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# On the Application of Machine Learning Techniques and High-Resolution Satellite Imagery for the Extraction of Shoreline Indicators and the Prediction of Future Shorelines

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## **Information**

### **Title**

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# Abstract

Coastal communities face increased risk from the challenges of erosion and flooding, combined by the rising threat of sea level rise (SLR). To understand the dynamics along global coastlines and accurately measure the rate of change, it is important to identify shorelines on a large scale over long periods (years - decades). The increase of remote sensing data, notably Multispectral Satellite Imagery (MSI), has provided opportunities to monitor shoreline change over long temporal periods. This thesis investigates the application of open-source MSI and Machine Learning (ML) techniques to quantify shoreline change across various beach types, through the automated extraction of the wet/dry boundary.

In this thesis, two key hypotheses are investigated. Firstly, the influence of coastline geomorphology and satellite imagery resolution on the feasibility of Shoreline Indicator (SI) identification is explored. It is expected that coastlines characterised by distinctive geomorphic features, combined with higher-resolution satellite imagery, will enhance the accuracy of visually discernible SI identification and extraction processes. Secondly, the hypothesis is posed that SIs can be reliably identified through ML methodologies. It is anticipated that by training ML algorithms on a diverse dataset of MSI, it will be possible to develop models that can accurately detect and classify SIs across different coastal regions worldwide.

This thesis initially assesses how previous Earth Observation (EO) studies mapped Shoreline Indicators from MSI. Recent emerging processing technologies, such as ML, are examined and considered regarding their capacity to identify and extract various shoreline features from local to global scales.

Two ML techniques, an Artificial Neural Network (ANN) and Classification and Regression Trees (CART) are developed for a two-step classification approach to identify the wet/dry boundary; these are tested against validation data derived from high resolution LiDAR and drone imagery. The ANN derived shorelines are then used to detect the wet/dry boundary line to allow for seasonal and multi-year analysis at three locations in the UK: Start Bay, Aldbrough and Sizewell.

This thesis subsequently investigates future prediction algorithms for forecasting shoreline change. A review of methods that are used for forecasting shoreline change is carried out and four ML techniques are tested for the prediction of future shorelines based on satellite derived

shorelines. This investigation examines the potential of ML for predicting future shoreline change from MSI.

In this thesis, a significant achievement has been demonstrated, showcasing the effective utilisation of an ANN to accurately detect and extract the wet/dry boundary SI from Sentinel-2 MSI at Start Bay ( $\pm 2.15\text{m}$ ), Aldbrough ( $\pm 10.67\text{m}$ ), and Sizewell ( $\pm 3.56\text{m}$ ). These measurements align well with the 10m pixel value of Sentinel-2, underscoring the reliability and applicability of the ANN approach. This thesis highlights the adaptability and effectiveness of the developed ANN model in tackling diverse shoreline types. Additionally, the analysis of these shorelines proved invaluable in understanding shoreline dynamics over both seasonal and multiyear periods, revealing short-term erosion trends and long-term evolution patterns. Complex behavioural patterns and subtle trends of change were successfully replicated, contributing to a deeper understanding of coastal dynamics at the sites. Furthermore, this research has highlighted the potential of utilising satellite-derived shorelines for future shoreline prediction applications. The machine learning models employed in this study have demonstrated their potential to discern intricate change patterns, and the wealth of available satellite imagery data presents an opportunity to construct more robust and accurate predictive models. This not only enhances our capacity to anticipate shoreline changes but also paves the way for more informed coastal management strategies.

# Lay Summary

Coastal communities are increasingly vulnerable to erosion, flooding, and the growing threat of rising sea levels. To effectively address these challenges, it is crucial to understand how coastlines are changing on a global scale. Advances in technology, like Multispectral Satellite Imagery (MSI)<sup>1</sup>, have given us the tools to monitor these changes over long periods and large (global) areas.

This thesis explores how we can use open-source MSI and Machine Learning (ML)<sup>2</sup> to measure shoreline changes across different types of beaches (sandy, gravelly, with and without headlands and cliffs). Specifically, it focuses on automatically identifying the boundary between the wet and dry beach sediment (called the wet/dry boundary), which is an important indicator of shoreline movement.

The thesis begins by reviewing how past studies have used MSI for mapping Shoreline Indicators (SIs)<sup>3</sup>. It also looks at how recent technologies like Machine Learning can help us extract various shoreline features, from local to global scales. The thesis develops two ML techniques, an Artificial Neural Network (ANN) and Classification and Regression Trees (CART), to identify the wet/dry boundary. These techniques are tested using shorelines extracted from high-resolution LiDAR and drone imagery (validation data). The ANN generated shorelines are then used to analyse seasonal and multi-year changes at three UK locations: Start Bay, Aldbrough, and Sizewell.

The thesis also explores predicting future shoreline changes. Different methods are reviewed for making these predictions and four of the ML methods are tested based on satellite-derived shorelines. This research sheds light on the potential of ML for forecasting future shoreline changes.

This thesis demonstrates that Sentinel-2 MSI, combined with ANN, can accurately identify the wet/dry boundary on a range of different shoreline types. Shorelines detected in this way, are valuable for assessing and understanding how coastlines change over time. Additionally, the study highlights the potential of using satellite data and Machine Learning for predicting future shoreline changes and outlines the steps needed for future work.

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<sup>1</sup> MSI are images captured by satellites equipped with sensors capable of recording information across multiple wavelengths of light.

<sup>2</sup> ML is a computer system's ability to learn and make decisions without being programmed.

<sup>3</sup> A SI serves as a proxy for a specific feature of a coastal environment.

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# **Declaration**

I declare that this thesis has been composed solely by myself and that it has not been submitted, either in whole or in part, in any previous application for a degree.

Except where otherwise acknowledged, the work presented is entirely my own.

Emma Mary McAllister

August 2023

# Acronyms

|        |                                                    |
|--------|----------------------------------------------------|
| AI     | Artificial Intelligence                            |
| ANN    | Artificial Neural Network                          |
| API    | Application Programming Interface                  |
| AR     | Auto Regressive                                    |
| ARIMA  | Autoregressive Integrated Moving Average           |
| AWEI   | Automatic Water Extraction Index                   |
| BN     | Bayesian Network                                   |
| BNG    | British National Grid                              |
| BODC   | British Oceanographic Data Centre                  |
| CART   | Classification and Regression Trees                |
| CCO    | Channel Coast Observatory                          |
| CGAN   | Convolutional Generative Adversarial Network       |
| CNN    | Convolutional Neural Network                       |
| DCGAN  | Deep Convolutional Generative Adversarial Networks |
| DSAS   | Digital Shoreline Analysis System                  |
| DT     | Decision Tree                                      |
| ED     | Euclidean Distance                                 |
| ELR    | Extrapolated Linear Regression                     |
| EO     | Earth Observation                                  |
| EPR    | End Point Rate                                     |
| ETS    | Error Trend Seasonality                            |
| EU     | European Union                                     |
| FFN    | Feed Forward Network                               |
| GAN    | Generative Adversarial Network                     |
| GbSAM  | Geomatic-based Shoreline Analysis Method           |
| GEE    | Google Earth Engine                                |
| GEOBIA | Geographic Object Based Image Analysis             |
| GIS    | Geographic Information Systems                     |

|         |                                                   |
|---------|---------------------------------------------------|
| HWL     | High Water Line                                   |
| ISODATA | Iterative Self-Organizing Data Analysis Technique |
| KNN     | K- Nearest Neighbour                              |
| LiDAR   | Light Detection and Ranging Technology            |
| LRR     | Linear Regression Rate                            |
| LSTM    | Long Short-Term Memory                            |
| MAE     | Mean Average Error                                |
| MHWL    | Mean High Water Line                              |
| ML      | Machine Learning                                  |
| MLP     | Multilayer Perceptron                             |
| MNDWI   | Modified Normalized Difference Water Index        |
| MQCNN   | Multi-Horizon Quantile CNN                        |
| MSI     | Multispectral Satellite Imagery                   |
| MSL     | Mean Sea Level                                    |
| NB      | Naïve Bayes                                       |
| NDWI    | Normalized Difference Water Index                 |
| NIR     | Near Infrared                                     |
| NSM     | Net Shoreline Movement                            |
| OBC     | Object Based Classification                       |
| OBIA    | Object-Based Image Analysis                       |
| OLS     | Ordinary Least Squares                            |
| PBIA    | Pixel-Based Image Analysis                        |
| PCA     | Principal Component Analysis                      |
| ReLU    | Rectified Linear Activation                       |
| RF      | Random Forest                                     |
| RMSE    | Root Mean Square Error                            |
| RNN     | Recurrent Neural Network                          |
| ROI     | Region of Interest                                |
| SAM     | Spectral Angle Mapper                             |
| SAR     | Synthetic-Aperture Radar                          |



|      |                             |
|------|-----------------------------|
| SD   | Standard Deviation          |
| SLR  | Sea Level Rise              |
| SSM  | Statistical Shape Modelling |
| SVM  | Support Vector Machine      |
| SWIR | Shortwave Infrared          |
| WLR  | Weighted Linear Regression  |

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# Chapter. 1 Introduction

## 1.1. Motivation Statement

This thesis investigates the application of open-source Multispectral Satellite Imagery (MSI) and Machine Learning (ML) techniques to quantify shoreline change across various beach types. In this first chapter, a background is provided on why it is important to monitor shorelines changes. This establishes the framework for exploring the aims, hypotheses, and research questions that will be examined throughout the thesis.

## 1.2. Published Papers

Papers related to the contents of this thesis are summarised below. These have been published in indexed journals, currently in publication or presented at conferences.

The following paper have been published during the development of this thesis:

- McAllister, E., Payo, A., Novellino, A., Dolphin, T. and Medina-Lopez, E., 2022. Multispectral satellite imagery and machine learning for the extraction of shoreline indicators. *Coastal Engineering*, 174, p.104102.

The following paper is currently in development and is due to be submitted in publication to Remote Sensing of Environment in late 2023:

- McAllister, E., Payo, A., Novellino, A., Dolphin, T. and Medina-Lopez, E., (2023)  
A novel approach for shoreline extraction using Machine Learning and Satellite Imagery

The following publications have been presented at conferences:

- McAllister, E., Payo, A., Novellino, A., Dolphin, T. and Medina-Lopez, E., (2021). Shoreline Extraction using High Resolution Satellite Imagery at Start Bay, UK. *ICE Coasts, Marine Structures and Breakwaters (2021)*
- McAllister, E. (2021). High-resolution satellite remote sensing of coastal morphology. *Cefas PhD Student Event 2021*
- McAllister, E., Payo, A., Novellino, A., Dolphin, T. and Medina-Lopez, E., (2021). Shoreline Extraction using High Resolution Satellite Imagery at Start Bay, UK. *Young Coastal Scientists and Engineers Conference (YCSEC) 2021*
- McAllister, E. (2022). Multispectral satellite imagery and machine learning for the extraction of shoreline indicators. *Cefas Conference 2022: Understanding the Past, Predicting the Future*
- McAllister, E. (2022). Shoreline Extraction Using High-Resolution Satellite Imagery at Start Bay, UK. *16th UK Young Coastal Scientists and Engineers Conference*
- McAllister, E. (2022). Shoreline Extraction using High Resolution Satellite Imagery at Start Bay, UK. 5811–5820. <https://doi.org/10.3850/IAHR-39WC2521711920221201>

- McAllister, E., Payo, A., Novellino, A., Dolphin, T. and Medina-Lopez, E., (2022). Multispectral Satellite Imagery and Machine Learning for the Extraction of Shoreline Indicators. *UK National Earth Observation Conference 2022*

### 1.3. Background

Around 40% of the world's population lives within 100km of the coastline, equating to 2.4 billion people (United Nations, 2017). The coastal zone is one of the most dynamic and high energy systems on Earth, where wind, waves and tides cause geophysical processes such as erosion, deposition and flooding to occur. These ongoing processes can present a serious risk to life, home security and economy, and wellbeing to the population living there. Increasing coastal erosion rates due to Sea Level Rise (SLR) is a concern for these coastal communities. Since 1900, global mean sea level has risen by 0.20 m, with the average rate of SLR being 3.7 mm/ year between 2006 and 2018 (IPCC, 2021). Athanasiou *et al.* (2020) projected that for Europe, SLR would create a median shoreline retreat of 97 m (under RCP 8.5) by 2100, which translates to 2,500 km<sup>2</sup> of coastal land loss. The threat of increased erosion and flooding has focussed the attention of coastal practitioners and local government on shoreline change rates, the need to protect communities and the longevity and maintenance of coastal assets. It is estimated that in the European Union (EU), 1.8 to 2.9 million people could be impacted by SLR by 2050 with damage costs expected to be €135 billion to €145 billion (COACCH, 2019), including protective infrastructure and planning for mitigation.

Understanding shoreline change has traditionally utilised field studies including *in situ* beach profiling/surveys and aerial imagery to provide high-resolution datasets for

analysis (Splinter *et al.* 2018). Other aerial remote image-based techniques, including photogrammetry, airborne Synthetic-Aperture Radar (SAR), airborne Light Detection and Ranging Technology (LiDAR) and video imaging from drones and manned aircrafts have been used to detect shorelines, however, they are limited in terms of temporal and spatial coverage and can be costly.

The alternative is spaceborne remote sensing, which began with the launch of EO satellites in 1972. EO satellites utilise many of the same features developed for airborne sensors, but they overcome the issues of high costs, limited spatial coverage, and low survey frequency, because EO satellite data is often free, has global coverage and regular revisit intervals. With freely available satellite imagery, the ability to monitor the coastline from space on a regular basis becomes possible. With this wealth of satellite imagery, the number of scientific publication and commercial products attempting to extract shoreline from space has radically risen (e.g., García-Rubio *et al.* (2009); Lira and Taborda (2014); Hagenaars *et al.* (2018); Splinter *et al.* (2018); Luijendijk *et al.* (2018); Mentaschi *et al.* (2018); Vos *et al.* (2019); Rogers *et al.* (2021)). It is essential to be able to monitor shoreline change on local to global scales, as sea level rise impacts the entire coastal system and shoreline dynamics. Satellite imagery is ideal for this type of analysis as it provides a global coverage and has a large historical database of imagery.

In order to monitor coastal change from satellites up to a global scale, the shoreline definition and an accurate extraction method must be determined. Various coastal features can be identified as ‘indicators’ or ‘proxies’ of the true shoreline position (the extracted waterline which has been corrected to the intersection of a tidal datum, e.g., Mean Sea Level (MSL)), whereas SIs are proxies’ representative of the entire coastline. The most identified SI from MSI is the instantaneous waterline, as it is the most visually discernible

feature (Xu, 2018; García-Rubio *et al.*, 2015). Most extracted shorelines need to be tidally corrected if they are to be consistently used to monitor shoreline change, except where tidal range is very low (e.g., < 30 cm). Tidal datum-based shoreline features are contours that are based on the known elevation of the mean sea level along the shoreline (e.g., Mean High Water Line (MHWL)). They are the most difficult features to extract from MSI, as these indicators rely on additional data, such as time and tidal elevation (Esmail *et al.*, 2019). Therefore, shoreline datasets from airborne and satellite imagery are not always comparable, as they depend on how the user defines the indicator and method applied to extract it.

Another major focus in shoreline studies is the methodology to extract SIs. Many delineation and classification methods have been applied to remote sensing imagery to extract the shoreline position, including manual extraction, water indexing techniques and ML. Whilst it is easy to apply these techniques to small scale studies (<100km) and produce highly accurate results, on a global scale the application needs to be considered and automated processing methods to be utilised (owing to the large spatial scale).

The aim of this thesis is to advance the understanding of shoreline change quantification using MSI and ML techniques. The findings contribute to the development of more accurate and reliable methods for shoreline extraction, enable the identification of representative SIs across diverse beach types, and explore the feasibility of predicting future shorelines based on past observations and environmental data. I seek this aim through two hypotheses that are explored in detail via three research questions.

## **1.4. Research Questions and Hypotheses**

### **1.4.1. Hypotheses**

Building on the critical analysis of the relevant work presented in this chapter, under this thesis I have developed the following two main hypotheses.

1. The geomorphology of a coastline and resolution of satellite imagery will influence whether a SI can be reliably identified. It is expected that coastlines with distinct geomorphic features and higher-resolution satellite imagery will enhance the identification and extraction of SIs.
2. ML based methodologies can reliably identify SIs. It is anticipated that by training ML algorithms on a diverse dataset of MSI, it will be possible to develop models that can accurately detect and classify SIs across different coastal regions worldwide.

### **1.4.2. Research Questions:**

Based on the hypotheses three research questions are presented:

1. How can open-source MSI be utilised to quantify global shoreline change along different beach types using Machine Learning?

The steps undertaken to answer this question are:

- a. Review the existing methods and techniques employed for shoreline extraction from satellite imagery, focusing on their applicability to different beach types.
- b. Investigate the utilisation of MSI for extracting shorelines and assess the effectiveness of this approach compared to other data sources.

- c. Explore the application of ML algorithms for shoreline extraction from MSI and evaluate their performance in quantifying shoreline change across various beach types.
2. Is the wet/dry boundary representative of all shoreline types that can be extracted using publicly available medium-resolution MSI as a data source?

The steps undertaken to answer this question are:

- a. Train ML algorithms, including both traditional ML algorithms and an ANN to detect shorelines from high-resolution MSI.
  - b. Compare and assess the accuracy and effectiveness of different methodologies for shoreline extraction, considering their ability to capture shoreline variations across diverse shoreline types.
3. Can future shorelines be predicted using past shorelines and other environmental data?

The steps undertaken to answer this question are:

- a. Review and analyse the existing methodologies employed for predicting coastal changes based on extracted shoreline positions, considering the integration of past shorelines and additional environmental data.
  - b. Apply ML techniques to develop a predictive model that incorporates past shorelines to forecast shoreline changes.

## **1.5. Thesis Outline**

This thesis consists of seven chapters, each contributing to a deeper understanding of coastal dynamics through the integration of remote sensing, SIs, and ML techniques. These chapters have been developed to answer the three research questions I formulated.

Chapter 1 introduces the thesis by presenting its rationale and background, focusing on the shoreline, ML, and remote sensing. It outlines the aim, objectives, and hypothesis, establishing the groundwork for exploring the application of ML and satellite imagery in shoreline analysis and prediction.

Chapter 2 examines the application of remote sensing, SIs, and machine learning in the coastal field, highlighting existing gaps and paving the way for further analysis within this thesis. By understanding the current state of the field, this chapter sets the stage for a new methodology developed during this PhD and detailed in Chapter 3.

Chapter 3 presents the development of a methodology specifically designed for this thesis. Building upon the critical review of the relevant work presented in Chapter 1, this chapter introduces the study sites, defines the chosen shoreline indicator, explains the satellite imagery used, and provides an overview of the ML and ANN method chosen. Furthermore, the chapter describes the validation procedures applied to the algorithms, ensuring the reliability and accuracy of the resulting shoreline outputs.

Chapter 4 presents the outcomes achieved through the implementation of the methodology described in Chapter 3. By comparing multiple methodologies, this chapter determines the most effective approach for shoreline extraction. The derived results are then validated against real-world validation data, allowing for an in-depth discussion of the findings and their implications.

In Chapter 5, an analysis of shoreline changes for three study sites is presented, covering both multi-year and seasonal periods. The ANN methodology discussed in Chapter 2 and detailed in Chapter 3 is utilised for this analysis. The changes at the three distinct study sites are examined, offering insights into the evolving nature of their shorelines.



Furthermore, the suitability of the selected SI for comprehending shoreline change is assessed.

Chapter 6 initially explores current employed methodologies for predicting future shorelines. Four methodologies are introduced that combines satellite-derived shorelines and advanced ML techniques, including Generative Adversarial Networks (GANs), Conditional GANs (CGANs), Long Short-Term Memory (LSTM), and ConvGANs. The chapter critically examines the results obtained from these predictive models and provides valuable insights for future research and applications in shoreline forecasting.

Chapter 7 concludes the thesis by providing an overview of the findings and highlighting the remaining research gaps and future directions. By reflecting on the contributions made in this thesis, it provides a guide for further advancements in understanding and managing coastal dynamics through the integration of remote sensing, SIs, and machine learning techniques.



# **Chapter. 2 Multispectral Satellite Imagery and Machine Learning for the Extraction of Shoreline Indicators**

In this chapter, Shoreline Indicators (SIs), Multispectral Satellite Imagery (MSI), and Machine Learning (ML) techniques are explored in relation to shoreline extraction. Addressing Research Question 1: "How can open-source MSI be utilized to quantify global shoreline change along different beach types using Machine Learning?" This chapter provides an introduction of how shorelines are defined, and which indicators can be measured. The main type of sensors and techniques used to monitor shorelines are mentioned, with a focus on previous Earth Observation (EO) studies used for mapping SIs from MSI. As part of the review, recent emerging processing technologies (e.g., ML or Artificial Intelligence) are analysed and considered regarding their capacity to extract different shoreline features on local to global scales. The benefits and drawbacks of ML

technologies are discussed to identify gaps, opening a new area of coastal research and techniques suitable for EO.

This literature review aspects of this chapter are based on a published paper: McAllister, E., Payo, A., Novellino, A., Dolphin, T. and Medina-Lopez, E., 2022. Multispectral satellite imagery and machine learning for the extraction of shoreline indicators. *Coastal Engineering*, 174, p.104102.

## 2.1. Shoreline Indicators

Boak and Turner (2005) define the shoreline as the physical interface between the land and water. This interface constantly changes over time due to water level and land fluctuations (waves, tides, weather, erosion, accretion), making it somewhat difficult to define a single, moderately static feature that represents the land-water interface and how it is physically changing, even over very short periods. Consequently, a consistent shoreline definition is critical in order to attempt to avoid inconsistencies or capture uncertainty to minimise it, between different shoreline positions and the potential for misleading erosion/accretion results that may be methodological rather than real (Liu, 2009). SIs are visual features used as a proxy to represent the shoreline position; these can be split into three groups:

- **Visually discernible coastal features** are features which can be physically seen and manually digitised, such as the previous high-water line (HWL) or the wet/dry boundary.
- **Tidal datum-based shorelines** are based on tidal datums (the standard elevation defined by a stage of the tide) determined by the intersection of the coastal profile with a specific vertical elevation. Proxies of tidal datum-based shorelines include the MHWL which depends on an extracted waterline contour and tidal datum-based data.

- **Indicators based on image processing techniques** define the shoreline by applying processing techniques such as spectral enhancement (e.g., spectral unmixing algorithm, Focal analysis, Convolutional filters), geometric enhancement (e.g., adaptive smoothing, edge detection and enhancement) or transformations (e.g., Principal Component Analysis) to extract proxy shoreline features from digital images, which are not visible to the human eye.

The way in which shoreline proxies are derived can also lead to inconsistencies in the results, as every user defines them differently or has their own interpretation of the SI for the specified method. Identifying these features can be difficult using MSI as a wide variety of SIs exist but are not always visible on a 2D multispectral image, which can be based on geomorphologic aspects such as coastal dunes, cliffs or the configuration of vegetation along the backshore. Comparisons between indicators and the true shoreline is difficult as no one indicator can be used for all types of coasts as all beach profiles differ (Toure *et al.* (2019)).

Due to the large range of SIs, an assortment of image processing tools has been used to detect shorelines in MSI, airborne LiDAR (Mason *et al.* (2000); Brock and Purkis (2009); Li *et al.* (2022); Lin *et al.* (2019); Ma *et al.* (2020); Caballero and Stumpf (2021)), SAR (Musa *et al.* (2015); Avtar *et al.* (2015); Li *et al.* (2021); Zhang *et al.* (2022); Choi and Kim (2018); Salameh *et al.* (2020); Martinis *et al.* (2015)) and video. A combination of these remote sensing techniques can be employed to extract the features presented by Boak and Turner. (2005) in Figure 1. However, highlighted in red in Figure 1 are the only SIs that can be identified using MSI as they are horizontal, visual, proxy-based features visible in imagery with ‘coarser’ resolutions (>10m) provided by MSI, compared to high resolution imagery (aerial photography). These SIs can be split into features along the

shoreline, such as morphological reference lines (Bluff top/cliff top, base of bluff), vegetation limits (vegetation line, seaward edge of dune vegetation line), and wetting limits (mean high water, wet/dry line, instantaneous waterline).

