seaboard, water movement along the Milnerton coastline is affected by the presence of Robben Island, infrastructural development along the Foreshore and the Milnerton lagoon (Hughes, 1992). Kommetjie beach is influenced by the Hout Bay headland, as well as the presence of kelp, which both help to diminish wave energy (Woodborne and Flemming, 2021). An elementary assumption would be that the location of the Strandfontein-Monwabisi and Strand beaches, in False Bay, are not exposed as those along the Atlantic seaboard such as Milnerton. However, they have been flagged as facing sea-level rise-induced coastal erosion (Fourie *et al*, 2015).

Several coastal engineering solutions have been implemented along Cape Town's coastline, where, by 2019, costs of at least US$ 113 000 on coastal repairs at Monwabisi and an estimated US$ 32 000 000 on repairs to the Cape Town city shore had been incurred (Dube *et al*, 2021). Furthermore, repairs were also necessitated on transportation routes[5], such as roads and railways covered by sand when spring and high tides inundate the shore, or during storms (Dube *et al*, 2021).

The 18.5km-long Strandfontein-Monwabisi beach is located on False Bay's northern shore and adjacent to the low-lying Cape Flats, which are home to poverty-stricken and mostly previously disadvantaged people of colour (Fourie *et al*, 2015). The recreational beaches have experienced extreme damage to their tidal pools, while visible erosion has also been observed on Baden Powell Road, along the beachfront, that has led to it being breached (Dube *et al*, 2021). In fact, between the years 2005 and 2019, at least 400m^2 of the beach and soil material along the road was removed through erosion (Dube *et al*, 2021).

Coastal engineering solutions for the Strandfontein- Monwabisi beach have failed owing to wave wash/run-up that can reach up to 1.7m above the high-tide level. Other research on this beach has determined a 30m stretch of lateral landward erosion, related to the southerly wave height and wave frequency, as well as the effect of the developed infrastructure on the underlying geology (Fourie *et al*, 2015).

Strandfontein-Monwabisi beach has been included in the present study because marginalized communities are often overlooked and under-served and it was thought that their issues should be aired.

It is also important to note that South Africa did not have a cohesive, inclusive coastal management strategy until 2008, when the Integrated Coastal Management Act (ICMA) was formulated (Department of Environmental Affairs, 2021).

[5] essential for tourist accessibility (e.g.,sites such as Table Mountain

Milnerton beach is along the residential Woodbridge Island, which borders on the Milnerton Golf Club and the Milnerton Lagoon (Hughes, 1992). With a sea-level rise of 2.1mm per year, it is also a major area of concern (Dube *et al*, 2021).

Whilst the ICMA has called for the use of coastal setback lines, there are still alarming numbers of infrastructural developments that will lead to huge financial losses in the event of an extreme coastal storm event (Desportes and Colenbrander, 2016; Hughes, 1992).

The combination of the underlying geology, meteorological and oceanographic influences are pertinent to understanding the sediment budget (Roebeling *et al*, 2011). In the case of Cape Town, sediment sources include reef outcrops that introduce sediment through longshore drift, Pleistocene deposits, aeolian sediment movement from the Cape Flats and the chemical weathering of exposed outcrops (Adelana *et al*, 2010). Cape Town's irregularly shaped coastline is due to the alternation of resistant and less resistant rock strata. The Malmesbury Group shales, the Table Mountain sandstones, and the intruding Cape granites are the major rock series in the area, and wave action exploits the existing rock weaknesses that occur in the form of faults and joints (Van Zyl, 2019). The shoreline of Table Bay is curved and interspersed with beach pockets, which means that the headlands between the beach pockets act as a buffer against the ocean swells (Woodborne and Flemming, 2021).

5. Conclusion, Recommendations and Future Work

The use of the CoastSat deep learning tool for monitoring the coastlines of Cape Town, South Africa, has demonstrated its significant potential in providing valuable insights into coastal dynamics. In summary, this research study successfully tested the deep learning-based CoastSat tool by Vos et al (2019b). By using an Artificial Neural Network classifier, it detected shorelines with different environmental, geomorphic, and hydrodynamic influences along the Cape Town coastline. The research study concluded that to include a tool such as the DSAS, along with aerial imagery, to create data continuity would contribute enormously to understanding how coasts change with time. A functional improvement to the tool would be to move beyond the mere detection of shoreline changes through wave and tidal erosion to the actual calculation of coastal erosion. The CoastSat GitHub toolkit is constantly being updated and has currently advanced to become an online interactive tool. However, at present, it reflects coastal data for only Australia and South and North America. With collaborative efforts, South Africa can easily achieve the same status.

Further work related to this study should focus on refining the accuracy and reliability of the CoastSat tool, particularly in complex coastal environments. Future research in the broader context of coastal monitoring should focus on improving the accuracy of remote sensing techniques, particularly in areas with challenging coastal environments. This could involve the development of more sophisticated methods for shoreline assessment that could account for complex factors such as rocky terrain. Additionally, the integration of emerging technologies, such as machine learning and artificial intelligence for data processing and analysis, have shown great promise in enhancing the precision and efficiency of coastal monitoring efforts.

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