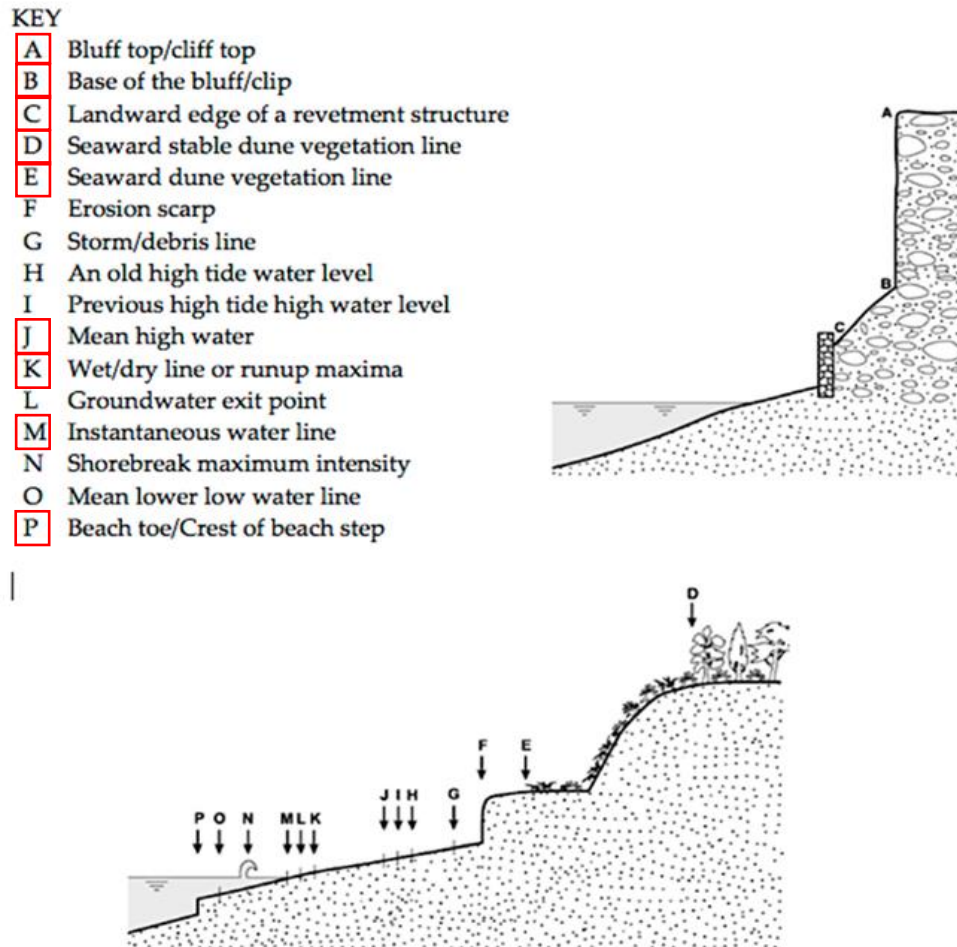


Figure 1: Shoreline indicators (Boak and Turner, (2005)). Shoreline indicators highlighted in red boxes are features which are identifiable using MSI, derived from Payo *et al.* (2020).

## 2.2. Remote Sensing and the Shoreline

Traditionally, shorelines were (and still are) mainly monitored through the use of historical maps, aerial imagery and *in situ* beach profiling (Gens, 2010). The SIs described here are visually discernible features that can be detected using conventional photography

and multispectral imaging. Some of these visually discernible features can be difficult to identify in 2D images, such as the difference between the cliff top and cliff base i.e., it may not be possible to distinguish the two if the image resolution is too coarse or if the cliff is toward the edge of the image and facing away from its centre (i.e., obscuration). These features (i.e., cliff top and base features) can be distinguished by 3D data such as SAR or LiDAR if conventional or multispectral image resolution is too low.

Tidal datum-based SIs are contours commonly identified remotely with the addition of 3D photogrammetric methods, LiDAR and SAR, as these can provide information on the vertical profile of the beach. These traditional airborne techniques are effective for shoreline monitoring as they provide high resolution data used to produce accurate results on coastal change. However, 3D (topographic) data tends to be costly, labour intensive and collected infrequently or on a relatively poor temporal resolution (compared to satellite revisits). Therefore, aerial surveys tend to be used for intensive, short-term studies or long-term monitoring on a regular but infrequent (typically missing seasonal patterns) basis.

Since the launch of Landsat-1 in 1972, which was the first satellite mission designed to obtain EO data (Masek *et al.* (2020)), the potential for satellite and remote sensing techniques has increased and has been further developed alongside the intention for continuous EO with the improvement of spatial and temporal resolution. For example, spatial and temporal resolution has improved in the last two decades (see Figure 2) since the launch of Landsat-7 in 1999, Landsat-8 in 2013 and Sentinel-2, in 2015 (European Space Agency (2017)), providing more data. In 2008, the entire Landsat archive of satellite imagery (1972 - present) became publicly available from United States

Geological Survey (USGS) (Woodcock *et al.* (2008)). The free availability of satellite data has increased the number of coastal studies.

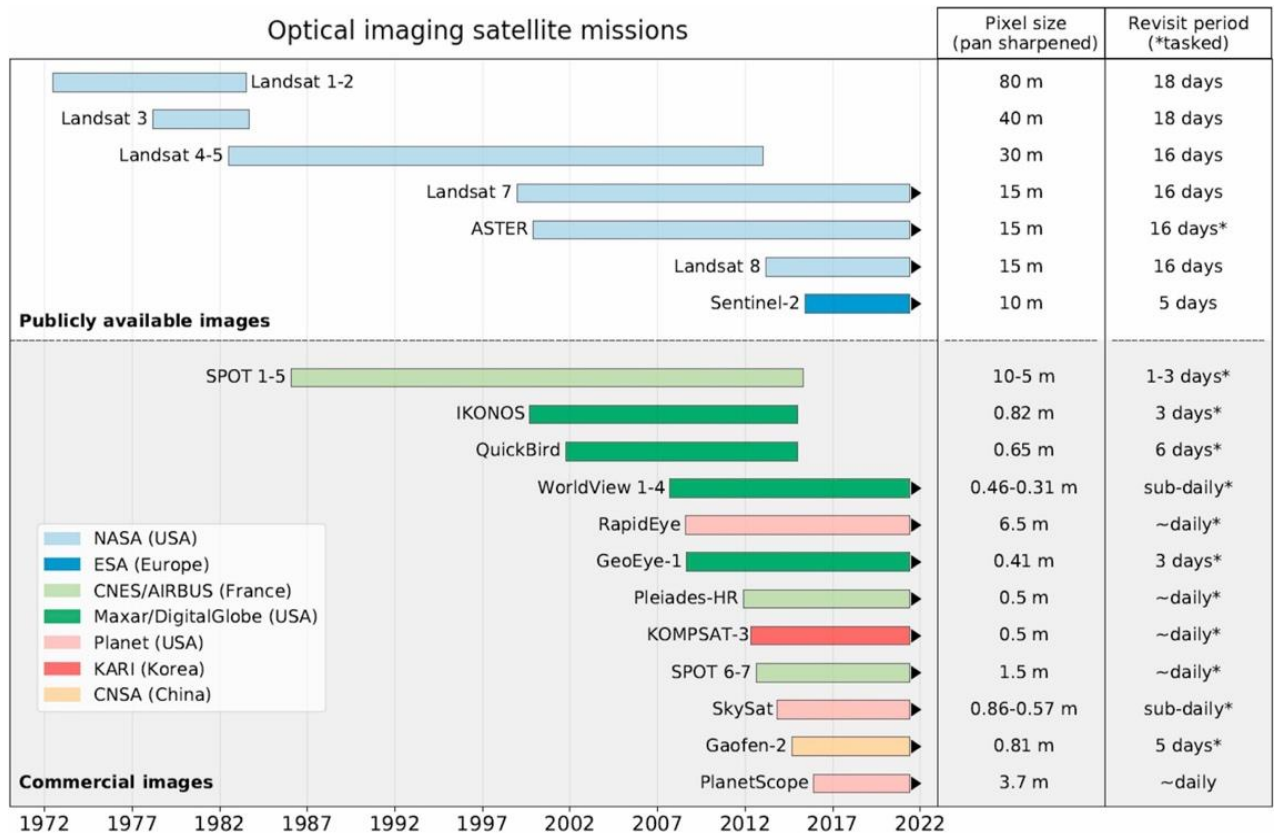


Figure 2: Timeline of publicly available and commercial satellite imagery (Turner et al. (2021))

### 2.2.1. Multispectral Satellite Imagery

MSI features discrete bands across the electromagnetic spectrum, including visible light and longer wavelengths such as Near Infrared (NIR) and Shortwave Infrared (SWIR) (Ose *et al.* (2016)).

EO satellite imagery provides 50-years of historical data on a global scale and will continue to provide consistent datasets into the future. The Landsat missions had MSI from the outset and span the whole EO timeline. Figure 2 is a timeline of the publicly and commercially available satellite imagery. The majority of the commercial data comes from SPOT 1-6 and Digital Globe satellites (WorldView, GeoEye, QuickBird, IKONOS)



(Maxar (2020)). The commercial satellite missions provide ‘tasked’ acquisitions of imagery over specific regions of interest for the customer, typically at very high (than freely available EO satellites) resolutions of  $< 5$  m. As highlighted, with the increase of satellites being launched, there has been a corresponding increase in the temporal (revisit period) and spatial scale (pixel size). Accordingly, this review will focus on both Commercial and publicly available satellites to understand their capabilities for identification and extraction of SIs over different spatial and temporal scales.

#### **2.2.1.1. Commercial Satellite Imagery**

SPOT (Satellite Pour l'Observation de la Terre) is a series of EO satellites currently being developed by the French space agency, Centre National d'Études Spatiales (CNES), in partnership with Airbus Defence and Space. The series began with the launch of SPOT 1 in 1986 and has since seen the deployment of six additional satellites. The most recent satellite, SPOT 7, was launched on June 30, 2014, and was operational until March 2023. Throughout the years, the SPOT satellites have made significant advancements in their multispectral resolutions. Since its inception in 1986, the series has witnessed an increase in resolution capabilities, progressing from 20 m to 6 m in 2014. This enhancement in resolution has been valuable for various applications in coastal studies from Chen and Rau (1998), Yu *et al.* (2013), Chen and Chang (2009), and Garcia-Rubio *et al.* (2015), which are discussed later in this chapter.

QuickBird-2 was a commercial EO satellite currently owned and operated by DigitalGlobe. The satellite was launched in 2001 and was decommissioned in 2015. QuickBird-2 is renowned for its very high-resolution imagery, offering a multispectral resolution of 2.4 m and a revisit time of 1.5 days. Coastal studies have extensively utilised

QuickBird-2 due to these exceptional capabilities including Dai *et al.* (2019), Tarmizi *et al.* (2014), Muzirafuti *et al.* (2020) and Zhu *et al.* (2019).

WorldView was a series of commercial EO satellites currently owned and operated by Maxar Technologies. The WorldView program has witnessed the launch of multiple satellites to date. It began with WorldView-1, which was launched on September 18, 2007, followed by WorldView-2 on October 8, 2009, WorldView-3 in 2014, and WorldView-4 in 2016, with it retiring in 2019. WorldView-1 primarily provides panchromatic images, while WorldView-2 offers a resolution of 8 m. WorldView-3 and WorldView-4 had an increased resolution of 1.24 m and offer a revisit time of approximately one day, making them highly suitable for monitoring and analysis purposes. Coastal studies have extensively utilised various WorldView satellites due to these capabilities including Sekovski *et al.* (2014), Dai *et al.* (2019), Alicandro *et al.* (2019), Bishop-Taylor *et al.* (2019), Darwish and Smith (2021), Minghelli *et al.* (2020), Domazetovic *et al.* (2021), Dominici *et al.* (2019) and Maglione *et al.* (2017).

RapidEye was a constellation of commercial EO satellites previously owned and operated by Planet Labs. The constellation consisted of five satellites that were launched together as a single payload on August 29, 2008. However, they were subsequently deactivated on March 31, 2020. RapidEye had a multispectral imagery resolution of 6.5 m and a revisit time of 5.5 days. RapidEye's data was utilised in coastal studies as well, as demonstrated by research papers by Mjiri *et al.* (2022), Duarte *et al.* (2018), DaSilva *et al.* (2021), and Janušaitė *et al.* (2021), among others.

PlanetScope is an active constellation of commercial EO satellites currently owned and operated by Planet Labs. The constellation comprises multiple satellites, with launches occurring over various missions since 2013. These satellites capture multispectral

imagery with a resolution ranging from approximately 3 to 4.1 m. One of the notable advantages of the PlanetScope constellation is its daily revisit time, allowing for frequent monitoring and up-to-date information. Researchers have utilised this data to explore various aspects of coastal environments (e.g., Rogers *et al.* (2021); Doherty *et al.* (2022); Abdelhady *et al.* (2022); Gabr *et al.* (2020); Darwish and Smith (2021); Shin *et al.* (2021)).

ResourceSat is a series of EO satellites developed and operated by the Indian Space Research Organisation (ISRO). Resourcesat-2 is a follow on mission to Resourcesat-1 and the eighteenth Indian remote sensing satellite built by ISRO. It was launched on 20 April 2011 and remains operational (ESA (2023)). The satellite has three spectral bands in the visible and Near Infrared Region (VNIR) with 5.8 m spatial resolution. This satellite has been utilised in a coastal study by Sekar *et al.* (2022).

#### **2.2.1.2. Publicly Available Satellite Imagery**

Landsat is the world's longest and continuously acquired collection of satellite data, spanning over four decades from 1972 to the present day (U.S. Geological Survey (2016)). The mission started with the launch of Landsat-1 in 1972, followed by successful launches of six more missions: Landsat 2, Landsat 3, Landsat 4, Landsat 5 Multispectral Scanner (MSS), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) (U.S. Geological Survey, 2016). Landsat-7, launched in 1999, has been instrumental in providing users with satellite data. It introduced higher spatial resolutions, with 30-meter resolution compared to the previous Landsat 1-5 missions that had resolutions of 60 m. The trend of acquiring higher-resolution satellite imagery continued with the launch of Landsat 8 (pan-sharpened 15 m resolution) in 2013, which also expanded the number of available bands. The latest

addition to the Landsat mission is Landsat-9, which was launched in September 2021 (U.S. Geological Survey (2019)). The sensors on-board Landsat-9 are improvements upon those deployed on Landsat-8, further enhancing radiometric and geometric capabilities compared to the older Landsat missions. Since 2020, Landsat-9 has been orbiting alongside Landsat-7, with the latter expected to be decommissioned in the future. Landsat-9 maintains a resolution of 30 m and captures images of the Earth every 16 days, with an 8-day offset from Landsat-8 (Masek *et al.* (2020)). Together, Landsat-9 and Landsat-8 contribute to the acquisition of nearly 1,500 new scenes per day, significantly expanding the USGS Landsat archive (U.S. Geological Survey (2019)). The extensive archive of Landsat data has facilitated numerous coastal studies (e.g., Pardo-Pascual *et al.* (2012); Luijendijk *et al.* (2018); Erdem *et al.* (2021); Acharya *et al.* (2016); Goncalves *et al.* (2015); Sagar *et al.* (2017); Xu (2018); Almonacid-Caballer *et al.* (2016); Bishop-Taylor *et al.* (2021); Sunder *et al.* (2017); Lira and Taborda (2014); Esmail *et al.* (2019); Dogru *et al.* (2006); Tung *et al.* (2021); Sekar *et al.* (2022)).

Sentinel-2, developed by the European Space Agency (ESA), is an advanced multispectral high-resolution imaging mission comprising twin satellites, Sentinel-2A and Sentinel-2B. Sentinel-2A was successfully launched in 2015, followed by the launch of Sentinel-2B in 2017. These satellites are phased at 180° from each other, providing a revisit time of five days (European Space Agency (2017)). The continuous data provided by Sentinel-2 has fuelled numerous studies (e.g., Seale *et al.* (2022); Hagenaars *et al.* (2017); Vos *et al.* (2019); Tung *et al.* (2021); Zollini *et al.* (2023); Novellino *et al.* (2020); Paz-Delgado *et al.* (2022); Athanasiou *et al.* (2020); Luijendijk *et al.* (2018)).

### 2.3. Shoreline Extraction of SIs

Satellite imagery plays a crucial role in the understanding shoreline change by enabling the identification and analysis of various shoreline features. These features include shoreline position, vegetation cover, beach morphology, coastal structures, and coastal landforms. The extraction of these features from satellite imagery provides valuable insights into erosion and accretion rates along coastlines. Among the different shoreline features, the shoreline position is of particular importance as it serves as a fundamental indicator for change assessment. The extraction of shoreline position from satellite imagery can be accomplished using various data sources, as discussed in Section 2.2.

The following sections elaborate on the techniques employed for extracting both visually discernible features and tidal datum SIs from satellite imagery.

Coastal features such as cliff top and cliff base can be used to register changes along the coast in a similar way to shorelines. Traditionally, researchers obtained information about cliff top or cliff base locations through manual techniques such as hand-digitizing aerial photographs, topographic maps, or *in situ* surveys (Moore and Griggs (2002); Young *et al.* (2009)). LIDAR has become the most commonly used data source for extracting cliff lines due to its high precision and ability to detect linear features such as cliff edges (e.g., Palaseanu-Lovejoy *et al.* (2016), Terefenko *et al.* (2019), Kuhn and Prüfer (2014), Young (2018), Sunamura (2015), Hapke and Reid (2007), and Chien *et al.* (2022)).

While LIDAR has proven to be highly effective, other data sources such as multispectral and aerial imagery have also been used in extracting cliff lines (e.g., Stanchev *et al.*, (2013); Moore and Griggs (2002); Eguchi and Albino (2018); Isla and Corizto (2014)). Isla and Corizto (2014) investigated cliff erosion rates by combining information extracted from aerial photographs, as well as modern referenced satellite images such as

Landsat 5 and Landsat 7. They primarily focused on the top of cliffs for monitoring, considering the foot of the cliffs as the most sensitive feature. In cases where the shadow cast by tall cliffs made it difficult to identify their feet accurately, the top of the cliffs was selected as a substitute for monitoring purposes.

The extraction of the vegetation line, as a shoreline proxy, at the coast is most commonly achieved through the utilisation of MSI. Although there are relatively few studies specifically focusing on identifying the vegetation shoreline, Tarmizi *et al.* (2014) and Rogers *et al.* (2021) have provided successful methodologies for this shoreline indicator. In their study, Tarmizi *et al.* (2014) employed QuickBird satellite imagery to identify the vegetation line as a key indicator of the shoreline. By analysing the spectral signatures of vegetation and sandy shore areas, they were able to distinguish and interpret these features based on different pixel values. This approach allowed for the extraction of the vegetation shoreline, providing valuable information about the coastal boundary. Similarly, Rogers *et al.* (2021) recognised the significance of the vegetation line as a proxy for shoreline extraction in their development of VEdge Detector, which automated the identification and extraction of the shoreline using the vegetation line. This approach proved effective in accurately delineating the coastline using PlanetScope and RapidEye satellite imagery and providing insights into the dynamics of shoreline change. These studies highlight the potential of MSI in extracting the vegetation line and utilising it as a valuable shoreline indicator. By leveraging the distinct spectral characteristics of vegetation and its interaction with the coastal environment, researchers can obtain crucial information about the position and dynamics of the shoreline.

The extraction of the instantaneous waterline, which represents the boundary between land and water at a specific moment in time, is a common and important SI in coastal

studies. Various remote sensing data sources have been utilised to extract this indicator and analyse shoreline dynamics. The use of MSI is widespread for extracting the instantaneous shoreline (e.g., Al-Mansoori and Al-Marzouqi (2016); Manaf *et al.* (2018); Dominici *et al.* (2019); Sunder *et al.* (2017); Luijendijk *et al.* (2018); Xu (2018); Hagenaaars *et al.* (2017); Hagenaaars *et al.* (2018); Choung and Jo (2017); Bishop- Taylor *et al.* (2019); Vos *et al.* (2019); Minghelli *et al.* (2020); Almonacid-Caballer *et al.* (2016); Ge *et al.* (2014); Kalkan *et al.* (2013); Garcia-Rubio *et al.* (2015)). Several studies have focused on shoreline change rates, global shoreline extraction, and testing new methodologies using MSI. For instance, Vos *et al.* (2019) extracted shorelines from over 30 years of publicly available satellite imagery (Landsat and Sentinel-2) to assess sub-annual to multi-decadal shoreline variability. Hagenaaars *et al.* (2018) presented a generic method for automated shoreline detection using publicly available satellite imagery, testing the accuracy against high-resolution *in situ* data. Luijendijk *et al.* (2018) conducted a global-scale assessment of sandy beach occurrence and shoreline change rates using optical satellite images captured since 1984 (these are further discussed in Section 2.6).

The wet/dry boundary line is an SI delineating the border between the submerged (wet) and exposed (dry) areas along the coast. Its extraction from MSI offers valuable insights into tidal influence, coastal inundation, and land-water interactions (including storm surge and wave setup). Although there have been limited studies focusing on this indicator, multispectral data has proven to be a valuable resource for shoreline identification. Sekar *et al.* (2022) employed an unsupervised pixel-based classification technique on Landsat-7 (ETM+) and Resourcesat-2, to extract proxy-based (wet/dry) shorelines along an open sandy coast. Similarly, Sekovski *et al.* (2014) utilised MSI to apply a proxy-based

shoreline extraction method for the wet/dry boundary. Their study employed a semi-automatic approach, processing high-resolution multispectral WorldView-2 satellite imagery over a 40km stretch of coastline. By leveraging the spatial and spectral capabilities of the satellite data, they successfully delineated the proxy-based shoreline, further highlighting the value of high-resolution satellite imagery for accurate shoreline extraction. While these studies didn't specifically examine the dynamics of storm surge and wave setup, it's crucial to consider these factors, as they can influence the extraction of the SI.

Tidal datum SIs play a crucial role in understanding the relationship between the shoreline and water level fluctuations. These indicators represent specific tidal datums, such as Mean High Water (MHW), Mean Low Water (MLW), or Mean Sea Level (MSL), serving as reference points for measuring shoreline positions. The extraction of tidal datum shorelines involves identifying specific elevation thresholds corresponding to the desired tidal datum. Various remote sensing techniques and data sources are utilised to extract tidal datum SIs. LiDAR data, obtained from airborne or terrestrial platforms, enables accurate elevation measurements along the shoreline (Morton and Miller (2005), Liu *et al.* (2007)). Researchers can identify corresponding shoreline positions by comparing LiDAR-derived elevation data with tidal datums. MSI has also been used for the extraction of shorelines related to tidal datums utilising multiple spectral bands to identify various land-water interfaces (e.g., El-Ashmawy *et al.* (2019); Chen and Chang (2009); Bishop-Taylor *et al.* (2021)).



## 2.4. Shoreline Feature Analysis

### 2.4.1. Temporal resolution

In terms of temporal resolution, most studies focus on shoreline change annually, over several years and use a single image per year to monitor change. The satellite images used are commonly from the summer months, as there is less cloud cover present and the influence of seasonal changes is at a minimum (e.g., Rogers *et al.* (2021); Chen and Chang, (2009); Almonacid-Caballer *et al.* (2016); Vos *et al.* (2019); Xu (2018); Al-Mansoori *et al.*, (2016)). Many studies maintain a consistent interval between images over several years, usually with Landsat and Sentinel-2 satellite imagery. However, some studies do not maintain a fixed interval between images (e.g., Al-Mansoori *et al.* (2016)), which may be due to the availability of the satellite imagery during specific seasons during the year and the cost associated with commercial imagery (Al-Mansoori *et al.* (2016); Lira and Taborda (2014)). Vos *et al.* (2019) and Hagenaars *et al.* (2018) are the only studies that examine intra-annual change, as cloud free imagery is difficult to obtain in most coastal locations year-round, especially during the winter months and the changing of seasons when the surrounding landcover can lead to misclassifications. Reduced cloud free images during winter months in the northern and southern hemisphere and along the equator during monsoon seasons hinders the study of shoreline change during cloudy seasons, which is a fundamental limitation to optical satellite data. There are >10 images available every month from Landsat and Sentinel-2 satellites (Hagenaars *et al.* (2017)), so only a 10% cloud-free return is required for monthly data over the cloudy seasons, which is still higher than most *in situ* monitoring (typically quarterly, bi-annual, or annual surveys). However, despite the potential increased sampling using satellite even during cloudy seasons, most EO studies do not focus on seasonal variability.

### 2.4.2. Spatial Coverage

The scale in which shoreline features are extracted should also be explored to understand the potential of satellite imagery for a further understanding of global shoreline change trends. The majority of studies focus on local ( $< 20\text{km}$ ) to regional ( $20\text{-}100\text{km}$ ) stretches of coastline (see Appendix A, Figure 1), with only 20% of studies at continental scales (e.g., Cenci *et al.* (2017); Bishop-Taylor *et al.* (2019)) and 5% at global scales (e.g., Luijendijk *et al.* (2018); Mentaschi *et al.* (2018)). This could be due to the type of SI or the method being used for the extraction process.

In terms of scale, a similar pattern is present: indexing and thresholding are consistently used from local to global scales, ISODATA (Section 2.5.3.1) and manual extraction are applied to local and regional scales ( $< 100\text{km}$ ) as manual extraction is time-consuming and has human bias. As the area size increases, the complexity of the problem grows with ISODATA, and the algorithm encounters challenges because the number of classes must be defined at the input stage. When implementing the algorithm in large areas with diverse land classes, there is a risk of overlooking certain land classes, potentially leading to the selection of less prominent classes in the image. Whereas supervised ML techniques are being used for larger continental to global scale studies as the algorithms can understand more complex problems and can be trained to identify specific features and changes in different areas, (Appendix A, Figure 2).

Luijendijk *et al.* (2018) and Mentaschi *et al.* (2018) show how global shorelines can be extracted using satellite imagery. Luijendijk *et al.* (2018) focuses on the extraction of all sandy beaches, whereas Mentaschi *et al.* (2018) extracts the shoreline position along almost all shoreline types (rocky/sandy/gravel beaches, deltas etc), excluding locations below latitudes of 63 degrees, due to cloud cover, snow occurrence and long polar night.

Both these studies produce erosion and accretion rates on a global scale. Mentaschi *et al.* (2018) uses a classifier to identify whether a pixel is “land”, “water” or “seasonal tide” and produces a result based on the in-between seasonal tide. Luijendijk *et al.* (2018) classifies sandy beaches worldwide by initially classifying them using CART and producing a waterline using the Normalised Difference Water Index (NDWI), a remote sensing index used to detect the presence of water bodies by measuring the contrast between visible and infrared wavelengths (Section 2.5.1). Although these studies were both able to create global shorelines, drawbacks are present on this scale. Mentaschi *et al.* (2018) had to filter out locations, with only 86% of coastlines below 63 degrees observed. Luijendijk *et al.* (2018) used the NDWI on sandy beaches to extract a waterline, however the length and type of the shoreline needs to be considered as a threshold applied after the NDWI won’t be representative of the area of shoreline if the surrounding coastline changes.

### **2.4.3. Shoreline Type**

Shoreline type is classically dominated by sandy beaches, then artificial shorelines (e.g., those including seawalls) The dominance of these two types correlates with populated study areas which are threatened by flooding and erosion or undergoing beach nourishment, a process involving the addition of sand or sediment to a beach to widen it or counteract erosion. There may also be a preference to sandy shorelines as their potentially higher rates of change are more easily detected in coarse satellite data over several decades, whereas rocky shores and cobble beaches are more likely to remain within a Landsat pixel over the last 50 years. By contrast, the lack of studies focusing on other shoreline features could be due to commonly used manual extraction techniques, which may not be transferrable to satellite imagery owing to its coarser resolutions. This

leads to question whether the methodologies presented can be applied/transferred to other beach types and if the resolution of the publicly available satellites are sufficient for the extraction of all features.

## **2.5. Shoreline Extraction Techniques**

There are a variety of different techniques available for shoreline extraction from MSI. These techniques are mainly based on the classification of the pixel values of satellite images, through Pixel Based Image Analysis (PBIA) to segment the image into different features, or through the use of Object-Based Image Analysis (OBIA), which integrates the spectral information of the pixels, shape, texture, and other topological features into the analysis process. From these two types of analysis, ML techniques can be applied (Kalkan *et al.* (2013)). Alongside image classification, segmentation of the shoreline can be carried out using edge detection and region growing algorithms, which are usually used in combination with the OBIA and PBIA. Edge detection creates continuous edges in images, the most common types include the canny edge detector (Chen and Chang (2009); Yasir *et al.* (2020)) and the Sobel edge detector (Sparavigna (2013); Mansoori *et al.* (2016)). The canny and Sobel edge detector algorithms are simple, and detection is fast, substituting for time consuming onscreen digitising (Yasir *et al.* (2020)). Region based segmentation divides the image into sections with similar features, where these regions contain a group of similar pixels (Hagenaars *et al.* (2017); Hagenaars *et al.* (2018)).

### **2.5.1. Water Indexing**

Water indexing is a valuable approach in assessing and analysing water content using remote sensing data. It involves utilising two or more bands of satellite imagery, such as the NDWI (Normalized Difference Water Index), MNDWI (Modified Normalized

Difference Water Index), and AWEI (Automated Water Extraction Index). Indexing refers to the process of combining and comparing the spectral information from different bands to highlight and quantify water features.

The NDWI is a band ratio technique that uses the Green and SWIR (McFeeters, 1996), or the NIR and SWIR (Gao, 1996) bands, to produce greyscale images that differentiate land and water pixels, using a threshold (discussed further in Section 2.5.2) between the land and water. The modified NDWI (MNDWI), replaces the NIR band with the Middle Infrared band and is used to help solve issues relating to shadows (e.g., cliffs, sea walls, buildings near the coast) in the NDWI, by increasing the contrast between water and other dark surfaces. This enhancement results in a more accurate extraction of the land-water features. The Automatic Water Extraction Index (AWEI) was introduced by Feyisa (2014) to improve the accuracy of water mapping with automatic suppression of classification noise from shadows and other non-water dark surfaces. This method uses five spectral bands to enhance class separability without the need for additional data.

### **2.5.2. Thresholding**

Thresholding is widely considered to be the simplest method of image segmentation. The most common thresholding method is an automatic histogram-based technique that transforms a greyscale image, such as one created from indexing methods, into a binary image (Otsu (1979)). Otsu's method can automatically derive threshold values, by iterating through all possible threshold values to calculate a measure of spread for the pixel levels on each side of the threshold value. Recently, the effectiveness of Otsu's technique has been improved by Bishop-Taylor *et al.* (2019), for the waterline using a subpixel approach. Other thresholds that have been used include the 'local adaptive' threshold, which is obtained through trial and error. The 'optimal' threshold or the

manually derived threshold, which represents a threshold that replicates the shoreline position, is found by iterating through a range of different thresholds for a certain beach until the derived shoreline is accurate and as close to the visible instantaneous shoreline present in the image. The ‘zero’ threshold is a constant threshold at zero that is used to extract the shoreline position, especially for large spatial extents (Bishop-Taylor *et al.* (2019); Sagar *et al.* (2017)). Similar to Otsu’s automatic thresholding, Almonacid-Caballer *et al.* (2016) and Pardo-Pascual *et al.* (2012) use a thresholding technique based on the *bimodal nature* of a histogram of the infrared band of water and land.

In a study conducted by Sunder *et al.* (2017), an inter-comparison of widely used shoreline mapping techniques was performed using multitemporal Landsat data along four coastal stretches in India, made up of sandy beaches with varying physical characteristics including rivers, estuaries, mudflats, man-made structures, and sediment transport. The evaluated techniques included the Normalized Difference Water Index (NDWI), Modified NDWI (MNDWI), Improved Band Ratio (IBR) Method, and Automatic Water Extraction Index (AWEI). The findings indicate that the AWEI algorithm consistently demonstrates superior performance, followed by MNDWI, regardless of the surrounding natural and manmade environment. In contrast, the performance of NDWI and IBR methods varied across different sites due to their dependence on specific physical characteristics, such as clear coastal waters compared to turbid water pixels. Hagenaars *et al.* (2018) present a novel method for automated shoreline detection using Landsat and Sentinel-2 data using the Normalized Difference Water Index (NDWI) to extract the instantaneous shoreline. This method was applied at the Sand Motor, a mega-scale nourishment site along the Dutch coast. The Sand Motor is a coastal engineering project involving the deposition of a massive amount of sand

extracted offshore (18.7 million m<sup>3</sup>) and deposited along the coast in a single operation (Taal. 2016). The study reveals that, under ideal conditions with cloud-free and wave-free images, the average accuracy of the shoreline detection system (SDS) for the Sand Motor is 1 m, which is well within the pixel resolution of the data (10 m). Bishop-Taylor *et al.* (2019) presents a comprehensive evaluation of a method that maps waterlines with sub-pixel accuracy using high-resolution WorldView-2 satellite imagery (8 m). They assess the method's performance in various coastal environments by employing multiple water indices (NDWI, MNDWI, AWEI) and thresholding approaches (optimal, zero, and automated Otsu's method). The study reveals that when absolute accuracy is crucial, combining automated index thresholding approaches like Otsu with sub-pixel methods yields waterline extraction results that approach the accuracy achieved by optimal thresholds, particularly for small study areas.

### **2.5.3. Machine Learning**

Machine learning is a type of artificial intelligence that enables self-learning from data and application of its learning without the need for human intervention. ML methodologies can be applied to image classification, using algorithms that correlate pixel values within the image and input training data (made up of pixel values and corresponding class names). The more bands a satellite image has, the more data there is available for the classification with ML, which can improve the results. ML can be split into two types: supervised and unsupervised. With supervised learning, the user has full control over the training process, where the number of classes, the size of input training data, and the way the machine learns can be predefined. Whereas with unsupervised

learning, the machine determines its own classes through clustering algorithms without any training data.

Figure 3 highlights the techniques that can be used for image-based extraction. These methods can be used on their own for classification (Garcia-Rubio *et al.* (2015); Hagenaaars *et al.* (2018)) or as a combination of each other (Vos *et al.* (2019); Luijendijk *et al.* (2018)). In the sections below, the techniques are explained as stand-alone methods, however they can be (and have been) combined to improve the overall results in identifying shoreline features. For example, Vos *et al.* (2019) use a combination of an MLP and the MNDWI to allow for a more accurate analysis on sandy shorelines by reducing the chance of misclassifications (due to white-water from breaking waves and the influence of surrounding land cover).

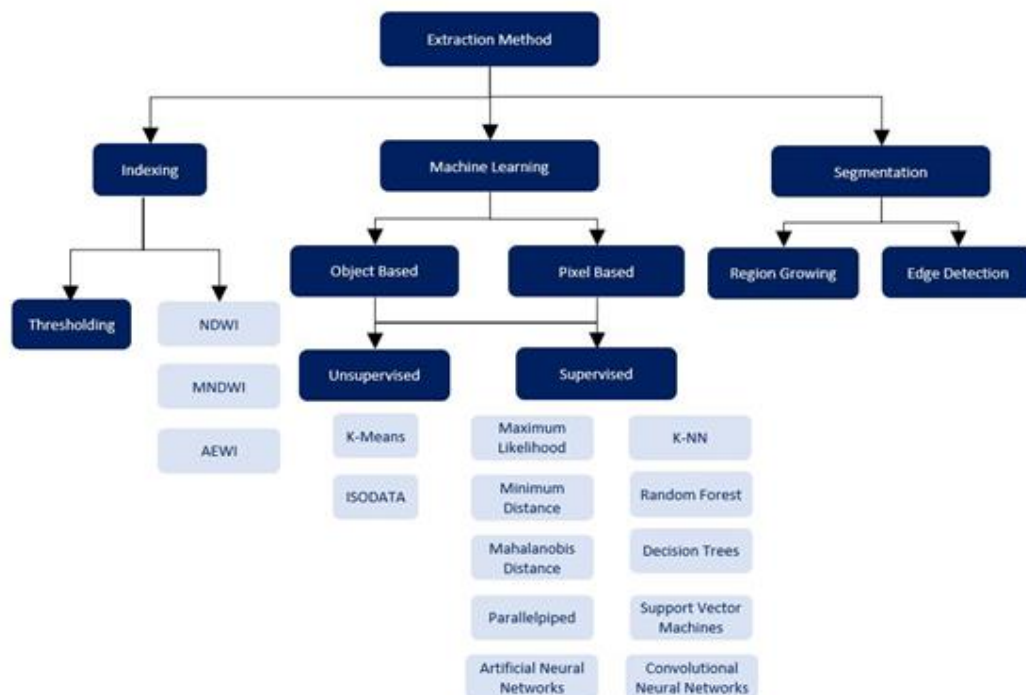


Figure 3: Techniques that have been used in the past which have been applied for the extraction of the shoreline (Source: McAllister *et al.* (2022)).



## **Unsupervised Machine Learning**

Unsupervised ML creates patterns from an image without any knowledge of labelled classes; the algorithms rely on pixels within a group to have intensities with a similar spectral pattern (Garcia-Rubio *et al.* (2015)). These techniques search for similarities between individual pixels and clusters of pixels and aims to find distinct features within the image (Esmail *et al.* (2019)). The two main types of unsupervised ML methods are ISODATA and K-Means.

## **Supervised Machine Learning**

Supervised ML requires prior knowledge of a dataset and its patterns before being applied for image classification. With supervised ML the user provides the chosen algorithm with a predefined training dataset, where the algorithm learns the patterns between the spectral values of the pixels and the output classes. The way these patterns are learnt and classified depends on the algorithm it is applied to, as described below.

### **2.5.3.1. ISODATA**

The ISODATA (Iterative Self-Organizing Data Analysis Technique) is an algorithm that iteratively performs an entire classification and recalculates statistics. It makes use of spectrally distinctive surfaces that can identify spectral clusters effectively within satellite imagery (Ali *et al.* (2015)). The algorithm allows the number of clusters to change from one iteration to the next, hence creating new cluster centres, which merge, or split based on a threshold determined by average intensity values between classes (Zheng and Sun (2008)). Iterations are performed with the new cluster centres which is then continued until the centre distance of the clusters fall below the defined threshold (Sekovski *et al.*, 2014). The ISODATA algorithm is already utilized in coastal science to identify characteristics such as wet and dry sand, sand dunes and vegetation. Sekovski *et al.* (2014)

showed that shorelines produced from ISODATA were closer to the reference shoreline positions than other methods applied for image classification.

#### **2.5.3.2. K-Means**

The K- Means algorithm clusters pixel values based on their similarity. This method is very similar to ISODATA, however ISODATA statistically examines clusters after each iteration (Sekovski *et al.*, (2014)) whereas with K-Means the number of clusters are pre-defined by the user. The algorithm initially assigns each pixel to a cluster randomly and finds the centroid of each cluster. It then reiterates based on reassigning data points to the cluster whose centroid is the closest, where a new centroid for each cluster is then calculated. This iteration continues until variation between the classes cannot be reduced any further (Borra *et al.* (2019)).

#### **2.5.3.3. K-Nearest Neighbour (K-NN)**

K-NN is a simple concept that assumes similar pixels in close proximity are likely to belong to the same class. In this method, an unknown pixel is labelled by examining the training pixels and choosing the class that is most represented among a specified number of nearest neighbours (Richards and Jia (2005)). K-NN can be effective especially when the boundaries between the classes are clearly distinguished (Ose *et al.* (2016)). This is beneficial for the extraction shoreline features such as the instantaneous waterline if the spectral values of the land and water are easily distinguishable, e.g., in clear water and white sand, compared to turbid water and darker sand combinations.

#### **2.5.3.4. Decision tree (DT)**

DT classification is a supervised technique where the training data is repeatedly split depending on whether a value is above or below a threshold that defines the nodes in the decision tree (Maxwell *et al.* (2018)). Classification and Regression Trees (CART) is a

versatile and widely used machine learning algorithm that can be applied to both classification and regression tasks. CART constructs a binary tree structure by recursively partitioning the feature space based on the selected input variables. At each node of the tree, the algorithm identifies the best split point by evaluating various splitting criteria, such as Gini impurity for classification or mean squared error for regression. Gini impurity is a measure used to evaluate the purity of a node when performing classification tasks. It helps the algorithm find the best split point at each node, ensuring that the resulting groups are as homogenous as possible concerning the target class labels. This iterative process continues until a stopping criterion, such as a maximum tree depth or minimum number of samples per leaf, is reached. The resulting tree structure allows for straightforward interpretation and decision-making, making CART a valuable tool in predictive modelling and data analysis.

#### **2.5.3.5. Support Vector Machines (SVM)**

SVM is a powerful and widely used supervised machine learning algorithm. It is primarily used for classification tasks but can also be adapted for regression. SVM aims to find an optimal hyperplane that separates different classes in the input data. By maximizing the margin between the hyperplane and the nearest data points of each class, SVM achieves a robust and efficient classification boundary. It can handle both linearly separable and non-linearly separable data through the use of kernel functions that map the input space to higher-dimensional feature space. SVM is a well-known method for identifying coastal features with different spectral-reflectance characteristics (Choung and Jo (2017)).

#### **2.5.3.6. Artificial Neural Networks (ANNs)**

ANNs are statistical learning algorithms that are inspired by properties of the biological neural networks in the brain. Neural networks are constructed from a collection of

interconnected artificial neurons that pass signals to each other. They are trained by initially assigning ‘random’ values for the weights of the neurons, which are then adjusted when the data is backpropagated through the network. These adjustments are based on the error associated with the output nodes. This training of the network is repeated until the error of the output is reduced to a minimum (Maxwell *et al.* (2018)). ANNs can be simple networks made up of a single hidden layer, or contain multiple hidden layers (Multilayer Perceptron), as the more layers are added to an ANN, the deeper the network becomes, and more complex problems can be solved.

#### **2.5.3.7. Multilayer Perceptron’s (MLP)**

MLPs belong to the class of feedforward ANN, where information flows in one direction, from input to output. MLPs are widely used for various tasks such as classification, regression, and pattern recognition. They consist of multiple layers of interconnected artificial neurons, including an input layer, one or more hidden layers, and an output layer. Each neuron receives input signals, applies weights, and biases, and applies an activation function to produce an output. MLPs are known for their ability to learn complex non-linear relationships and are commonly trained using algorithms like backpropagation. Their flexibility and capability to handle diverse data make MLPs a popular choice in ML applications.

#### **2.5.3.8. Convolutional Neural Networks (CNNs)**

Convolutional Neural Networks (CNNs) are a powerful ML classification technique that excels in analysing both spatial and spectral components of data, resulting in improved accuracy compared to traditional ANNs. CNNs are composed of different layers, including convolutional layers, pooling layers, and fully connected layers (Cheng *et al.* (2017)). These networks have gained significant attention in recent years due to their

ability to effectively detect and identify edges in satellite imagery. Unlike conventional ML techniques, CNNs consider the value of the pixel of interest and its neighbouring pixels, enabling more comprehensive analysis (Rogers *et al.* (2021)). This unique feature of CNNs makes them highly suitable for image processing tasks, particularly in the field of remote sensing and satellite image analysis.

## 2.6. ML Applications to Shoreline Extraction

This section examines how ML algorithms have been applied to identify different shoreline features as proxies for the shoreline position from MSI. This is to gain an understanding of the current state-of-the-art techniques and advancements in the field while allowing for an evaluation of the strengths and limitations of different machine learning approaches for shoreline identification.

The **ISODATA** algorithm is currently being utilised in coastal science to identify various characteristics, including wet and dry sand, sand dunes, and vegetation. Garcia-Rubio *et al.* (2015) employed SPOT MSI with a pixel size of 10 m to extract the instantaneous waterline and consistently found seaward bias, averaging 5.6 m from the *in situ* shoreline. In a similar study, Ali *et al.* (2015) utilised high-resolution (5 m) RapidEye imagery for extracting the instantaneous waterline, finding an average distance of 0.25 m between corresponding points on the extracted and reference shorelines. These studies demonstrate the algorithm's simplicity and minimal user interaction allows for accurate results. Sekovski *et al.* (2014) utilised high-resolution multispectral WorldView-2 satellite imagery to extract the wet/dry waterline. Their results showed that shorelines derived from ISODATA were, on average, 2.2 m closer to the reference shoreline positions compared to other methods (such as Parallelpiped, minimum distance,

Mahalanobis, and maximum likelihood) employed for image classification. Here the waterline was more landward using the ISODATA approach.

In a recent study conducted by Sekar *et al.* (2022), the wet/dry boundary was extracted using ISODATA, K-means, NDWI, and maximum likelihood from Resourcesat-2 satellite imagery, which has a resolution of 10 m. 87.5% of the extracted shorelines exhibited an accuracy of less than 2 m. In comparison, the K-means, NDWI, and maximum likelihood methods showed accuracies of 83%, 79%, and 75% respectively. The ISODATA technique, employed for shoreline extraction, demonstrated consistent results. These studies highlight the advantages of using the ISODATA algorithm for shoreline and coastal feature extraction from satellite imagery, but also point out the need for further validation and testing, particularly over extended periods and larger geographical areas.

Luijendijk *et al.* (2018) is the only study that uses the **CART** algorithm for detecting shoreline proxies. They produced a two-step methodology to identify sandy beaches worldwide. This particular algorithm was chosen due to its ability to minimize omission errors (false negatives) and achieve a high percentage of positive identifications. Subsequently, the researchers applied the NDWI (Normalized Difference Water Index), Canny edge detection filter, and Otsu thresholding techniques to accurately determine the land-water boundary.

The **SVM** algorithm has been widely employed for the extraction of the instantaneous waterline (e.g., Rostami *et al.* (2022); Choung and Jo (2017); Minghelli *et al.* (2020); Bamdadinejad *et al.* (2021)). Rostami *et al.* (2022) utilised Sentinel-2 satellite images with a resolution of 10m to extract the instantaneous waterline and compared the Support Vector Machine (SVM) and Random Forest (RF) algorithms. With the images split into

4 land cover classes, the results revealed that the random forest algorithm exhibited higher accuracy in classifying all images. The overall accuracy of the classified maps using the RF algorithm exceeded 95%. Comparatively, the SVM algorithm demonstrated low accuracy across all maps. Rostami *et al.* (2022) states that the primary reason for the SVM algorithm's poor performance in this study is the high number of classes. As the number of classes increases, the performance of the SVM algorithm tends to decrease. SVM algorithms are most effective in two-class classifications and can convert an image into a two-class map using a linear kernel.

Choung and Jo (2017) compared the accuracy of the NDWI shoreline and SVM shorelines on Worldview-2 images. They chose the SVM classifier, as it is known for its ability to produce highly accurate results and minimize classification noise and classified the images into three classes. The SVM shoreline demonstrated greater accuracy with a mean accuracy of 0.79 m, outperforming the NDWI shoreline, which had a mean accuracy of 2.6 m. The superiority of the SVM shoreline can be attributed to its ability to recognize irregular coastal shapes and identify shaded areas that were missed by the NDWI shoreline. However, both methods exhibited inefficiencies in mapping shorelines in coastal zones with significant shading, where pixels representing shaded areas have lower intensity values compared to other pixels in all multispectral bands.

Rostami *et al.* (2022) and Choung and Jo (2017) reported varying accuracies in their studies and had differing opinions regarding the effectiveness of the SVM algorithm. These outcomes can likely be linked to two key factors. Firstly, Choung and Jo utilised very high-resolution satellite data (8 m), enabling them to capture more intricate details of shoreline features and potentially improving the SVM model's accuracy and they used a smaller set of classes, leading to a more simplified representation of shoreline features.

In their study, Minghelli *et al.* (2020) focused on shoreline analysis in the presence of foam, which often introduces distortions in shoreline positions. They utilised WorldView-2 imagery and applied an SVM classifier to categorize the image into three classes (land, water, foam). The inclusion of a new foam class resulted in a remarkable reduction in the false negative error, with a maximum improvement factor of 4.9 observed across the four images. Additionally, the SVM method was compared with four other classification techniques (Euclidian Distance (ED), Spectral Angle Mapper (SAM), Maximum Likelihood (ML), and Neural Network (NN)). Both the SVM and NN methods demonstrated superior performance, achieving false positive and false negative errors of less than 2%.

Currently, there are only a few studies utilizing **ANN/ MLPs** for shoreline analysis, specifically focusing on instantaneous waterlines. One notable study is CoastSat (Vos *et al.* (2019)), which highlights the advantages of using an MLP combined with the MNDWI for shoreline identification. The MLP is trained to classify four landcover features (water, sand, white-water, and other) based on the pixel values of satellite imagery. This methodology proves beneficial for shoreline extraction as it eliminates the influence of surrounding pixels related to vegetation, buildings, roads, rocky headlands, etc., allowing the classification to focus solely on land/water classes.

Luijendijk *et al.* (2018) followed a similar process to extract the instantaneous waterline, but CoastSat demonstrated improved results, achieving a 60% reduction in Root Mean Square Error (RMSE). Another study by Manaf *et al.* (2018) compared different machine learning methods (MLPs, ANNs, DTs, Naïve Bayes (NB), KNN, and SVM) and found that MLP-ANN was the most effective classifier for identifying instantaneous waterlines,



achieving the highest overall accuracy. However, it should be noted that this approach may have longer training and testing times.

Convolutional neural networks (CNNs) have gained increasing popularity for shoreline identification, as demonstrated in several studies (Seale *et al.* (2022); Cheng *et al.* (2017); Li *et al.* (2018); Erdem *et al.* (2021); Rogers *et al.* (2021)). Cheng *et al.* (2017) applied the deep convolutional neural network called "SeNet" to identify the land-water boundary using Google Earth imagery with a resolution of 3-5m. Their results showed higher accuracy compared to traditional methods and DeconvNet (designed to work similar to convolutional networks but in reverse).

Li *et al.* (2018) developed a novel deep convolutional neural network named "DeepUNet" specifically designed for delineating the land-water boundary using Google Earth images. Their findings demonstrated that the proposed method was not only efficient but also more accurate than other CNN architectures such as U-Net, SegNet, and SeNet.

Erdem *et al.* (2021) utilised Landsat 8 imagery and an automatic shoreline segmentation system called "WaterNet" to automatically extract shorelines. The WaterNet framework achieved the highest accuracy of 99.797% among the tested methods (Standard U-Net, Dilated U-Net, Fractal UNet, FC-DenseNet, Pix2Pix and AWEI). It provided spatially consistent results and outperformed other deep learning models and AWEI in both quantitative and qualitative comparisons for shoreline segmentation.

Seale *et al.* (2022) utilised Sentinel-2 satellite imagery and employed four convolutional neural network (CNN) models for training and testing purposes. They introduced a novel Sobel-edge loss function in their research, which resulted in a CNN model that exhibited enhanced sensitivity to fine-scale and narrow coastline features. By incorporating this

innovative loss function, they were able to improve the model's ability to accurately identify and delineate intricate coastal characteristics.

The majority of studies involving CNNs in the context of shoreline analysis and shoreline change have primarily focused on the development and evaluation of CNN models rather than their practical application. These studies have aimed to enhance the accuracy and effectiveness of CNNs in identifying shoreline features and analysing shoreline dynamics. The researchers have explored various techniques such as loss functions, network architectures, and training strategies to optimize the performance of CNN models. However, there is still a need for further research and application of these CNN models in real-world scenarios to fully exploit their potential for shoreline analysis and monitoring.

## **2.7. Conclusion**

This chapter provides a comprehensive overview of the research question concerning the utilisation of open-source MSI for quantifying global shoreline change across various beach types using ML. It delves into previous EO studies to understand the mapping of SIs from MSI, while also analysing processing technologies like ML and Artificial Intelligence (AI) to extract shoreline features at different scales. It was determined that not one method can be used for the extraction of entire world's coastlines when considering the extraction of SIs and there is a need to trial more methods for the identification of different SIs for different shoreline settings and on different scales.

The current research on the application of different methods for extracting SIs from MSI, has mainly been for the instantaneous waterline shoreline indicator. Which increases the need for other indicators to be extracted from MSI. Although cliffs and sand dunes are shoreline indicators, they have not been extracted from MSI as frequently as other

indicators. It is worth noting that these indicators are also not universally present across all shorelines worldwide. Therefore, to ensure comprehensive shoreline extraction globally, a shoreline indicator present on all shoreline types should be thoroughly tested. The wetting limit, or the wet/dry boundary, emerges as a promising shoreline indicator due to its stability compared to the instantaneous waterline. However, its application with ML techniques remains limited to smaller scales, warranting further exploration.

It is important to utilise the information acquired on available techniques and the freely available satellite imagery to monitoring shoreline change over a global scale to create a more automated and frequently updated method of monitoring our shorelines for understanding patterns and relationships of change and for the prediction of our future coastlines. In evaluating techniques for shoreline identification, it has been found that in recent years there has been an increase in the popularity of deep AI/ML approaches such as CNNs and ANNs, due to their increased accuracy. However, the complexity and time-consuming nature of image processing should be considered, recognising that not all problems require intricate algorithms. Given these considerations, both shallow and deep ML techniques will be evaluated and applied to the wet/dry boundary to determine the feasibility of extracting the from MSI. This assessment will also determine whether the algorithm requires complexity or can be simplified.



# **Chapter. 3 An Automated Methodology for Extracting Historical Shoreline Change**

In Chapter 2, the extraction of shorelines from MSI is explored and an overview of ML techniques for extracting SIs has been examined. The discussion reveals notable research gaps that align with the research questions proposed in Chapter 1. Indeed, Chapter 2 emphasises the prevalence of extracting instantaneous shorelines as the most common shoreline indicator. However, it also suggests that other waterline indicators, such as the wet/dry boundary (see Section 3.2) may offer more valuable insights into shoreline change dynamics.

The majority of recent studies employ ANNs and CNNs for shoreline extraction (See Chapter 2). However, other ML algorithms such as SVM, CART and RFs are still beneficial for shoreline extraction due to the nature through which they learn from data.

The objective of this chapter is to develop a methodology for extracting the wet/dry boundary SI using open source MSI. To accomplish this, Sentinel-2 satellite imagery is used, as it offers 10 m resolution data (the best resolution available from open-source satellite data) and has a continuous dataset spanning back to 2015.

### **3.1. Study Sites**

Start Bay, Aldbrough and Sizewell (all in the UK) have been selected as study sites for this thesis because: (a) they represent three different types of coastlines (including flat coastlines and cliff coastlines) as described in Payo *et al.* (2020), (b) these study sites have varying tidal ranges, sediment compositions, and beach slopes, providing a diverse range of beach characteristics, allowing for a comprehensive examination of whether the SI can be effectively identified across different coastal environments, and (c) there is good quality, cloud-free, very high-resolution data (<10 m) over the study period against which Sentinel-2 results could be validated. This allows the proposed method to be tested in different environments. The three study sites are shown in Figure 4 with additional information about beach characteristics shown in Table 1.

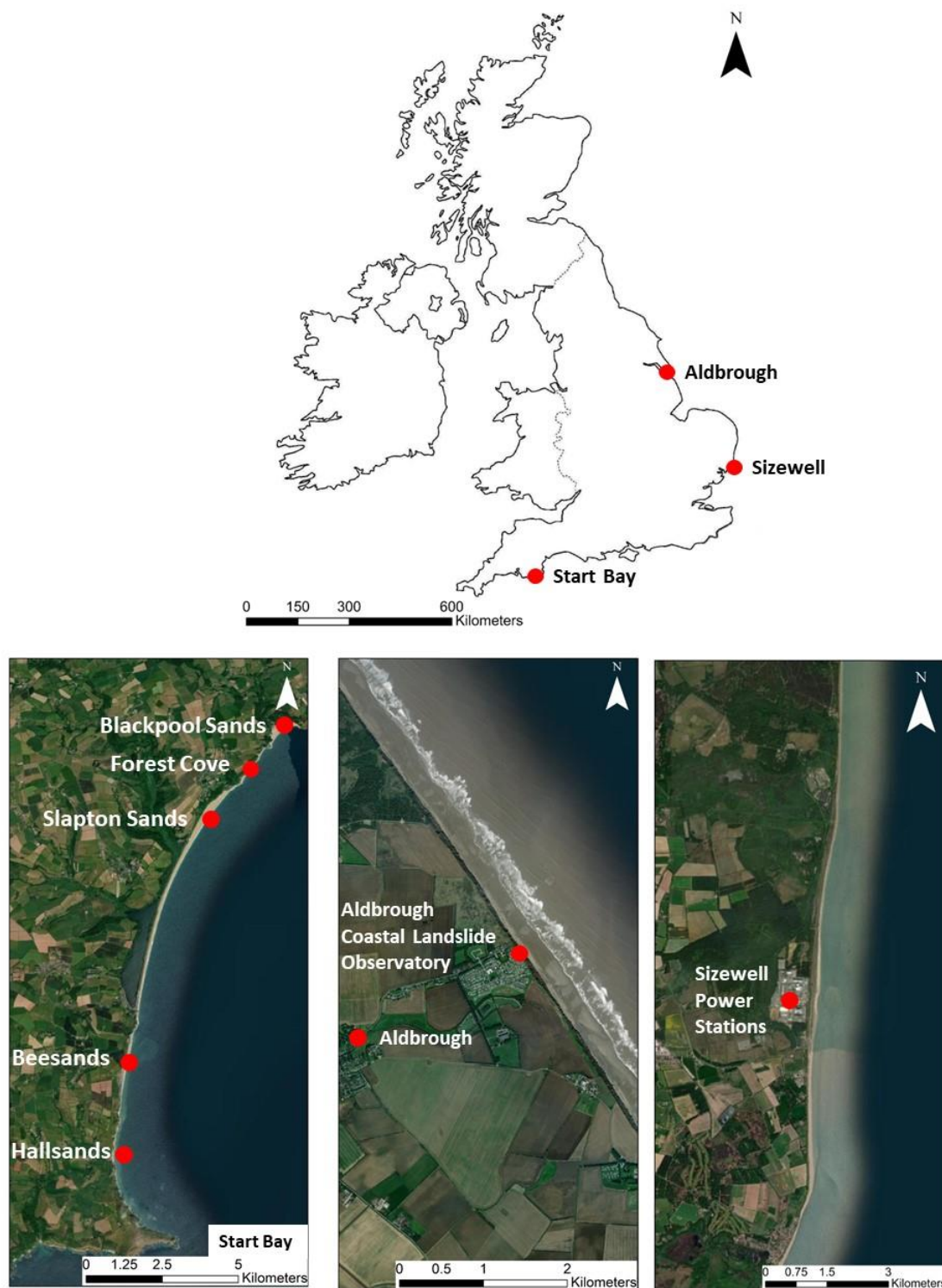


Figure 4: Top: Map of the British Isles showing the three study sites. Bottom Row: Location maps of Start Bay, Aldbrough and Sizewell, with corresponding points of locations referred to throughout the thesis.

Table 1: Beach characteristics of the study sites. Source (Channel Coast Observatory (CCO) and British Oceanographic Data Centre (BODC))

|                                | <b>Start Bay</b>                     | <b>Aldbrough</b>          | <b>Sizewell</b>                                                     |
|--------------------------------|--------------------------------------|---------------------------|---------------------------------------------------------------------|
| Mean Spring Range <sup>4</sup> | 1.40 m                               | 5.59 m                    | 2.1 m                                                               |
| Mean Neap Range <sup>5</sup>   | 0.84 m                               | 2.25 m                    | 1.21 m                                                              |
| Class                          | Micro-tidal                          | Macro-tidal               | Micro-tidal                                                         |
| Wave exposure                  | Oceanic (Atlantic)                   | Fetch-limited (North Sea) | Fetch-limited (North Sea)                                           |
| Mean annual wave height (m)    | 0.71                                 | 0.79                      | 0.78                                                                |
| Wave direction <sup>6</sup>    | Weakly bidirectional                 | Unidirectional            | Bidirectional, weak net southerly                                   |
| Hinterland <sup>7</sup>        | Headlands, cliffs and beach barriers | Cliff                     | Low hills (Sizewell) and beach barrier to low-lying Minsmere Levels |
| Sediment                       | Gravel beaches                       | Very fine sand            | Composite beach, sandy subtidal, mixed pebble/sand subaerial        |
| Beach Slope (m)                | 0.14                                 | 0.095                     | 2.71                                                                |

Start Bay is a 12 km long embayment located in the south coast of Devon in the United Kingdom. Of this coastline, 10 km was analysed in this thesis, based on the validation data available for the study site (refer to Section 3.8). The study site consists of five shingle beaches (Figure 5); Hallsands (50°14'20.26"N, 3°39'34.80"W), Beesands (50°15'27.23"N, 3°39'18.39"W), Slapton Sands (50°17'0.76"N, 3°38'46.44"W), Forest

<sup>4</sup> the average difference in height between the high-water level during spring tides and the low water level.

<sup>5</sup> the average difference in height between the high-water level during neap tides and the low water level.

<sup>6</sup> the average height of waves observed over a year-long period at a specific location.

<sup>7</sup> the inland area or region beyond a coastal boundary.



Cove ( $50^{\circ}18'42.75''\text{N}$ ,  $3^{\circ}37'8.94''\text{W}$ ) and Blackpool Sands ( $50^{\circ}19'8.42''\text{N}$ ,  $3^{\circ}36'32.83''\text{W}$ ), which are separated by short headlands/rocky outcrops (Wiggins *et al.* 2019). Start Bay is effectively a closed system, bound by two large headlands with no external sediment sources aside from some localised cliff erosion. The bay undergoes sub-embayment rotation (the localised movement or circulation patterns within smaller sections or subdivisions of a bay or embayment) when there is a shift in the dominance of a particular wave direction, and under high-energy wave conditions such as persistent seasonal or storm energy, full embayment rotation (the larger-scale circulation patterns encompassing the entire bay or embayment) can occur (Wiggins *et al.* 2019).

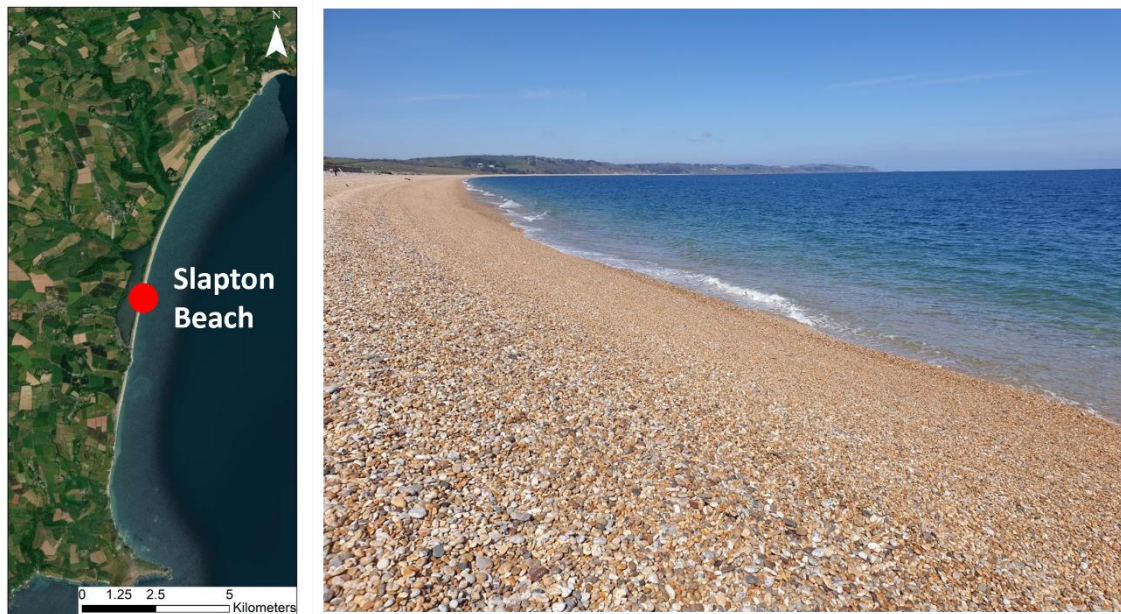


Figure 5: Left: Location Map of Slapton Sands, Start Bay. Right: Photo of Slapton Sands (Source: Google Maps)

Aldbrough Beach ( $53^{\circ}50'9.23''\text{N}$ ,  $0^{\circ}5'22.91''\text{W}$ ) is a cliff backed shoreline in Yorkshire that forms part of the 50 km long Holderness Coast on the North Sea (Figure 6). In this thesis, a stretch of 6 km of this coastline was analysed, based on the validation data available for the study site (refer to Section 3.8). The cliffs at Aldbrough have an average

height of 20 m and are one of the fastest-eroding coastlines in Europe, at a rate of 2 m per year (Hobbs *et al.* (2019)). Aldbrough has mixed sand and shingle beaches with additional till from eroding cliffs. Since 2001, the site has been part of the Coastal Landslide Laboratory of the British Geological Survey (Pennington *et al.* (2021)) which allows for regular laser scanning of the cliffs needed to assess erosion rates and their relationships with deep-seated landslide activity.



Figure 6: Top Left: Location Map of Aldbrough. Top Right: Photo of beach at Aldbrough (Source, Flickr). Bottom: Cliffs at Aldbrough (Source: BGS)

Sizewell Beach ( $52^{\circ}12'51.11''\text{N}$ ,  $1^{\circ}37'26.02''\text{E}$ ) is the 6.5 km long section located between Thorpeness and Minsmere Sluice on the Suffolk Coast of the North Sea. In this thesis, 2 km of this coastline was analysed, based on the validation data available for the study site (refer to Section 3.8). It consists of mixed sand and gravel (dominant) and is backed by a gravel barrier with dune vegetation and sand (Dolphin *et al.* (2020)), shown in Figure 7. Landward of Sizewell Beach are the Sizewell A and Sizewell B nuclear power stations, and the site for a new Sizewell C power station. To avoid inevitable coastal erosion exposing Sizewell C's hard coastal defences (over its  $100^{+}$  year life), which would disrupt natural longshore sediment transport causing downdrift erosion, the station will be built with an enlarged shingle beach. The beach will be maintained when beach volumes fall below a volumetric threshold, using beach recharge, recycling, or bypassing techniques (NNB Generation Company (Sizewell C), (2021a)). The Sizewell A and Sizewell B frontage fluctuates but has a net stability since the stations were constructed (1961–1966 and 1987–1995 respectively), however north of Sizewell C (between the station and Minsmere Sluice) there is a localised zone of shoreline erosion (Wallbridge *et al.* (2019), Burningham and French (2016)).

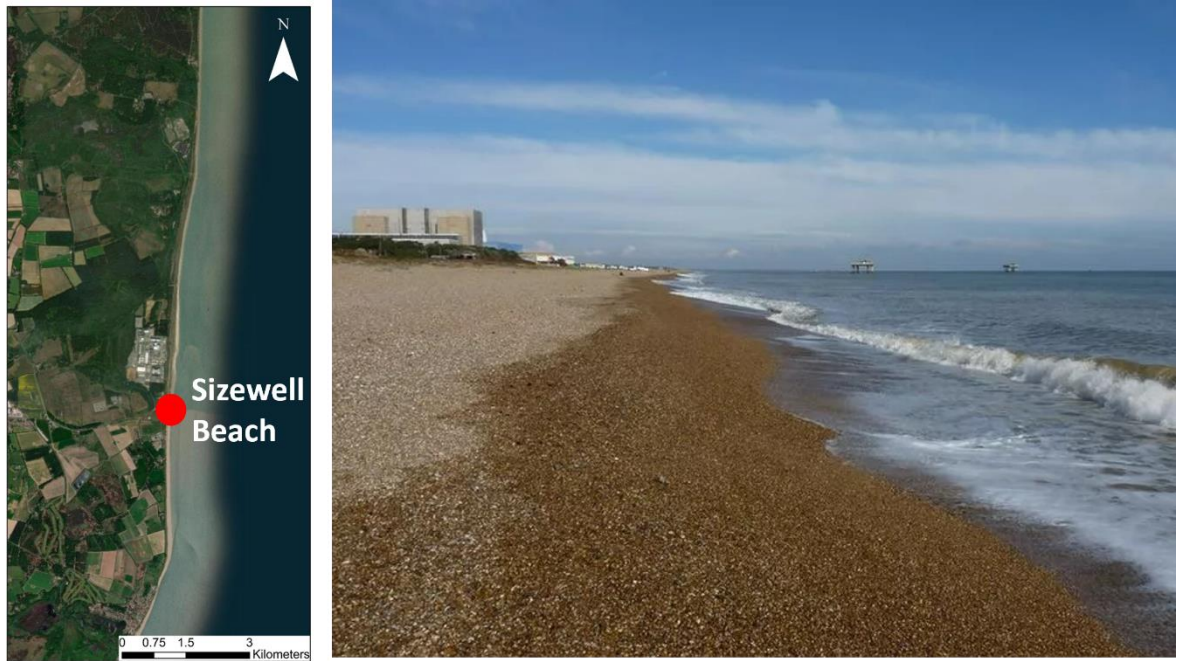


Figure 7: Left: Location map of Sizewell Beach. Right: Photo showing Sizewell beach with Sizewell Power Plant in background (Source: SuffolkLive)

### 3.2. The Wet/Dry Boundary as a Shoreline

The chosen SI for determining the shoreline position in this thesis is the wet/dry boundary. The wet/dry boundary represents the visible band parallel to the sea that shows the extent of the previous high tide (Boak and Turner (2005)). It belongs to the **Visually discernible coastal features** described in Section 2.3.

The wet/dry indicator was chosen because it is easy to interpret on MSI (Sekar *et al.* (2022)), it should not need to be tidally corrected, and it represents the furthest point the tide has reached. Given that all beaches in used in this thesis experience a semidiurnal tide pattern (with two high and low tides per day), there is an enhanced likelihood of accurately capturing the wet/dry boundary. This probability is further increased by the band information of Sentinel-2 (Section 3.3), where even if the sand appears dry visually, the bands should still be capable at detecting moisture on the beach.



The wet/dry boundary is beneficial as in the past it has been compared to shorelines such as the HWL, which are widely used in the coastal community. The HWL is the furthest extent the shoreline reaches up the beach and during survey (including aerial photography) (Boak and Turner (2005)), the image/shoreline is obtained at the point of high tide, which is a good horizontal comparison for proxies such as the wet/dry boundary (Pajakt and Letterman (2002)). The wet/dry boundary shorelines represent the furthest extent of the tide during the tidal cycle and can be used to provide an average of the MHWL over temporal scales.

As the wet/dry boundary is representative of the tides it can also be compared to datum shorelines, e.g., MHW datum, which represents the average level of all high tides over a specific period. It can be compared to help assess the variations between individual high tides and the overall average high tide level. It can also be compared to the MSL datum shoreline.

The wet/dry boundary is an important shoreline indicator for delineating shoreline position; however, it is influenced by wave runup relative to tidal levels. Unlike the tidal level, which solely reflects the water level governed by tidal forces, the wet/dry boundary integrates both the tidal level upon reaching the beach and the additional impact of wave runup. With wave runup denoting the maximum vertical extent of waves reaching onto the shore during wave events.

### **3.3. Sentinel-2 Multispectral Satellite Imagery**

Sentinel-2 Level-1C MSI from the European Space Agency is utilised in this research (more details are available on the European Space Agency website (ESA (2023))). Level-1C processing encompasses radiometric and geometric corrections, including

orthorectification (removing image distortions or displacements caused by sensor tilt and topographic relief) and spatial registration, which are conducted on a global reference system to achieve sub-pixel accuracy, providing a more accurate representation of the Earth's surface for analysis. These corrections are performed by ESA, leveraging advanced algorithms and precise calibration techniques to ensure the reliability of the data captured by Earth observation satellites. At the equator, the revisit frequency of each individual Sentinel-2 satellite is 10 days, while the combined revisit frequency of the constellation is 5 days. This low revisit period facilitates the understanding of short-term changes, including, potentially, the impacts of storms. Simultaneously, the ongoing data acquisition supports the comprehension of changes spanning from seasonal to annual durations.

High spatial resolution is achieved across 13 bands: four bands at 10 meters, six bands at 20 meters, and three bands at 60 meters (Table 2) (Copernicus, 2019). The spectrum of wavelengths offered by Sentinel-2 enables the identification of distinct features with enhanced precision and detail (Figure 8). Within these spectral bands, Top of Atmosphere (TOA) reflectance is corrected, this is the radiance measured by the satellite sensor at the top of Earth's atmosphere, before it interacts with any surface features or atmospheric constituents contributing to the enhancement of remote sensing data quality, accuracy, and comparability.

The use of Sentinel-2 satellite imagery in this thesis is attributed to its availability as a publicly available global dataset, its high resolutions, and its increasing significance within coastal studies, aligning with the expansion of the database over time with almost 570pb of data downloaded over the mission timespan (further information available on the Copernicus website at Copernicus (2023)).

Landsat 7 and Landsat 8 datasets could have been considered as alternative sources of data as they are also publicly available. However, there are some limitations associated with these datasets that make them less suitable for analysis compared to Sentinel-2 data. Landsat 7 and Landsat 8 images have a spatial resolution of 30 m, which is too coarse for the study sites which have a tidal range within 30 m. Landsat 7 also experienced a hardware malfunction known as the Scan Line Corrector (SLC) failure, which caused gaps and stripes of missing data in every image acquired after May 2003. This significantly limited the availability of continuous and consistent imagery for analysis. While Landsat 8, launched in 2013, provides additional data and continues the Landsat program's legacy, its temporal resolution is not as frequent as Sentinel-2. Landsat satellites have a revisit time of approximately 16 days, whereas Sentinel-2 has a revisit time of 5 days (with both Sentinel-2A and Sentinel-2B in operation). This means Sentinel-2 can provide more frequent observations, which is important for capturing rapid changes or events along the coastline. However, Landsat 8 data could be valuable as complementary data to Sentinel-2, providing additional temporal coverage and different spectral bands (including thermal bands).

Table 2: Sentinel-2 band information including central wavelengths and resolutions (Copernicus, 2019)

| Bands      |                 | Wavelength<br>( $\mu\text{m}$ ) | Resolution<br>(m) |
|------------|-----------------|---------------------------------|-------------------|
| <b>B1</b>  | Coastal/Aerosol | 0.443                           | 60                |
| <b>B2</b>  | Blue            | 0.49                            | 10                |
| <b>B3</b>  | Green           | 0.56                            | 10                |
| <b>B4</b>  | Red             | 0.665                           | 10                |
| <b>B5</b>  | Red Edge 1      | 0.705                           | 20                |
| <b>B6</b>  | Red Edge 2      | 0.74                            | 20                |
| <b>B7</b>  | Red Edge 3      | 0.738                           | 20                |
| <b>B8</b>  | NIR             | 0.842                           | 10                |
| <b>B8A</b> | Red Edge 4      | 0.865                           | 20                |
| <b>B9</b>  | Water Vapour    | 0.945                           | 60                |
| <b>B10</b> | Cirrus          | 1.375                           | 60                |
| <b>B11</b> | SWIR 1          | 1.61                            | 20                |
| <b>B12</b> | SWIR 2          | 2.19                            | 20                |

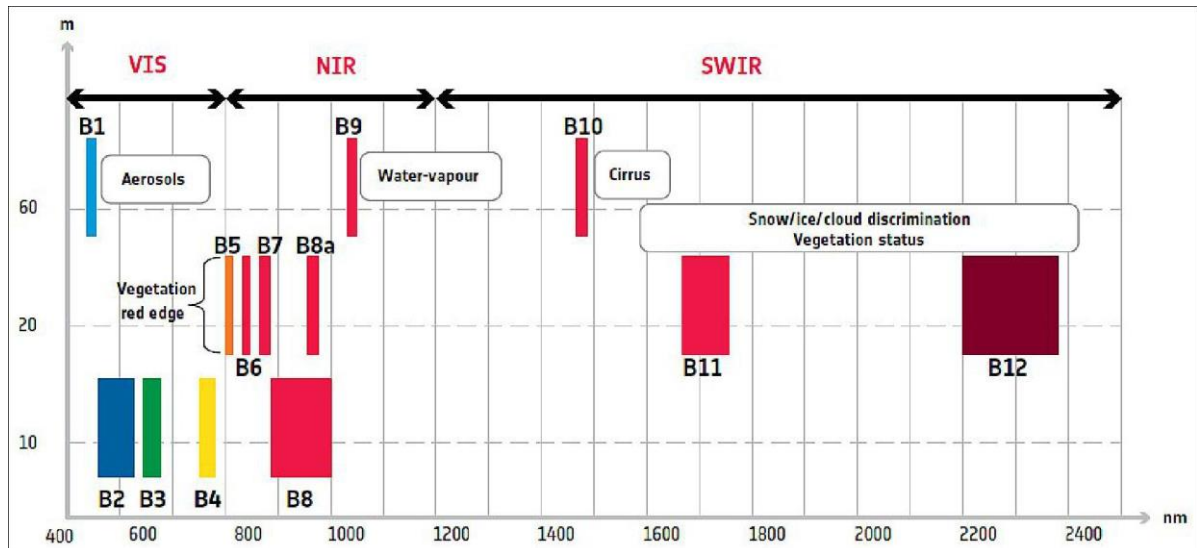


Figure 8: Variation in Spatial Resolution and Wavelength Intervals in Sentinel-2 Images. The sensor covers a spectrum of 13 spectral bands, spanning from visible and near-infrared to shortwave infrared (Source eoPortal).



### **3.4. Google Earth Engine (GEE) and the Python Application Programming Interface**

Given the large size of the Sentinel-2 datasets needed for the analysis, the data was processed on a cloud computing environment, Google Earth Engine (GEE). The latter is an online platform containing a multi-petabyte catalogue of satellite imagery (including Sentinel-2), and geospatial datasets with planetary-scale analysis capabilities (Gorelick *et al.* (2017)). This platform offers numerous advantages to satellite specialists, as it allows for rapid and accurate analysis directly within a unified interface, eliminating the need for data downloads. Sentinel-2 data for this thesis was obtained from GEE and was filtered by date (2016-2022), Region of Interest (ROI) (see, Section 3.1), and cloud cover (see Section 3.5).

The filtered Sentinel-2 data is transferred to Google Colab (short for Collaboratory). Google Colab is a free cloud-based platform provided by Google, where Python code can be written and executed within a Jupyter Notebook environment. Here the GEE Python Application Programming Interface (API) is utilised, enabling the application of external Python libraries including Keras (Chollet *et al.* (2015)), PyTorch (Paszke *et al.* (2019)), and Scikit Learn (Pedregosa *et al.* (2011)) needed for AI-based classification and for waterline extraction.

## **3.5. Pre-processing**

### **3.5.1. Cloud cover**

Cloud cover was initially sorted based on the full Sentinel-2 tile size (110x110km<sup>2</sup>) and only images with less than 10% cloud cover were included in the collection. This is because coasts in the UK tend to be cloudier and when the full scene is considered it is

easier to filter the collection of imagery making processing less demanding and leading to unnecessary postprocessing.

Subsequently, after defining the ROI, a cloud filter was applied to the ROI, enabling the selection of images with cloud cover less than 2%. Images with cloud cover higher than 2% were excluded, as they contained a significant number of clouds, making them unsuitable for analysis.

### **3.5.2. Principal Component Analysis**

Principal Component Analysis (PCA) is a widely used dimensionality reduction and data analysis technique in the field of statistics, ML, and data science (Festa *et al.* (2023)). PCA is used for the reduction of variance in the band information to understand if there are bands highly sensitive to wet and dry sand. It is essential to ensure that the data with the highest variance is used, as it contains a larger amount of information, allowing it to pick up the spectral differences in the wet sand, which may not be detectable using the original band information.

In an image, band information is correlated in a way that it can contain redundant information, i.e., if the band information is correlated, then no extra information is being gained by retaining the information of both bands, as one can be expressed as the linear combination of the other. So, PCA transfers the variance of the second band information onto the first by the translation and rotation of original axes, discussed further below, and then projected onto new axes. The first step in order to identify these correlations through PCA involves the computation of a covariance matrix (Equation 1). This matrix serves as a tool to determine the connections and relationships among the band information.

$$cov_{x,y} = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{N - 1}$$

Equation 1: Covariance equation

Equation 1, shows how covariance is calculated, where  $Cov_{x,y}$  is the covariance,  $x_i$  is the pixel reflectance values of the first band,  $\bar{x}$  is the mean of the band values,  $y_i$  is the values of the second band,  $\bar{y}$  is the mean of these band values and  $N$  is the number of values.

The covariance matrix is a  $P \times P$  matrix (pixel x pixel) (Equation 2), where the values are the covariances associated with all possible pairs of the bands.

$$\begin{bmatrix} cov(x, x) & cov(x, y) & cov(x, z) \\ cov(y, x) & cov(y, y) & cov(y, z) \\ cov(z, x) & cov(z, y) & cov(z, z) \end{bmatrix}$$

Equation 2: A 3x3 covariance matrix

The eigenvectors and eigenvalues are then calculated to determine the principal components (Jolliffe and Cadima (2016)). The eigenvector is the direction of the largest variance from the matrix and the eigenvalue shows how much variance exists in that direction. The eigenvector with the highest eigenvalue (variance), is the principal component, and the data is changed onto a new set of dimensions (Figure 9).

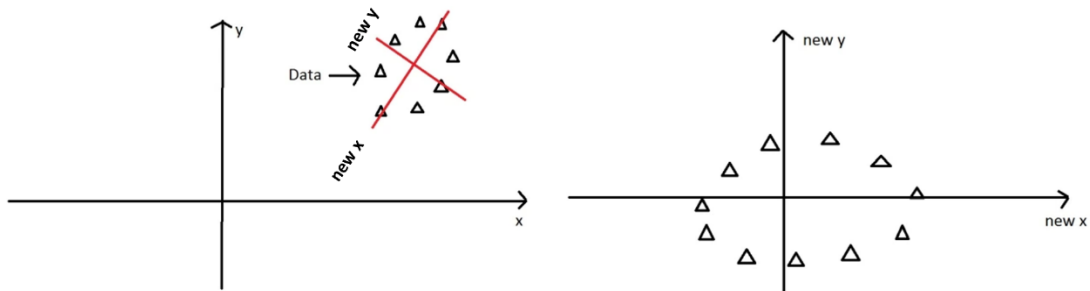


Figure 9: How the distribution of data on a normal X, Y axis is changed into a new dimension of data based on the highest Eigen value.

These axes are much more intuitive to the shape of the data now, as the new set of axes align more naturally with the inherent patterns and variations present in the data. The

eigen pairs (eigenpairs provide insights into the inherent properties and transformations of matrices) are sorted based on the magnitude of their eigenvalues which allows us to find the principal components (PCs) in order of significance. Once sorted, a decision is made about how many of these PCs to retain for the purpose of dimensionality reduction.

The first three Principal Components were chosen, as they provide 97% of the variance in the data. As the PCA is already choosing band information with the highest variance, the bands which were used as training data were adjusted. When the bands were having no impact on the PCA results, they were removed as they do not contain useful or relevant information and do not contribute much to the overall variability in the data. The process of removing bands that have no impact on PCA results helps simplify the analysis and reduce computational load.

### **3.6. Image Classification**

Image classification plays a crucial role in the division of satellite images into distinct feature classes, based on their spectral values. The spectral values refer to the bands deemed as relevant from the PCA analysis. In this thesis, a two-step classification approach has been adopted specifically to identify the wet/dry boundary (Figure 10). Two ML techniques have been tested and compared for the classification, a CART and an ANN (see Section 3.6.3).

The classification of the satellite image is initially divided into five land cover classes, namely Artificial Surfaces, Agriculture, Forest, Sand, and Water. Each of these classes represent distinct features present within the image. To accurately delineate the wet/dry boundary from the image, a more refined classification is necessary. Therefore, a

reclassification process is carried out and the 'Sand' class is further categorised into wet sand and dry sand classes.

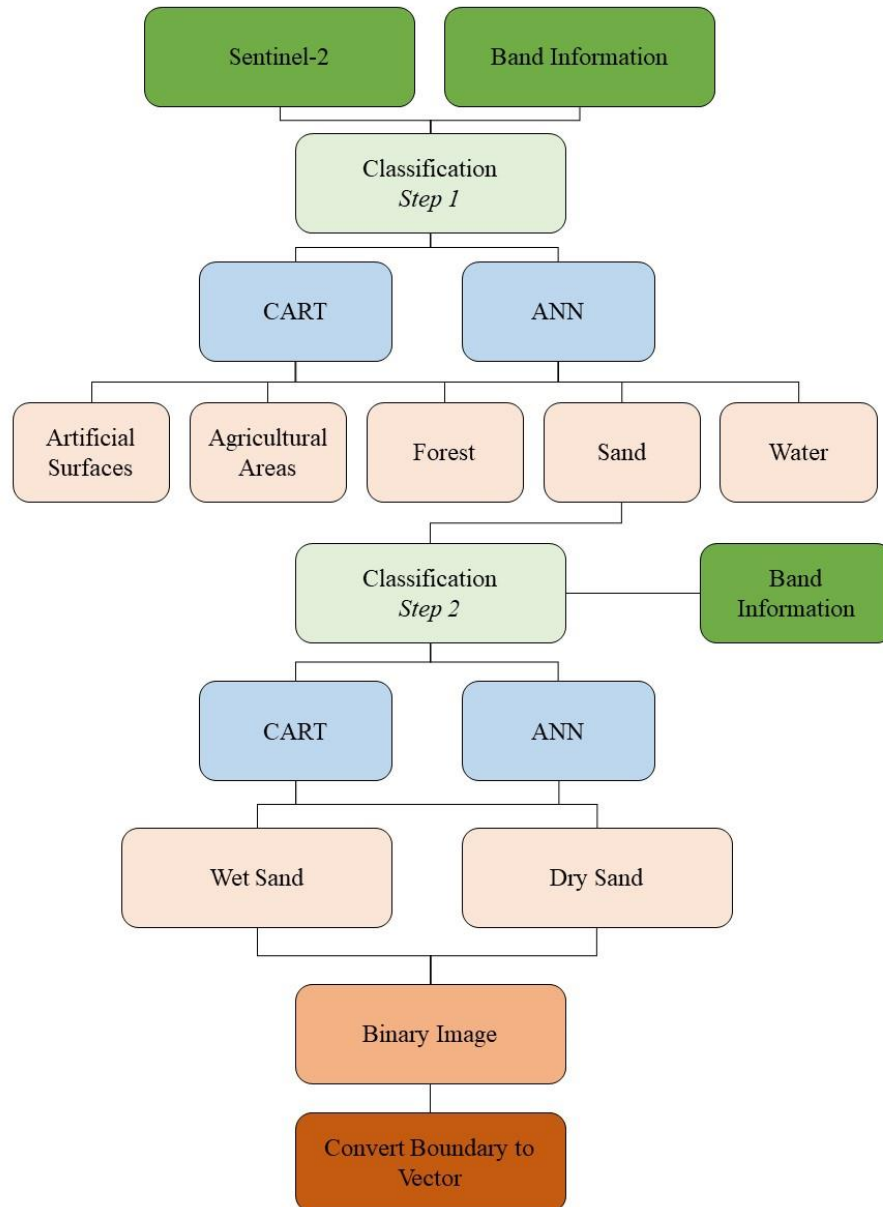


Figure 10: Flow diagram showing methodology for the two-step classification process.

### 3.6.1. Machine Learning

Two ML techniques are used to extract the shoreline position, a CART and an ANN. These are compared to see if a CART has improved accuracy results compared to validation shorelines (Section 3.8) than a complex and commonly applied technique (ANN). These ML algorithms are described in more detail in Section 3.6.3. The structures for these algorithms are described in the following sections as well as the training data used.

### 3.6.2. Training Datasets

To train the CART and ANN models, training datasets were generated for each study area by splitting the satellite imagery into five landcover classes and differentiating between wet and dry sand. This process was conducted using the GEE platform, where data points or pixels were manually selected to represent each class. By concatenating these data points across multiple satellite images, a more extensive training dataset was generated, which is presented in the accompanying Table 3.

Table 3: Table showing the satellite images and training data used for the three study sites.

|                                        | <b>Start Bay</b>                                                                 | <b>Aldbrough</b>                                                                                                           | <b>Sizewell</b>                                                                                                            |
|----------------------------------------|----------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------------------------------------|
| <b>Number of satellite images used</b> | 4                                                                                | 6                                                                                                                          | 6                                                                                                                          |
| <b>Dates of the satellite images</b>   | <i>27/09/2018</i><br><i>04/07/2019</i><br><i>17/09/2019</i><br><i>29/01/2021</i> | <i>20/04/2018</i><br><i>26/02/2019</i><br><i>29/06/2019</i><br><i>28/02/2021</i><br><i>30/04/2021</i><br><i>28/05/2021</i> | <i>11/06/2018</i><br><i>30/06/2018</i><br><i>05/08/2018</i><br><i>29/06/2019</i><br><i>30/05/2020</i><br><i>20/07/2021</i> |
| <b>5 class pixels</b>                  | 3,115                                                                            | 4,573                                                                                                                      | 3,571                                                                                                                      |
| <b>2 class pixels</b>                  | 1,238                                                                            | 1,595                                                                                                                      | 1,269                                                                                                                      |

For the first step of training, six multispectral bands: Blue (B2), Green (B3), Red (B4), Near-Infrared (B8), Thermal band (B10), and SWIR (B12) are utilised to create the training dataset that separates the image into five classes. The combination of these bands covers a wide range of spectral information, making them well-suited for distinguishing the specified classes. For example, water bodies can be detected by their unique reflectance in the B2 and B8 bands, while vegetation can be identified based on differences in the B3 and B8 bands. Urban and artificial surfaces may exhibit distinct signatures in the visible and B10 bands (GISGeography (2022)). The inclusion of the SWIR band further enhances the discriminative power of the classification as it is particularly sensitive to mineral composition, moisture content, and geological features. The selection of these bands takes advantage of their sensitivity to key features of the classes, enhancing the accuracy and interpretability of the classification process.

Subsequently, for the second step, three multispectral bands ('B2', 'B4', 'B8') are employed to differentiate between wet and dry sand. The selection of bands was based on the findings of the PCA (Section 3.5.2) while considering the data's spectral characteristics and the specific requirements to differentiate between wet and dry sand. The combination of these bands allows for a comprehensive assessment of the sand's moisture content and related properties. The B2 response to water absorption, the B4 band's sensitivity to organic and mineral content, and the B8 band's sensitivity to water content collectively provide a robust feature set for distinguishing wet and dry sand.

The input pixel data from several images was used instead of feeding the algorithm images one by one to prevent overgeneralisation. This approach ensured that the model learned from a diverse set of examples and was not overly reliant on specific

characteristics of individual images, mitigating the risk of the model memorising specific patterns from the training data and performing poorly on unseen data.

The input data into the ML algorithms was split, allocating 70% of pixels for training purposes and keeping the remaining 30% for testing. This split allowed for the algorithm to be trained on a substantial portion of the data while still having a separate unseen pixel dataset to evaluate the model's performance. Allocating 70% of the data for training and reserving 30% for testing is a common split ratio in ML (Tan *et al.* (2021)). The process of the two-step classification is visualized in Figure 11 - Figure 13, illustrating the progression and flow of the classification process at all three sites.

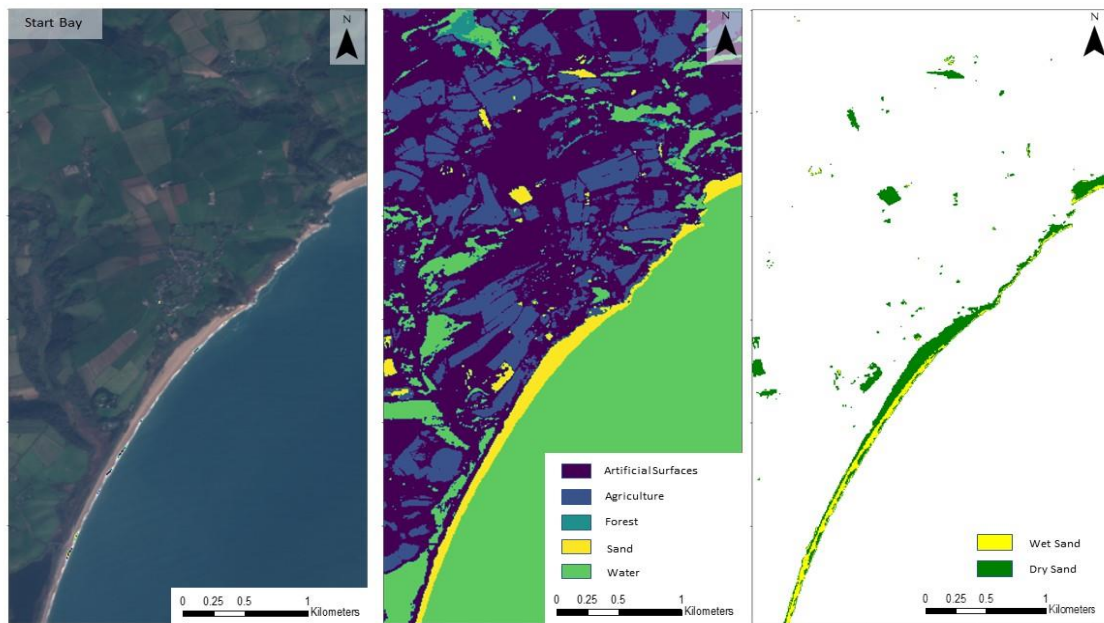


Figure 11: a) RGB Multispectral Satellite Image of Slapton Sands at Start Bay. b) First output of image classification with each pixel being labelled into a class. c) Output of the second stage of classification where the sand has been reclassified and the wet & dry sand has been classified. Here, areas of 'Dry Sand' not contained within the sand class are removed in postprocessing (Section 3.7). Bands of 'Dry Sand' visible on the water side of the 'Wet Sand' created due to breaking waves are corrected in post processing (Section 3.7)



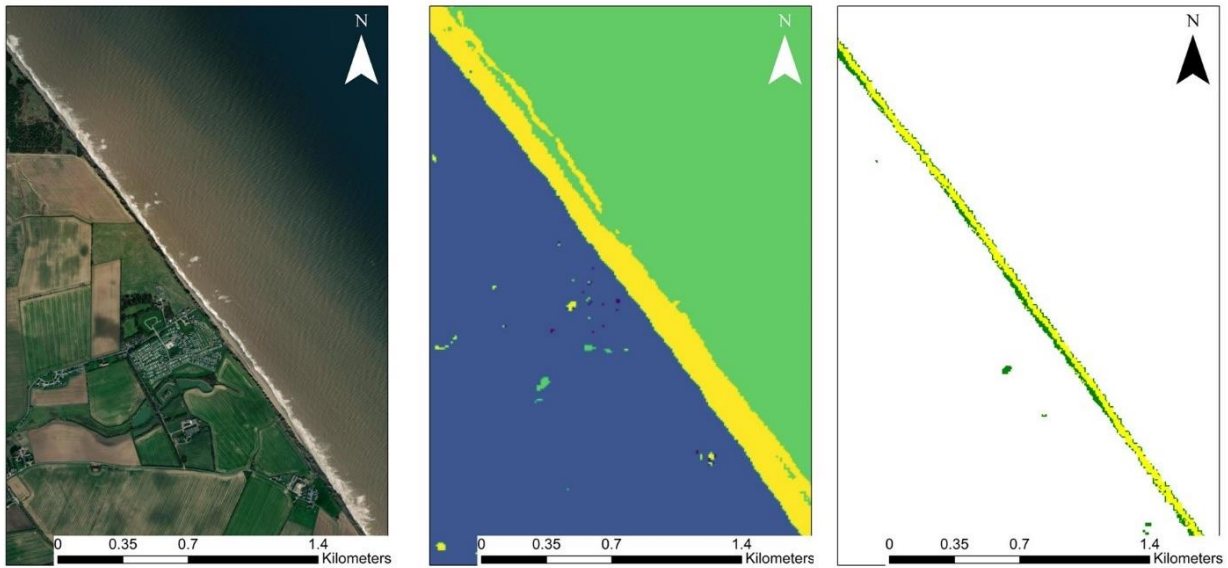


Figure 12: a) RGB Multispectral Satellite Image of Aldbrough. b) First output of image classification with each pixel being labelled into a class. c) Output of the second step of classification where the sand has been reclassified and the wet & dry sand has been classified. Here, areas of 'Dry Sand' not contained within the sand class are removed in post processing (Section 3.7). Bands of 'Dry Sand' visible on the water side of the 'Wet Sand' created due to breaking waves are corrected in post processing (Section 3.7)

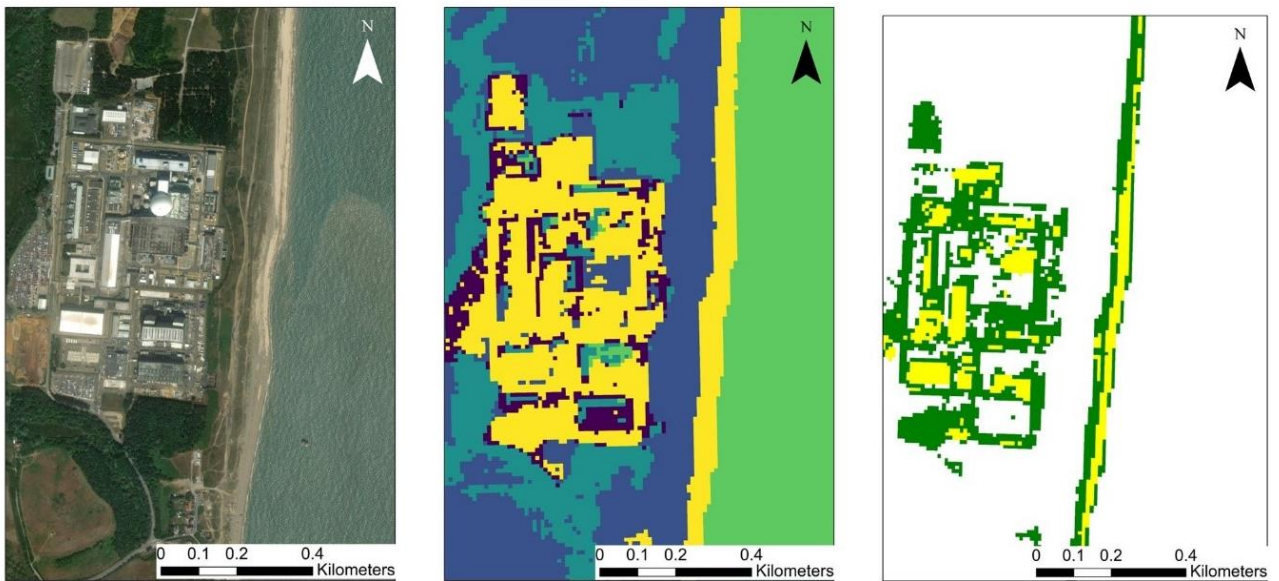


Figure 13: a) RGB Multispectral Satellite Image of Sizewell. b) First output of image classification with each pixel being labelled into a class. c) Output of the second step of classification where the sand has been reclassified and the wet & dry sand has been classified. Here, areas of 'Dry Sand' not contained within the sand class are removed in post processing (Section 3.7). Bands of 'Dry Sand' visible on the water side of the 'Wet Sand' created due to breaking waves are corrected in post processing (Section 3.7)

### **3.6.3. Model Set-Up**

#### **3.6.3.1. CART Structure**

CART is a predictive algorithm structured as a decision tree where each fork is split into a predictor variable and each node has a prediction for the target variable at the end (Loh (2011)). This decision tree operates by segmenting nodes into sub-nodes using a threshold value associated with an attribute. The process initiates with the root node, which is split into two in terms of the chosen criterion (Gini impurity). Gini impurity is used to evaluate the impurity of a dataset by quantifying the probability of incorrectly classifying a randomly chosen element in the dataset (Suthaharan (2016)). The algorithm chooses the best feature (band) and threshold for splitting based on the selected criterion. This split creates two child nodes, each representing a subset of the data. The process is repeated recursively for each child node, further splitting the data into smaller subsets. At each step, the algorithm selects the best feature and threshold to split the data based on the criterion. The growth of the tree ceases either when the last pure subset is achieved or when the maximum feasible number of leaves (or layers) in the tree is reached (structure of CART shown in Figure 14).

The functioning of the CART algorithm involves the subsequent steps:

- Identifying the most suitable split point for each input.
- Determining the new “best” split point by considering the optimal splits from the first step.
- Dividing the selected input based on the determined “best” split point.

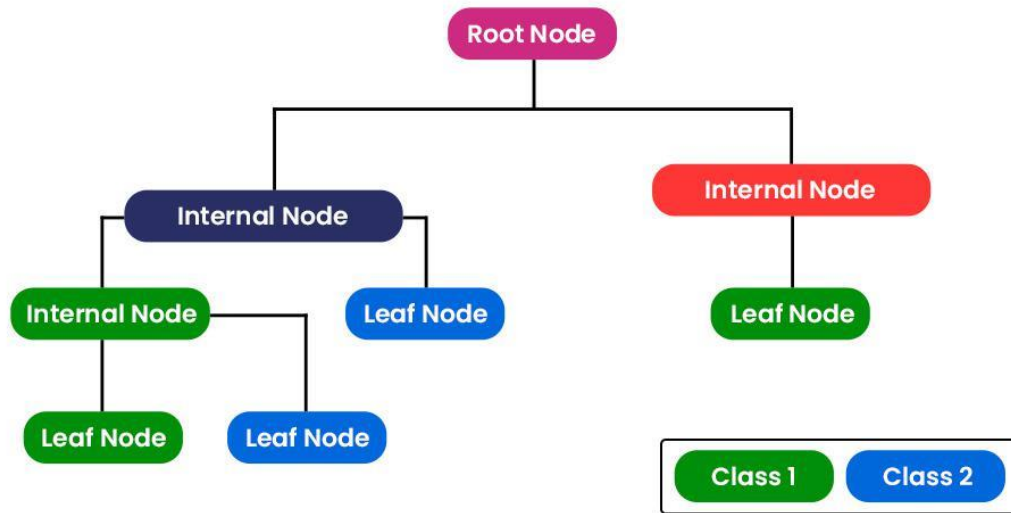


Figure 14: Structure of a Classification and Regression Tree (CART) Diagram. The diagram depicts the hierarchical branching of nodes, where each fork represents a predictor variable split, guiding the tree’s decision-making process. This structured approach enables the classification and prediction of target variables based on a sequence of attribute threshold values.

Scikit Learn was used to develop the CART structure as it allows more flexibility with the parameters compared to the GEE CART algorithm (shown in Table 4). For the classifier, the `max_depth`, that determines the maximum depth (number of layers) of the decision tree is adjusted for each step of the classification. This controls the complexity and overfitting of the model. Table 5 shows the maximum depth for each study site for both stages of classification. The maximum depth for classification varies for each site. In the case of Start Bay, due to the distinctiveness and clarity in distinguishing between various landcover types and the wet and dry boundary, the model finds it simpler to classify pixels accurately into their respective classes. On the other hand, at Aldbrough and Sizewell, a greater maximum depth is required. The determination of these depths was decided through trial and error and it is due to the complex relationships between the input features and the resulting output classes at these locations that different layers for each site exist.

Table 4: Parameters and values of the Classification and Regression Tree (CART) model from scikit-learn.

| Parameter                | Explanation                                                                                                                 | Default Value |
|--------------------------|-----------------------------------------------------------------------------------------------------------------------------|---------------|
| criterion                | The function to measure the quality of a split. Supported criteria are "gini", "log_loss", and "entropy".                   | "gini"        |
| splitter                 | The strategy used to choose the split at each node. Supported strategies are "best" and "random".                           | "best"        |
| max_depth                | The maximum depth of the tree. If None, nodes are expanded until all leaves are pure or until min_samples_split is reached. | See Table 5   |
| min_samples_split        | The minimum number of samples required to split an internal node.                                                           | 2             |
| min_samples_leaf         | The minimum number of samples required to be at a leaf node.                                                                | 1             |
| min_weight_fraction_leaf | The minimum weighted fraction of the sum total of weights required to be at a leaf node.                                    | 0.0           |
| max_features             | The number of features to consider when looking for the best split.                                                         | None          |
| random_state             | Controls the randomness of the estimator.                                                                                   | None          |
| max_leaf_nodes           | Grow a tree with max_leaf_nodes in best-first fashion.                                                                      | None          |
| min_impurity_decrease    | A node will be split if this split induces a decrease of the impurity greater than or equal to this value.                  | 0.0           |
| class_weight             | Weights associated with classes.                                                                                            | None          |
| ccp_alpha                | Complexity parameter used for Minimal Cost-Complexity Pruning.                                                              | 0.0           |

Table 5: Maximum Depth Values for Two-Step Classification using the CART model at Three Study Sites.

|                  | <b>Max Depth</b> |                |
|------------------|------------------|----------------|
|                  | <b>5 Class</b>   | <b>2 Class</b> |
| <b>Start Bay</b> | 6                | 8              |
| <b>Aldbrough</b> | 20               | 5              |
| <b>Sizewell</b>  | 15               | 6              |

### 3.6.3.2. ANN Structure

An ANN is a computational model inspired by the structure and functioning of the human brain. It consists of multiple layers, each serving a specific purpose in the information processing and feature extraction process (Jain *et al.* (1996)) (Figure 15). These layers work together to transform input data into meaningful outputs. The main types of layers within an ANN include:

- **Input Layer:** This is the first layer of the network and is responsible for receiving the input data. The number of nodes in the input layer corresponds to the number of features or dimensions in the input data.
- **Hidden Layers:** These are the intermediate layers between the input and output layers. Hidden layers play a crucial role in feature extraction and transforming the data into higher-level representations that the network can learn from. ANNs can have multiple hidden layers, each containing one or more nodes (neurons).
- **Output Layer:** The output layer provides the final prediction or classification of the network. The number of nodes in the output layer depends on the type of task the network is designed for.

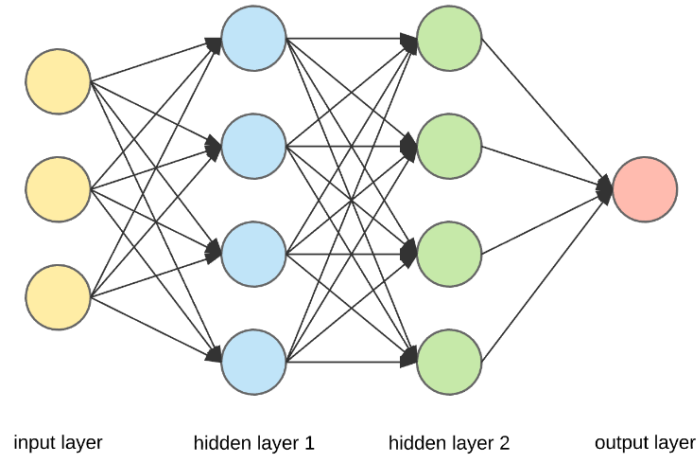


Figure 15: This diagram showcases the basic architecture of an ANN, featuring input, hidden, and output layers. Neurons within each layer are interconnected by weighted connections, while activation functions contribute to the transformation of signals.

The training process for the ANN involved utilising a deep neural network architecture implemented using Python's PyTorch library. This framework allowed for the flexibility to define the number of layers, nodes, epochs, learning rate, optimizer, and loss function.

The selection of the number of layers and nodes in the neural network architecture was defined during training. Different configurations were employed for each study site to optimize performance and achieve the most accurate predictions.

The ANN model incorporates Linear (Fully Connected) Layers, which facilitate fully connected operations. In this configuration, each node within the current layer establishes connections with every node present in the preceding layer. The linear layer applies a linear transformation to the input data followed by a bias term. It is used to learn weights that relate the input features to the output.

Between each layer of the ANN, the Rectified Linear Activation (ReLU) function (Equation 3) was applied. The ReLU activation function is applied separately to the output of the linear layers. It introduces non-linearity to the network, allowing it to learn

and capture complex relationships in the data. The ReLU activation function is defined as follows:

$$f(x) = \max(0, x)$$

Equation 3: ReLU Activation Function

“x” is the input to the function, and the output of the ReLU function is the maximum of "x" and 0. If "x" is a positive value or zero, the output will be "x". If "x" is a negative value, the output will be 0.

The LogSoftmax (Equation 4) layer is applied to the final linear output to convert the logits into log-probabilities. It is often used in multi-class classification tasks with a corresponding negative log likelihood (cross-entropy) loss. The LogSoftmax is defined by:

$$\log(\exp(x) / \sum(\exp(x))) = x - \log(\sum(\exp(x)))$$

Equation 4: LogSoftmax equation

where ‘x’ represents the input value (often referred to as the "logit" or "raw score") associated with a particular class or category. ‘exp(x)’ is the exponential of the input value x. It transforms the raw score into a positive value. ‘ $\sum(\exp(x))$ ’ represents the sum of the exponentials of all raw scores over all classes. It is the denominator of the softmax function and is used to normalize the scores.

Optimizers are used to iteratively update the model's parameters to find the optimal values which result in the best performance according to the chosen objective. This process involves adjusting the parameters in the direction that reduces the loss on the training data. The Adam optimizer (short for Adaptive Moment Estimation) is the optimiser used for the ANN. It is an advanced optimization algorithm commonly used in training ANNs

and other ML models. An advantage of Adam is its adaptive learning rate mechanism. It adjusts the learning rates of each parameter individually based on the historical gradient information. This adaptive behaviour helps overcome challenges presented by different scales of gradients and varying learning rate requirements for different parameters.

The loss function is a critical component of the optimization process in ML. It measures the discrepancy between the model's predictions and the actual target values, guiding the model to improve its performance on the task at hand. The CrossEntropyLoss (Equation 5) (Bishop. 2006) function is used for the ANN. It measures the difference between the predicted probabilities (usually obtained from a softmax activation) and the actual target probabilities (one-hot encoded or class indices) for each class. Entropy  $H(x)$  can be calculated for a random variable with a set of  $x$  in  $X$  discrete states discrete states and their probability  $P(x)$  as follows:

$$H(X) = - \sum x \text{ in } X P(x) * \log(P(x))$$

Equation 5: CrossEntropyLoss equation

The Learning rate is a hyperparameter used in many ML algorithms. It controls how quickly or slowly the model learns from the data. It governs the magnitude of updates made to the model's parameters as the algorithm iteratively adjusts them to minimize the loss function, which measures the error between the model's predictions and the actual target values. For all ANN models in this thesis, the learning rate is set at 0.001.

An epoch is a single pass through the entire training dataset during the training process. The number of epochs, defined during training, determined how many times the entire training dataset was iterated through the neural network during training. Different epochs



were applied for each study site to achieve the best accuracy results from the dataset. The optimal number of epochs was determined through iterative testing, with the assessment of these epochs relying on the accuracy measurements and the confusion matrices produced during each testing iteration.

In the training of neural networks, data is typically divided into smaller subsets called batches. Batch size refers to the number of training examples or data points used in each iteration or update of the neural network's parameters during the training process.

At Start Bay, an architecture with four fully connected layers is used for both stages of the classification with the same number of nodes per layer (Table 6). At Aldbrough, for the classification of the five classes, the architecture of the ANN consists of four fully connected layers with increasing node sizes. For the classification of the wet and dry sand, the architecture of the ANN consists of 6 fully connected layers with progressively decreasing node sizes (Table 7). For Sizewell, an architecture with four fully connected layers is used for both stages of classification with the same number of nodes per layer (Table 8). The architecture of the structure varies for each site due to differences in the clarity of defining wet and dry areas. For instance, the distinction was clearer for sites like Start Bay, while it was more intricate for sites like Aldbrough, due to surrounding environmental conditions (e.g., turbidity of water).

Table 6: Training Parameters and Model Architecture for Artificial Neural Network (ANN) at Start Bay.

| Start Bay           |     |            |     |
|---------------------|-----|------------|-----|
| 5 Class             |     | 2 Class    |     |
| Training Parameters |     |            |     |
| Epochs              | 100 | Epochs     | 150 |
| Batch Size          | 10  | Batch Size | 100 |

| Model Architecture |                        |        |                        |
|--------------------|------------------------|--------|------------------------|
| Layer              | Operation              | Layer  | Operation              |
| fc1                | Linear(inputSize, 150) | fc1    | Linear(inputSize, 150) |
| relu1              | ReLU                   | relu1  | ReLU                   |
| fc2                | Linear(150, 100)       | fc2    | Linear(150, 100)       |
| relu2              | ReLU                   | relu2  | ReLU                   |
| fc3                | Linear(100, 50)        | fc3    | Linear(100, 50)        |
| relu3              | ReLU                   | relu3  | ReLU                   |
| fc4                | Linear(50, numClasses) | fc4    | Linear(50, numClasses) |
| logsm1             | LogSoftmax(dim=1)      | logsm1 | LogSoftmax(dim=1)      |

Table 7: Training Parameters and Model Architecture for Artificial Neural Network (ANN) at Aldbrough.

| Aldbrough           |                         |            |                       |
|---------------------|-------------------------|------------|-----------------------|
| 5 Class             |                         | 2 Class    |                       |
| Training Parameters |                         |            |                       |
| Epochs              | 100                     | Epochs     | 25                    |
| Batch Size          | 10                      | Batch Size | 10                    |
| Model Architecture  |                         |            |                       |
| Layer               | Operation               | Layer      | Operation             |
| fc1                 | Linear(inputSize, 50)   | fc1        | Linear(inputSize, 50) |
| relu1               | ReLU                    | relu1      | ReLU                  |
| fc2                 | Linear(50, 100)         | fc2        | Linear(50, 100)       |
| relu2               | ReLU                    | relu2      | ReLU                  |
| fc3                 | Linear(100, 500)        | fc3        | Linear(100, 250)      |
| relu3               | ReLU                    | relu3      | ReLU                  |
| fc4                 | Linear(500, numClasses) | fc4        | Linear(250, 100)      |
| logsm1              | LogSoftmax(dim=1)       | relu4      | ReLU                  |

|  |  |        |                        |
|--|--|--------|------------------------|
|  |  | fc5    | Linear(100, 50)        |
|  |  | relu5  | ReLU                   |
|  |  | fc6    | Linear(50, numClasses) |
|  |  | logsm1 | LogSoftmax(dim=1)      |

Table 8: Training Parameters and Model Architecture for Artificial Neural Network (ANN) at Sizewell.

| Sizewell            |                        |            |                        |
|---------------------|------------------------|------------|------------------------|
| 5 Class             |                        | 2 Class    |                        |
| Training Parameters |                        |            |                        |
| Epochs              | 50                     | Epochs     | 250                    |
| Batch Size          | 50                     | Batch Size | 50                     |
| Model Architecture  |                        |            |                        |
| Layer               | Operation              | Layer      | Operation              |
| fc1                 | Linear(inputSize, 50)  | fc1        | Linear(inputSize, 50)  |
| relu1               | ReLU                   | relu1      | ReLU                   |
| fc2                 | Linear(50, 100)        | fc2        | Linear(50, 100)        |
| relu2               | ReLU                   | relu2      | ReLU                   |
| fc3                 | Linear(100, 50)        | fc3        | Linear(100, 50)        |
| relu3               | ReLU                   | relu3      | ReLU                   |
| fc4                 | Linear(50, numClasses) | fc4        | Linear(50, numClasses) |
| logsm1              | LogSoftmax(dim=1)      | logsm1     | LogSoftmax(dim=1)      |

### 3.7. Automatic Waterline Extraction

Automatic extraction of the waterline was carried out in Google Colab. After classifying the satellite images into wet and dry sand, three land classes (Artificial Surfaces, Agriculture, Forest) were merged with the dry sand, while the water class was combined with the wet sand to create a binary image with a definitive boundary line representing the wet/dry boundary. Any pixels classified as wet sand (visualised in Figure 11c, Figure

12c and Figure 13c), which are seaward of the dry sand, get removed when the shoreline is extracted into a vector, as discussed further below.

The binary image was processed to extract the contours between the boundaries of the wet and dry region. The pixel coordinates of the contours were converted to world coordinates, enabling the vector representation in real-world spatial units, such as latitude and longitude. The contours were then transformed to the spatial reference system (EPSG:27700) of the British National Grid (BNG), ensuring alignment with the chosen coordinate system. Contours with a length greater than or equal to 200 m were retained to filter out very small contours that did not correspond to the shoreline but to small water bodies instead. The output contours of x and y coordinates represented the shoreline as a polyline vector. This process is similar to the one conducted by Vos *et al.* (2019), who employed a function to convert contours from image coordinates to world coordinates. When exporting the shoreline vectors as shapefiles (a set of files that collectively represent geographic features and their attributes), the study area's BNG coordinate system was utilised to ensure accurate georeferencing of the vector data. This alignment enabled each shoreline vector to incorporate latitude and longitude coordinates within the designated UTM zone projection.

By utilising a predefined coordinate system obtained from the original satellite image, when creating the GeoDataFrame (a tabular data structure with an additional column that holds geometry data) and exporting it as a shapefile, the shoreline vectors were accurately georeferenced and seamlessly overlaid with other geospatial data in geographic information systems (GIS) software for further analysis and visualization.

Once obtained, the shoreline vectors were downloaded locally and integrated into various applications, including QGIS and ArcMap. This integration facilitated advanced analysis alongside additional datasets and enabled comprehensive visualization of the coastal areas in GIS.

### 3.8. Validation and Accuracy Assessment

Validation shorelines were derived using LiDAR data obtained for Start Bay (Channel Coast Observatory (CCO)) and Aldbrough (British Geological Survey (BGS)). With drone-based shorelines (representing MSL) used for validation at Sizewell (Centre for Environment, Fisheries and Aquaculture Science (Cefas)) (Table 9). Due to data availability constraints, the validation LiDAR data and drone-based shorelines do not correspond to the same acquisition date as the satellite images. To address this, satellite images captured within 6 months of the LiDAR surveys and drone shorelines were employed for validation purposes. This approach was taken because validation data was either limited on certain extraction dates or because the availability of cloud-free imagery constrained the extraction of shorelines.

Table 9: LiDAR and drone data Sources and tidal gauge locations for validation data

|           | <b>Data Source</b> | <b>Dates</b>                                                       | <b>Resolution (m)</b> | <b>Length (km)</b> | <b>Tide Gauge</b>                        |
|-----------|--------------------|--------------------------------------------------------------------|-----------------------|--------------------|------------------------------------------|
| Start Bay | CCO                | 27/04/2017<br>14/09/2018<br>12/09/2018<br>21/04/2019<br>20/09/2020 | 1m                    | 9.34               | Weymouth<br>(50° 36.51'N<br>2° 26.876'W) |
| Aldbrough | BGS                | May-2018<br>Jun-2018<br>Sep-2018                                   | 1m                    | 0.6                | Whitby<br>(54° 29.4'N<br>0° 36.862'W)    |

|          |       |                                                                                                              |    |     |                                               |
|----------|-------|--------------------------------------------------------------------------------------------------------------|----|-----|-----------------------------------------------|
|          |       | Feb-2019<br>Jun-2019<br>Sep-2019<br>Jun-2020<br>Sep-2020<br>Dec-2020                                         |    |     |                                               |
| Sizewell | Cefas | 28/10/2019<br>21/10/2020<br>07/05/2020<br>03/06/2020<br>20/08/2020<br>16/04/2021<br>14/05/2021<br>24/06/2021 | 1m | 3.5 | Lowestoft<br>(52°<br>28.374'N<br>1° 44.994'E) |
|          | CCO   | 04/11/2018<br>12/09/2018<br>16/12/2019<br>21/04/2019<br>12/11/2020<br>19/09/2020                             | 1m | 1   |                                               |

The LiDAR data was combined with Sea Level data obtained from British Oceanographic Data Centre (BODC). The tidal datum used was the Ordnance Datum (Newlyn), this was chosen as it provides a consistent reference level for elevation measurements. Tidal gauges were chosen to be as close to each study site as possible (Table 9). The water level obtained by tidal gauges every 10 minutes are coincided with the time the satellite images were collected. This is to obtain the current water level and extent of the sea during the time the image was taken.

The water level during the time frame of each satellite image was used to generate a waterline using the elevation information from the LiDAR data. This process was completed within ArcMap, where shoreline contours were generated through the application of the surface contour tool, tailored to the specific water elevation.

As the current water level at the time of the image being taken does not fully represent the furthest extent of the tide, the wave run-up equation is used.

Wave run up on the beach face was estimated using the Maximum Runup equation (Equation 6) (Hunt, 1959):

$$R_{max} = \xi H_0 = \tan \beta \sqrt{H_0 * L_0}$$

Equation 6: Maximum Runup equation

Where  $H_0$  is wave crest height, determined from wave data obtained from CCO,  $\beta$  is beach slope which is calculated from the LiDAR topography. Beach slope was calculated in ArcMap where a shapefile outlining the beach area was created. The ‘Slope’ tool was used to calculate the slope of the entire beach area. Zonal Statistics was used to calculate the ‘MEAN’ as the statistic type, providing the mean slope for each LiDAR map.  $L_0$  is wavelength (Equation 7), which is calculated using:

$$L_0 = gT^2/2\pi$$

Equation 7: Wavelength equation

Where  $g$  refers to acceleration due to gravity, " $T$ " represents the peak period of the wave and " $\pi$ " ( $\pi$ ) is a mathematical constant.

Subsequently, the tidal level contour derived from the LiDAR data is refined by incorporating the run-up level, delineating the position of the furthest extent the tide would have reached at that point. This adjustment involves modifying the shoreline's

placement within ArcMap, with adjustments made along transects spaced at intervals of 10 meters.

### 3.8.1. Calculating Shoreline Uncertainties

In this thesis, uncertainty analysis for shorelines is conducted using three key statistical metrics: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Standard Deviation of Differences (SD). Each metric plays a vital role in evaluating the accuracy and uncertainties associated with the extracted shorelines compared to validation data.

Root Mean Square Error (RMSE) (Equation 8) is a statistical measure that quantifies the average magnitude of the differences between predicted and observed values. Higher RMSE values indicate larger discrepancies, highlighting increased uncertainties in the accuracy of the extraction method. RMSE is calculated by:

$$RMSE = \sqrt{\frac{\frac{1}{n} \sum_{i=1}^n (observed_i - predicted_i)^2}{n}}$$

Equation 8: RMSE equation

Where “n” is the number of transects, “*observed<sub>i</sub>*” represents the observed (validation) values, “*predicted<sub>i</sub>*” represents the predicted (model-generated) values for the corresponding *i*th data. A higher RMSE value typically signifies a lower level of accuracy, and conversely, a lower RMSE indicates a higher level of accuracy.

Mean Absolute Error (MAE) (Equation 9) quantifies the average magnitude of the absolute differences between predicted and observed values. A higher MAE indicates larger average discrepancies, which can suggest higher uncertainties in the accuracy of the extraction method.



$$MAE = \frac{1}{n} \sum_{i=1}^n |observed_i - predicted_i|$$

Equation 9: MAE equation

Where “n” is the number of transects, “*observed<sub>i</sub>*” represents the observed (validation) values, “*predicted<sub>i</sub>*” represents the predicted (model-generated) values for the corresponding *i*th data, and |x| denotes the absolute value of x.

The Standard Deviation of Differences (SD) (Equation 10) is a statistical measure that quantifies the spread or dispersion of a set of values around the mean. A higher SD suggests larger variability in the differences, reflecting greater uncertainties in the accuracy of the extraction method.

$$SD = \sqrt{\frac{1}{n} \sum_{i=1}^n (observed_i - predicted_i)^2}$$

Equation 10: SD equation

Where “n” is the number of transects, “*observed<sub>i</sub>*” represents the observed (validation) values, “*predicted<sub>i</sub>*” represents the predicted (model-generated) values for the corresponding *i*th data.

### 3.9. Comparing Shoreline Proxies.

The Digital Shoreline Analysis System (DSAS) version 5.1 (Himmelstoss *et al.* (2021)) is a ArcGIS software extension developed by the U.S. Geological Survey (USGS) for analysing and comparing shorelines, regardless of the extraction method. DSAS is commonly used to assess shoreline changes over time and to quantify erosion or accretion rates along coastlines.

The extracted shorelines and validation shorelines were analysed using the DSAS tool, which calculates shoreline change statistics at multiple cross-shore transects (Figure 16). Transects were uniformly positioned at intervals of 10 m along all shorelines. This deliberate spacing aimed to enable an examination of changes happening at each 10 m pixel size and providing a comprehensive insight into changes across both the local and extended segments of the shorelines studied in this thesis. The extracted shorelines were compared with the validation shorelines using distance measurements including the Net Shoreline Movement (NSM) (Equation 11) and statistics, including the End Point Rate (EPR) (Equation 12). The equations used two shorelines the initial start shoreline and the end shoreline (Figure 16).

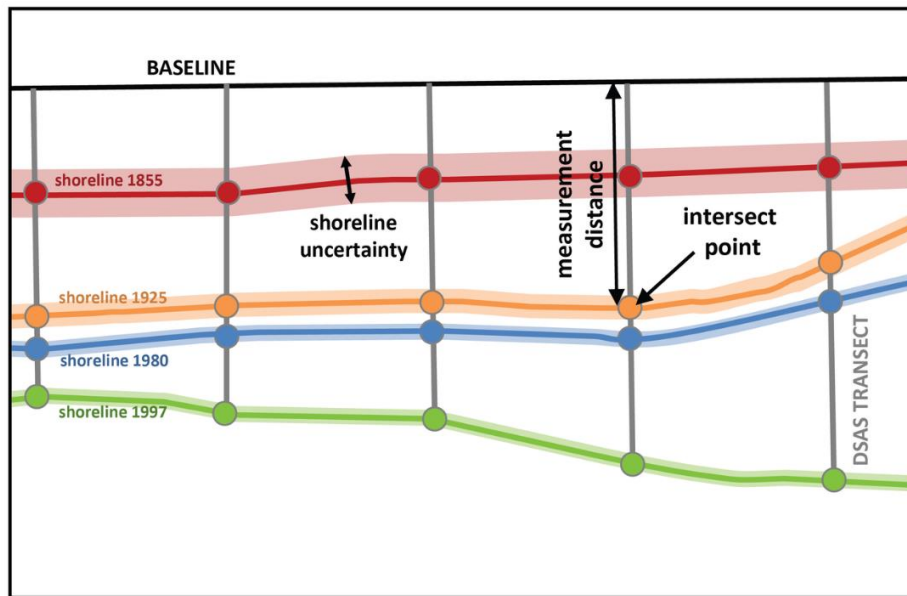


Figure 16: An example of how DSAS is used to calculate shoreline change over time (Himmelstoss *et al.* (2021)). The red, orange, blue and green lines represent shorelines from different time periods (1855, 1925, 1980 and 1997). The Net Shoreline Movement (NSM) is calculated as the distance between the red and green lines using Equation 11. Additionally, the End Point Rate (EPR) is calculated as the rate of change between the red and green shorelines over a given time interval, using Equation 12.

The NSM is the absolute distance between the oldest and the youngest shorelines for each transect. The NSM was employed to assess the extent of shoreline movement during each time step. It helped quantify the net change in the shoreline position over the specified periods and provided valuable information about the net sediment transport patterns and long-term shoreline stability or instability.

$$NSM = \text{End Shoreline Position} - \text{Start Shoreline Position}$$

Equation 11: Net Shoreline Movement (NSM) equation

The EPR is calculated by dividing the distance of shoreline movement by the time elapsed between the oldest and the most recent shoreline. The EPR was utilised to comprehend the rate of change during these periods and is useful for detecting and identifying hotspots of erosion or accretion. For long-term analysis, the EPR was measured in meters/year, providing insights into the average annual rate of shoreline change.

$$EPR = \frac{\text{End Shoreline Position} - \text{Start Shoreline Position}}{\text{Time Interval}}$$

Equation 12: End Point Rate (EPR) equation

### 3.10. Summary

The methodology outlined in this chapter sets the foundation for subsequent chapters. In Chapter 4, the two ML models, CART and ANN, are validated using the validation dataset discussed in Section 3.8. In Chapter 5, the extracted shorelines are then used to explore the effectiveness of the wet/dry boundary as an indicator for comprehending seasonal and multi-year analysis.



# **Chapter. 4 Historically Derived Shorelines using Satellite Imagery and Machine Learning.**

In this chapter, historically derived shorelines using satellite imagery and ML techniques are explored. Initially, the shorelines generated by the CART algorithm are compared with validation shorelines. Next, the ANN algorithm is applied to generate shorelines, which are then compared to validation data. The objective is to investigate potential differences in the results obtained through the use of different algorithms.

This chapter addresses Research Question 2: “Is the wet/dry boundary representative of all shoreline types that can be extracted using medium-resolution MSI as a data source?”. To derive the wet/dry boundary, the methodology and study sites discussed in Chapter 3 are employed. By leveraging the techniques and data presented in the previous chapter, the historically derived shorelines are effectively generated for further analysis and evaluation for each study site.

## **4.1 Algorithm Application**

Shorelines were produced for satellite images between 2016-2022 using the trained CART and ANN algorithms. While the LiDAR data and drone-based shorelines available for validation data was limited, extracted waterlines within the 6 months of the LiDAR and drone-based data were compared to the validation shorelines (see Appendix B, Table 1). At every site and for every example given, the difference error between the extracted waterline and the validation line was calculated.

## **4.2 CART versus Validation**

The shorelines generated by the two-step image classification approach for CART (see Chapter 3) were compared to the validation shorelines. The shorelines produced by the CART algorithm did not produce accurate results at all three sites and large errors were found (Table 10). The Root Mean Square Error (RMSE) values were 68.10 m, 17.97 m, and 28.91 m for Start Bay, Aldbrough, and Sizewell respectively. The most favourable results were obtained at Aldbrough (RMSE = 17.97 m, MAE = 15.91 m, SD = 8.56 m), while the least favourable results were observed at Start Bay (RMSE = 68.10 m, MAE = 27 m, SD = 9.83).

Table 10: Table illustrating the Average Difference, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Standard Deviation (SD) and Bias to depict shoreline uncertainties between CART derived shorelines and validation shorelines at each site.

| Site      |      | Average<br>(m) | RMSE (m) | MAE<br>(m) | Standard<br>Deviation<br>(m) | Bias (m) |
|-----------|------|----------------|----------|------------|------------------------------|----------|
| Start Bay | CART | -19.73         | 68.10    | 20.78      | 12.12                        | - 5.26   |
|           | ANN  | 2.15           | 5.66/    | 4.9        | 3.84                         | 3.46     |
| Aldbrough | CART | 14.24          | 17.97    | 15.91      | 8.56                         | 7.23     |
|           | ANN  | 10.67          | 14.90    | 13.31      | 7.10                         | 8.46     |
| Sizewell  | CART | 26.0           | 28.91    | 27.0       | 9.83                         | 8.36     |
|           | ANN  | 3.56           | 12.18    | 10.4       | 7.90                         | 9.36     |

#### 4.2.1 Start Bay

Figure 17 to Figure 20 show the extracted CART shorelines for the wet/dry boundary line at Slapton Sands, Start Bay. This 0.9 km stretch of coastline was chosen to be focused on as it is the largest horizontal section of the beach and changes within the wet and dry sand are most visible here. Here, the shorelines have a significant landward bias (bias = - 5.26 m). None of the shorelines recorded errors smaller than a pixel (10 m), with 37.5% having an errors less than two pixels (20 m). The boxplots shown in Figure 21, highlight the shoreline extraction results ranging between 0 m and -20 m. The boxplots for the shorelines extracted on 05/05/2018 (shorelines shown in Figure 17), 27/09/2018 (shorelines shown in Figure 18), and 21/10/2020 have high variability. This variability may be due to underfitting of the algorithm, as it struggles to differentiate between the wet and dry sand. In contrast, the boxplots for 24/02/2019 (shorelines shown in Figure

19) and 29/05/2020 have less variability, indicating that the shorelines extracted on these dates are closer to the validation shorelines and exhibit less variability. Less variable results are what is expected for a site such as Start Bay as the difference between the wet and dry sand is visible to the human eye and the algorithm should not struggle with clear differences. Given the pronounced biases observed for Start Bay, it's crucial to account for the time gap between the extraction and validation dates of the shorelines. Figures 17, 19, and 20 illustrate shorelines extracted two months prior to validation, with high variability. Despite the temporal difference, upon examination of the extracted shorelines, it becomes evident that the biases are not due to the validation shorelines.

The biases shown for Start Bay could potentially be attributed to the complexity of the decision tree during the training process. When training the CART algorithm without setting any tree depth limit or when the tree depth limit was set excessively high, the algorithm overfits the data, leading to substantial variance and the emergence of speckle or noisy artifacts within the wet and dry classes. Conversely, setting the tree depth threshold too low resulted in underfitting, causing increased variance and, in this specific scenario, a higher degree of bias. Therefore, it is plausible to suggest that the CART algorithm employed for classifying the wet/dry classes may have suffered from underfitting. This could be due to the size of the training dataset (Table 3) (discussed in Chapter 3), which may have been small and insufficient to adequately represent the data, also leading to underfitting. Another factor to consider involves the dimensions of the study area and the model's capacity to effectively classify the imagery. The division of the five beaches at Start Bay by headlands also introduces a potential challenge for the model, as it struggles with the task of accurately processing and interpreting the presence of headlands.





Figure 17: Comparison of CART-derived shoreline (red line) and validation shoreline (black line) at Slapton Sands on 05/05/2018. The validation shoreline, obtained from LiDAR data on 12/09/2018, is tidally corrected to align with the date of the captured satellite image.



Figure 18: Comparison of CART-derived shoreline (red line) and validation shoreline (black line) at Slapton Sands on 27/09/2018. The validation shoreline, obtained from LiDAR data on 14/09/2018, is tidally corrected to align with the date of the captured satellite image.



Figure 19: Comparison of CART-derived shoreline (red line) and validation shoreline (black line) at Slapton Sands on 24/02/2019. The validation shoreline, obtained from LiDAR data on 21/04/2019, is tidally corrected to align with the date of the captured satellite image.





Figure 20: Comparison of CART-derived shoreline (red line) and validation shoreline (black line) at Slapton Sands on 23/06/2020. The validation shoreline, obtained from LiDAR data on 20/09/2020, is tidally corrected to align with the date of the captured shoreline.

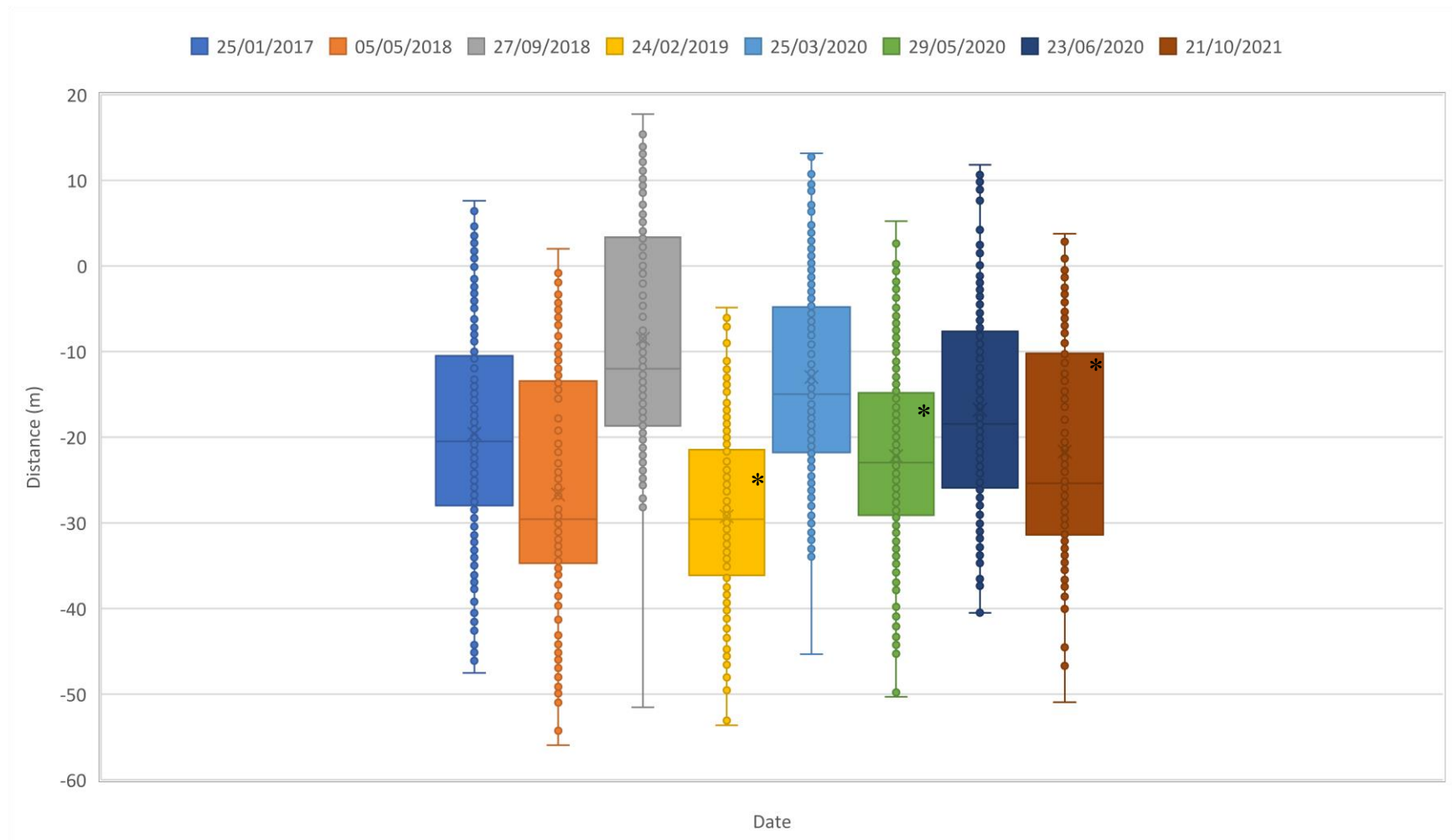


Figure 21: Box plot illustrating the distances between the CART shorelines and the validation shorelines at Start Bay. A positive skew indicates a seaward bias, while a negative skew indicates a landward bias. Plots marked “\*” indicate whitewater from breaking waves being present in the images.

#### 4.2.2 Aldbrough

At Aldbrough, Figure 22 to Figure 25 show that the extracted shorelines tend to have a seaward bias. Here, 33% of the shorelines had an error of less than one pixel, and 83% had an error of less than two pixels. The seaward bias may be due to the turbidity in the water in the North Sea, resulting in murky conditions which could have created difficulties in differentiating between the water and sand, or it could be attributed to the presence of breaking waves or "white water" (refer to Figure 23). This trend has been documented to pose challenges in previous studies as well (Hagenaars *et al.* (2018); Vos *et al.* (2019)).

At Aldbrough, the boxplots (Figure 26) display a distribution of shoreline extraction results ranging from -10 m to -30 m. The size of the boxplots for Aldbrough are significantly shorter compared to those observed in Start Bay, suggesting that the extracted shorelines at Aldbrough have less variability. The variability found here could be because at Aldbrough the difference between low and high tide is ~80 m. When the shoreline is extracted during high tide, the variability may stem from breaking waves and turbidity. Conversely, during low tide extraction, the distinction between the wet/dry boundary becomes clearer, potentially reducing variability. The boxplots, with greater variability, are associated with the dates 17/10/2019 (shoreline shown in Figure 24) and 27/10/2019, which can be attributed to the presence of breaking waves (Figure 23) as well as the positioning of the validation data in relation to the extracted shoreline, where the extracted shoreline visually aligns itself correctly with the wet/dry boundary (shown in Figure 22).



Figure 22: Comparison of CART-derived shoreline (red line) and validation shoreline (black line) at Aldbrough on 05/05/2018. The validation shoreline, obtained from LiDAR data from May 2018, is tidally corrected to align with the date of the captured shoreline.

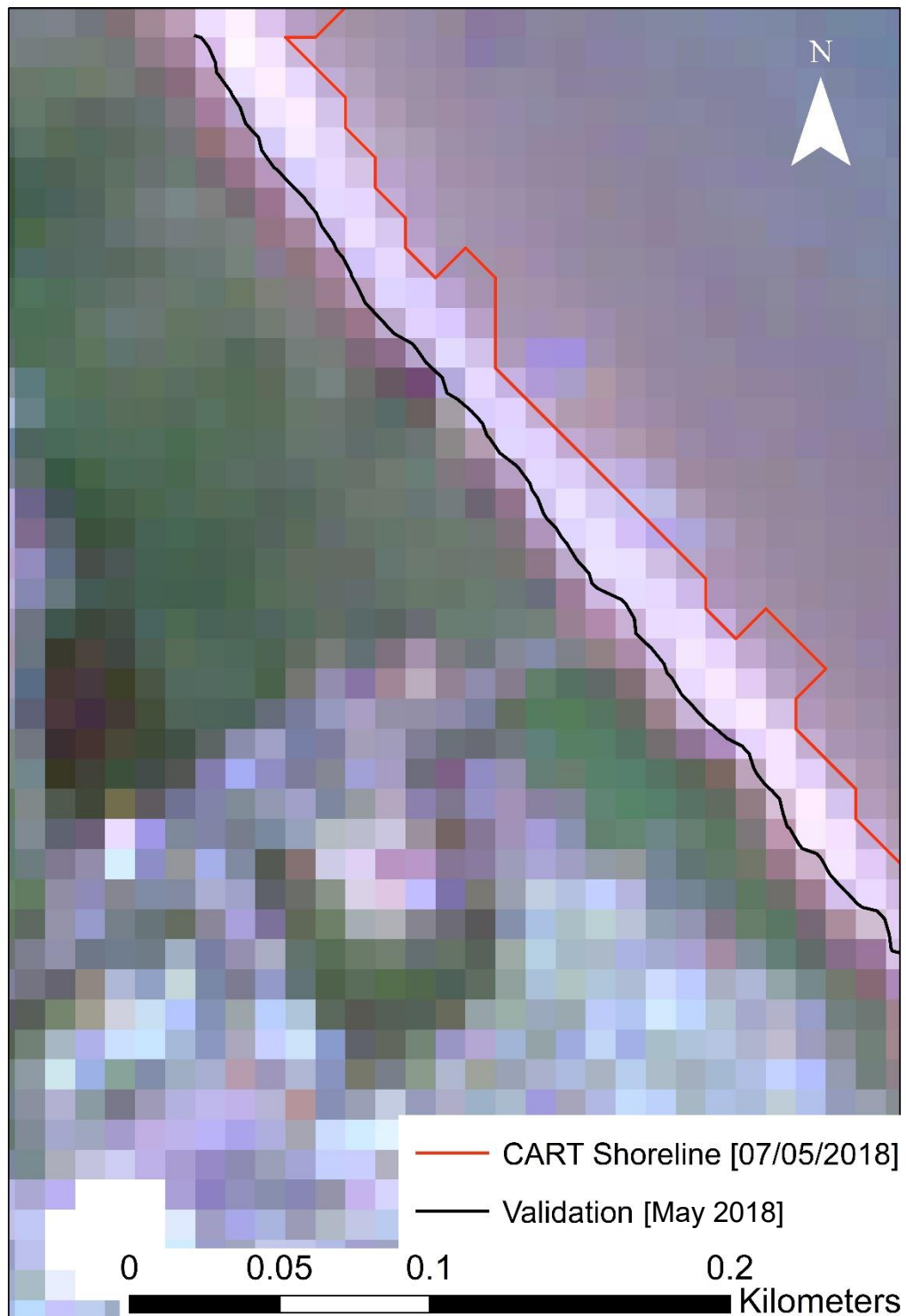


Figure 23: Comparison of CART-derived shoreline (red line) and validation shoreline (black line) at Aldbrough on 07/05/2018. The validation shoreline, obtained from LiDAR data from May 2018, is tidally corrected to align with the date of the captured shoreline.





Figure 24: Comparison of CART-derived shoreline (red line) and validation shoreline (black line) at Aldbrough on 17/10/2019. The validation shoreline, obtained from LiDAR data from Sept-2019, is tidally corrected to align with the date of the captured shoreline.

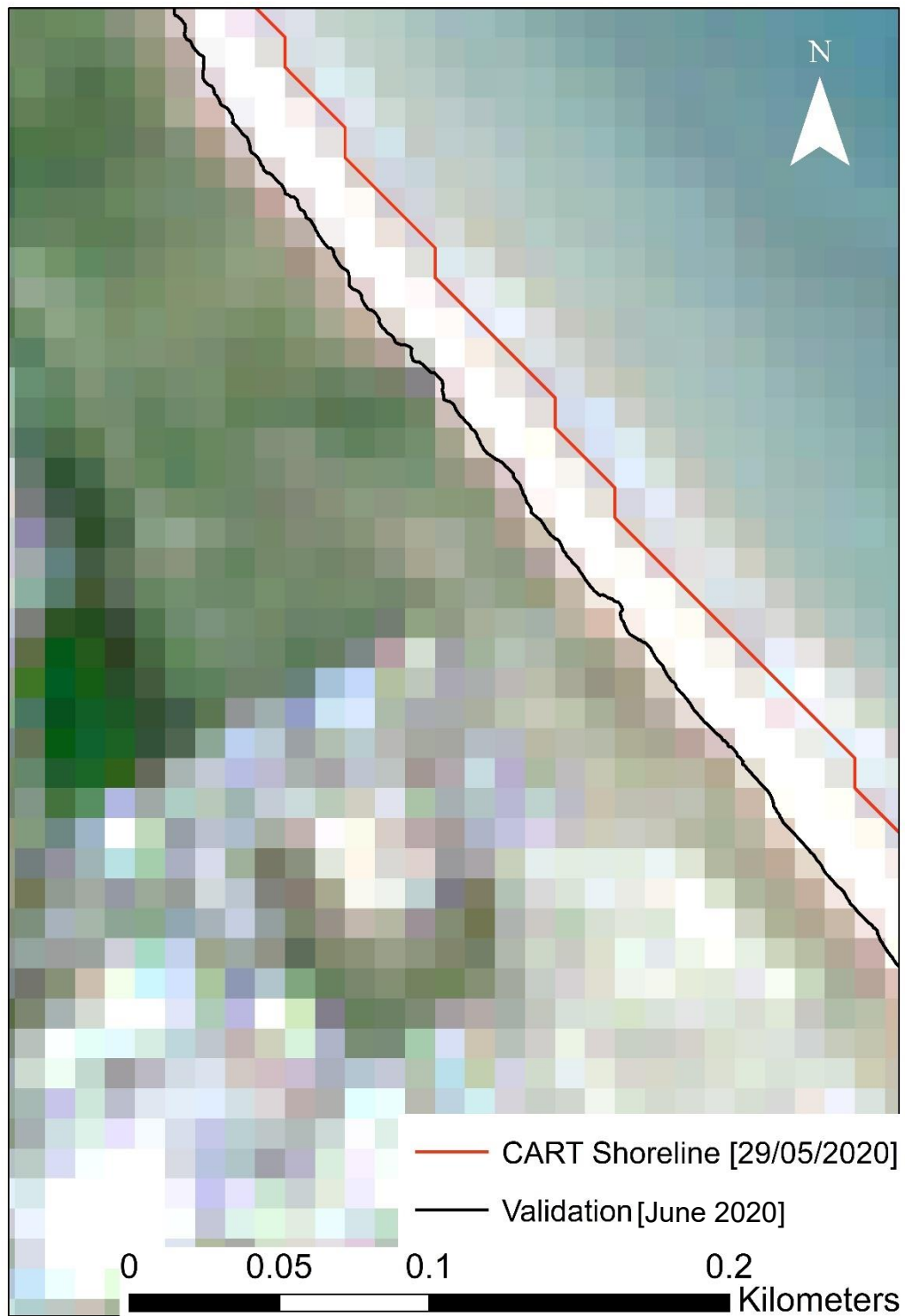


Figure 25: Comparison of CART-derived shoreline (red line) and validation shoreline (black line) at Aldbrough on 29/05/2020. The validation shoreline, obtained from LiDAR data from Jun-2020, is tidally corrected to align with the date of the captured shoreline.

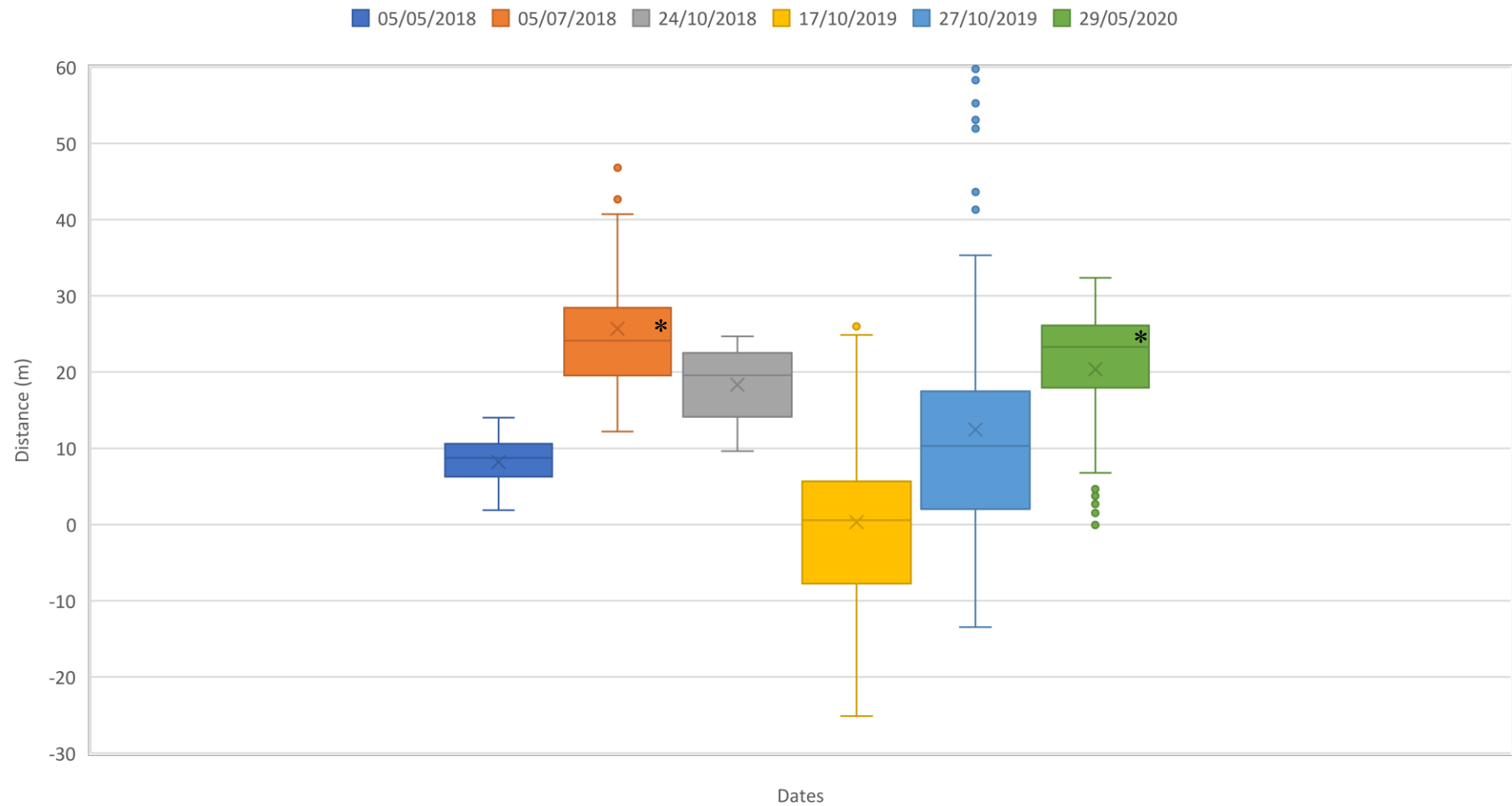


Figure 26: Box plot illustrating the distances between the CART shorelines and the validation shorelines at Aldbrough. A positive skew indicates a seaward bias, while a negative skew indicates a landward bias. Plots marked “\*” indicate whitewater from breaking waves being present in the images.

### 4.2.3 Sizewell

At Sizewell, Figure 27 to Figure 30 show the variation in the extracted waterlines, which have an overall seaward bias. Here, none of the shorelines had an error less than 10 m, and 42% had an error less than 20 m. This is an unusual result for Sizewell as the beach is steep and the distance between high as low tide is ~15 m.

Figure 27, 29 and 30 all show shorelines extracted which were significantly seawards and not extracting any visible features. This mirrors what occurred at Start Bay, where the algorithm encountered difficulty in distinguishing between different classes, potentially resulting from underfitting. Figure 28 displays a landward bias, where the algorithm distinguishes between sand and gravel compositions effectively but struggles to accurately classify the wet and dry sand boundary. This highlights the algorithm's difficulty in discerning the difference between the wet/dry boundary and the beach composition.

At Sizewell, the boxplots (Figure 31) reveal a wide distribution in the results, spanning from -20 m to 60 m. The majority of these boxplots are relatively short, with the shortest observed on 07/01/2018 and 07/05/2018. In contrast, the longest boxplots are associated with the dates 04/04/2019 and 28/05/2020 (shoreline shown in Figure 30). This is mainly due to the algorithm struggling to identify the wet/dry sand, as Figure 29 shows the extracted shoreline fluctuating around the validation shoreline but not consistently following a single feature.

Another challenge to consider at Sizewell is the beach slope, as there is a horizontal difference of 15 m between high and low tide. Though the wet/dry sand boundary remains visible due to its coverage of the 10 m pixel size, this presents a challenge. Changes

occurring within a 15 m range might not be effectively or accurately detected using Sentinel-2 imagery. Consequently, the shoreline might mistakenly be identified as the instantaneous waterline, failing to consider the wet/dry boundary accurately. Alternatively, if the tide extends beyond the 10 m pixel size, the change in shoreline could be interpreted as spanning two pixels, totalling 20 m. This could potentially increase the likelihood of classifying areas as landward, altering the probability distribution accordingly. Even slight variations in pixel values can result in misclassified pixels, ultimately influencing the delineation of high and low tide at Sizewell and leading to skewed results.



Figure 27: Comparison of CART-derived shoreline (red line) and validation shoreline (black line) at Sizewell on 07/05/2018. The validation shoreline, obtained from drone-based shorelines from 08/06/2018, is tidally corrected to align with the date of the captured shoreline.



Figure 28: Comparison of CART-derived shoreline (red line) and validation shoreline (black line) at Sizewell on 19/01/2020. The validation shoreline, obtained from drone-based shorelines from 07/05/2020, is tidally corrected to align with the date of the captured shoreline.





Figure 29: Comparison of CART-derived shoreline (red line) and validation shoreline (black line) at Sizewell on 28/05/2020. The validation shoreline, obtained from drone-based shorelines from 07/05/2020, is tidally corrected to align with the date of the captured shoreline.





Figure 30: Comparison of CART-derived shoreline (red line) and validation shoreline (black line) at Sizewell on 31/05/2021. The validation shoreline, obtained from drone-based shorelines from 14/05/2021, is tidally corrected to align with the date of the captured shoreline

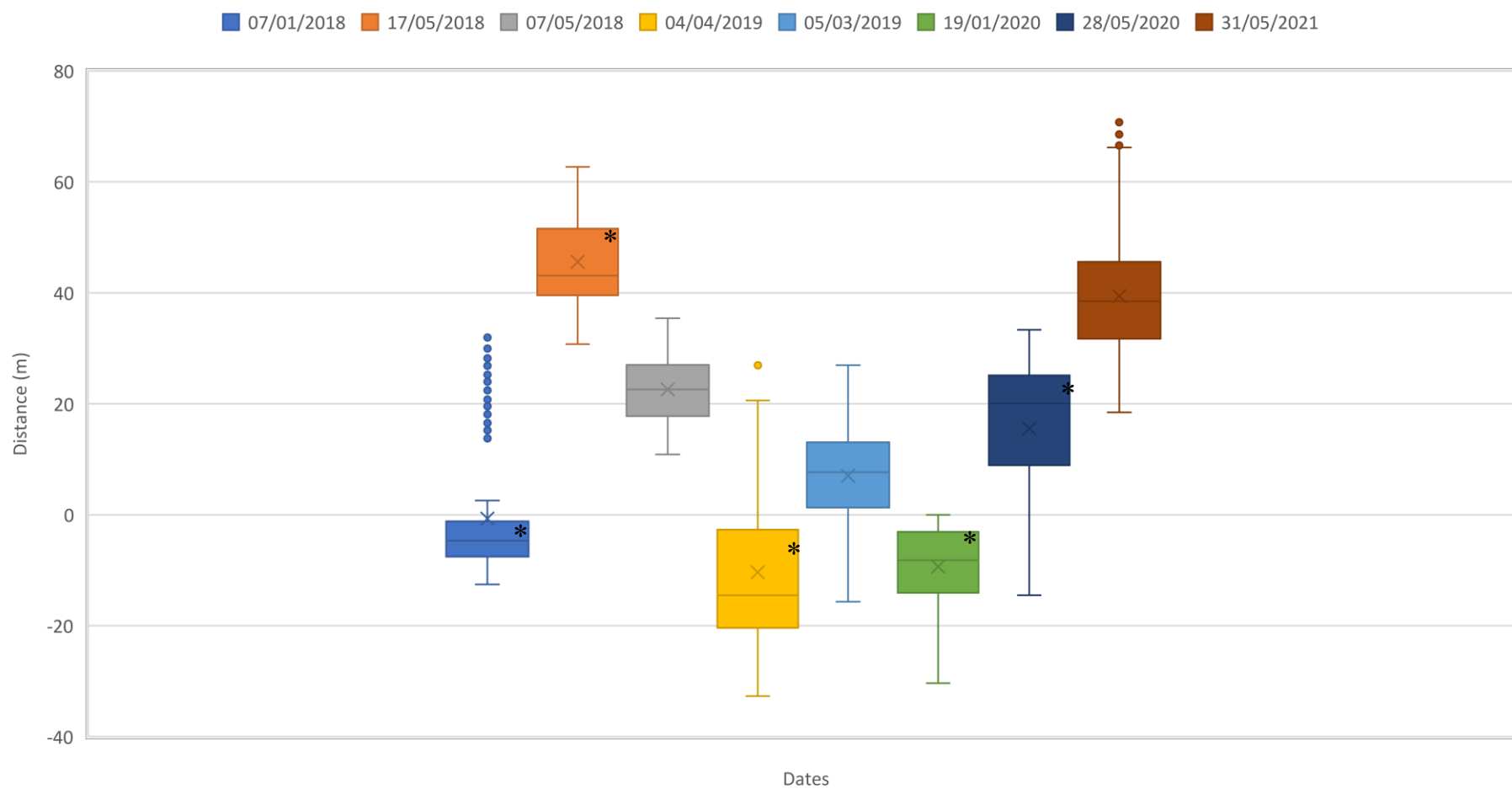


Figure 31: Box plot illustrating the distances between the CART shorelines and the validation shorelines at Sizewell. A positive skew indicates a seaward bias, while a negative skew indicates a landward bias. Plots marked “\*” indicate whitewater from breaking waves being present in the images.

### 4.3 ANN versus Validation

The ANN was formulated using a similar approach to that of the CART algorithm, involving a two-step classification process detailed in Chapter 3. The ANN was validated against the same validation shorelines in order to determine if it could produce more accurate results with fewer errors than the shorelines generated by the CART classifier.

The results indicated that the shorelines generated by the ANN algorithm yielded better outcomes compared to the CART classifier. Specifically, the ANN algorithm showed a better performance, with RMSE values of 5.66 m, 14.90 m, and 12.18 m for Start Bay, Aldbrough, and Sizewell, respectively. Notably, the most accurate results were observed at Start Bay, where the average variation was 2.15 m (MAE = 4.9 m; SD = 3.84 m). Conversely, the least accurate results were obtained at Aldbrough (MAE = 13.31 m; SD = 7.10 m) and Sizewell (MAE = 10.4 m; SD = 7.90 m).

Figure 36, Figure 41 and Figure 46 show box plots for the distance between the validation and the extracted ANN shorelines for the three sites. For the ANN algorithm, more shorelines were extracted due to the model's ability to identify clearer boundaries between the wet and dry sand. From these figures it is worth noting that all sites has a seawards bias, as indicated in Table 10. Specifically, Start Bay exhibited a seaward bias of 3.46 m (Figure 36), Aldbrough had a seaward bias of 8.46 m (Figure 41), and Sizewell demonstrated a seaward bias of 9.36 m (Figure 46).

#### 4.3.1 Start Bay

Illustrated in Figure 32 to Figure 35 are the ANN extracted shorelines for Start Bay. Here, all shoreline estimations had errors of less than 10 m with an average difference in shorelines of 2.15 m, falling well within the pixel size of Sentinel-2 imagery. Figure 32 shows a high agreement between the shoreline and the validation line, with variations

existing mainly due to the coarseness of the extracted shoreline (10 m) compared to the very high-resolution validation shoreline (1 m). This high agreement could be because at Start Bay the beach has a clear delineation between the wet and dry sand and that the ANN has the capability to identify the difference in the pixel values, whereas the CART classifier struggled to produced accurate results as it could not generalise the data. Figure 35 similarly demonstrates a strong agreement between the extracted shoreline and the validation shoreline, with a bias toward the seaward direction. Notably, the validation line appears to be positioned further up the beach compared to the visible wet/dry boundary, hence showing the shoreline as more seaward than its actual position. This inconsistency may stem from the validation shoreline being derived from a shoreline profile captured three months after the initial shoreline extraction.

Figures 33 and 34 exhibit significant seaward trends in the shorelines, deviating from both the validation line and the visible wet/dry boundary. Figure 33, extracted 13 days before the validation data, should theoretically demonstrate high agreement if the algorithm accurately extracted the shoreline, however this is not evident in the present case. Meanwhile, Figure 34, extracted two months prior to validation, displays variability, yet it's evident that the extracted shoreline closely follows the instantaneous waterline, suggesting potential challenges in identifying the wet/dry boundary in that specific image.

The boxplots for the ANN shorelines against the validation data for Start Bay are shown in Figure 36. Here, the majority of the boxplots show a distribution between 10 m and -10 m, indicating a high level of agreement between the ANN-extracted shorelines and the validation data.



Figure 32: Comparison of ANN-derived shoreline (blue line) and validation shoreline (black line) at Slapton Sands (in Start Bay) on 05/05/2018. The validation shoreline, obtained from LiDAR data on 12/09/2018, is tidally corrected to align with the date of the captured shoreline.



Figure 33: Comparison of ANN-derived shoreline (blue line) and validation shoreline (black line) at Slapton Sands on 27/09/2018. The validation shoreline, obtained from LiDAR data on 12/09/2018, is tidally corrected to align with the date of the captured shoreline.



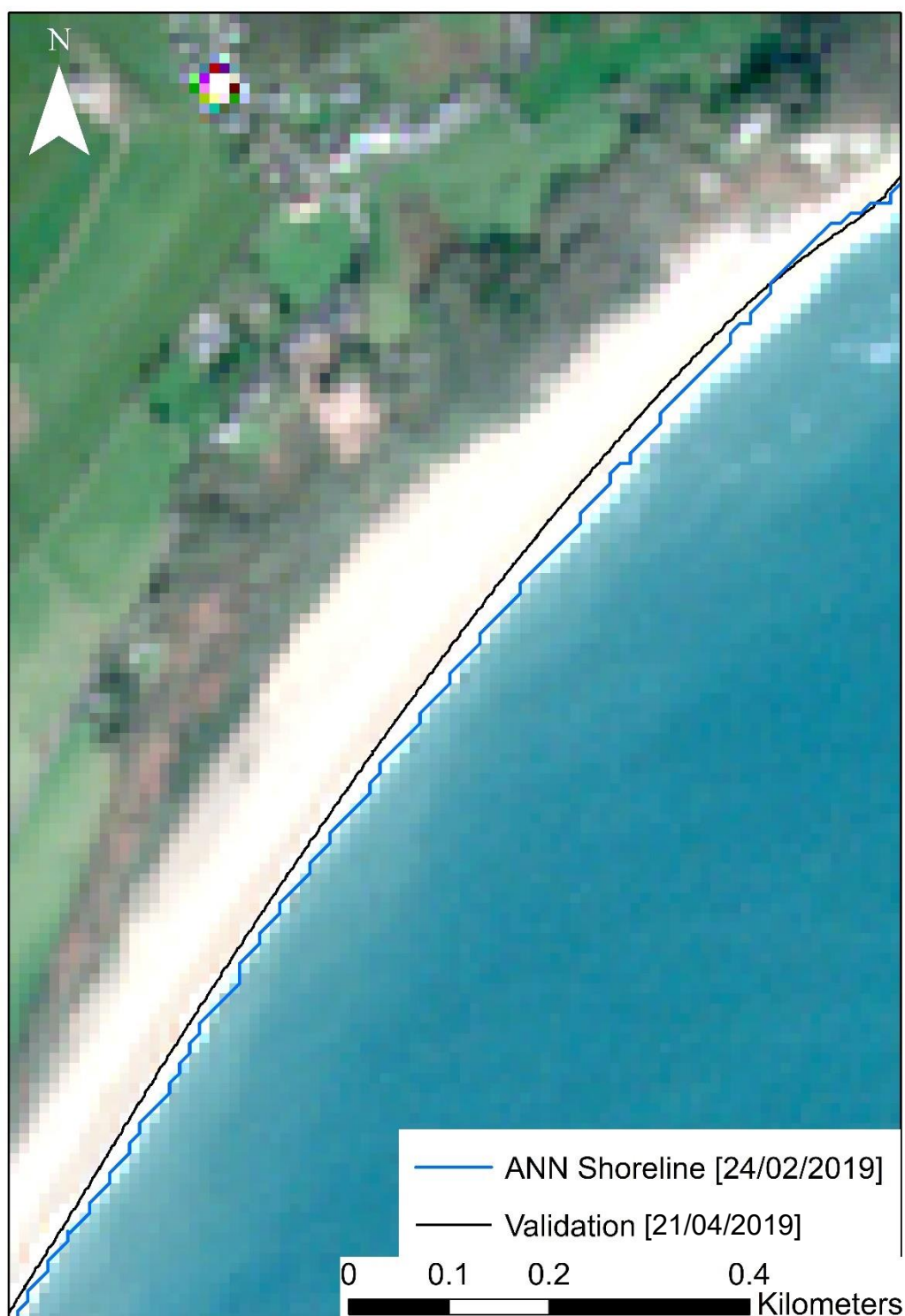


Figure 34: Comparison of ANN-derived shoreline (blue line) and validation shoreline (black line) at Slapton Sands on 24/02/2019. The validation shoreline, obtained from LiDAR data on 21/04/2019, is tidally corrected to align with the date of the captured shoreline.



Figure 35: Comparison of ANN-derived shoreline (blue line) and validation shoreline (black line) at Slapton Sands on 23/06/2020. The validation shoreline, obtained from LiDAR data on 20/09/2020, is tidally corrected to align with the date of the captured shoreline.



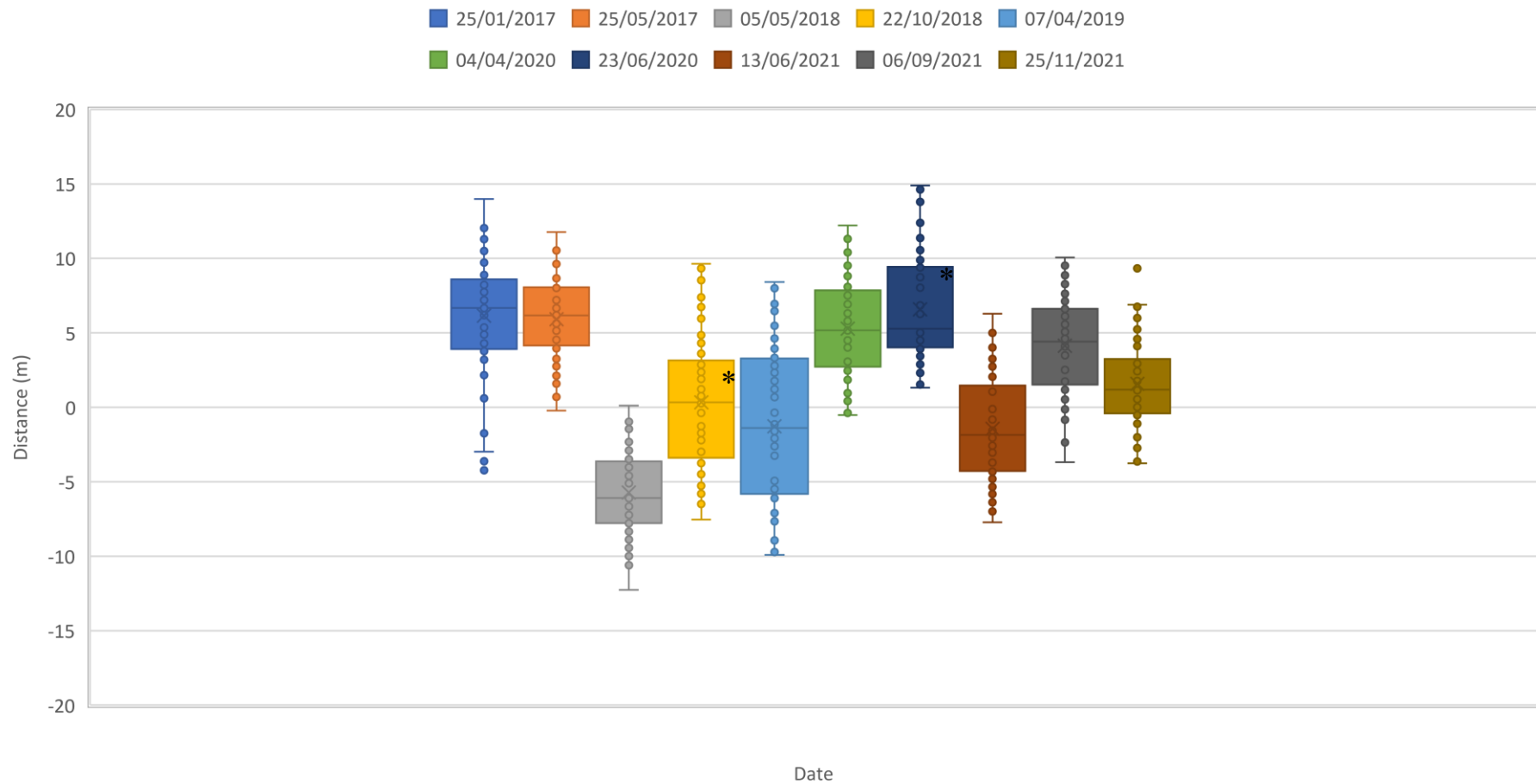


Figure 36: Box plot illustrating the distances between the ANN shorelines and the validation shorelines at Start Bay. A positive skew indicates a seaward bias, while a negative skew indicates a landward bias. Plots marked “\*” indicate whitewater from breaking waves being present in the images.

### 4.3.2 Aldbrough

At Aldbrough (examples illustrated in Figure 37 - Figure 40), 53% of shorelines had errors of less than 10 m, and 85% of errors of less than 20 m.

The results for the ANN shorelines and the validation data for Aldbrough are shown in Figure 41. Among these results, the most agreeable plot was observed for 05/05/2018 (shoreline shown in Figure 37), with a distribution ranging from 0 m to 10 m. However, it is important to note that most of the plots are variable, with the most notable example being 10/01/2020, which exhibits a wide distribution from -5 m to 45 m. Others like this include 27/05/2018, 17/10/2019 (shown in Figure 39), and 27/10/2019.

Figure 38 highlights that variability is present due to breaking waves, pulling the extracted shoreline seawards. The presence of breaking waves contributes to the misclassification of dry sand, consequently impacting the accuracy of the results. During testing, the addition of a 'breaking waves' class resulted in more misclassifications, particularly where the sand and breaking waves shared similar pixel values. In these instances, including the 'breaking waves' class detracted from accurately identifying the sand class. Figure 39 presents a lot of variability, which may be due to the colour of the Sentinel-2 satellite image. During training, the algorithm might not have encountered pixels of this colour and could associate darker pixels with wet sand, thus explaining the observed variation across the dry sand. Figure 40 shows the shoreline with a seaward's bias, with the validation line is positioned along the base of the cliff line. The extracted shoreline appears to follow the dry sand primarily due to the visibility of "wet" sand seaward of the shoreline. However, considering the turbidity of the water at Aldbrough, it's reasonable not to expect the sand to be visible once it's submerged by the sea. Therefore, what is visible could be breaking waves.

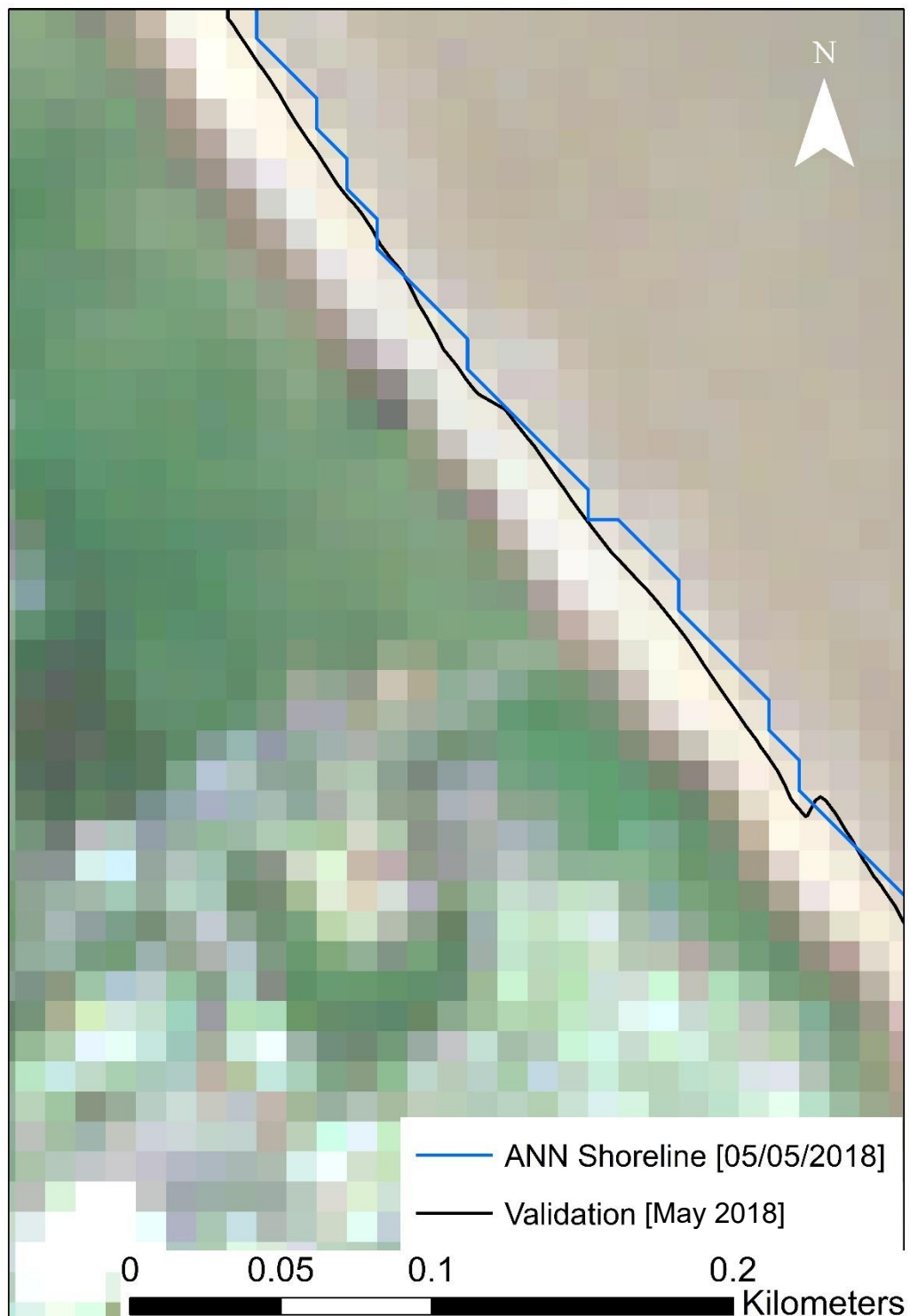


Figure 37: Comparison of ANN-derived shoreline (blue line) and validation shoreline (black line) at Aldbrough on 05/05/2018. The validation shoreline, obtained from LiDAR data on May-2018, is tidally corrected to align with the date of the captured shoreline.

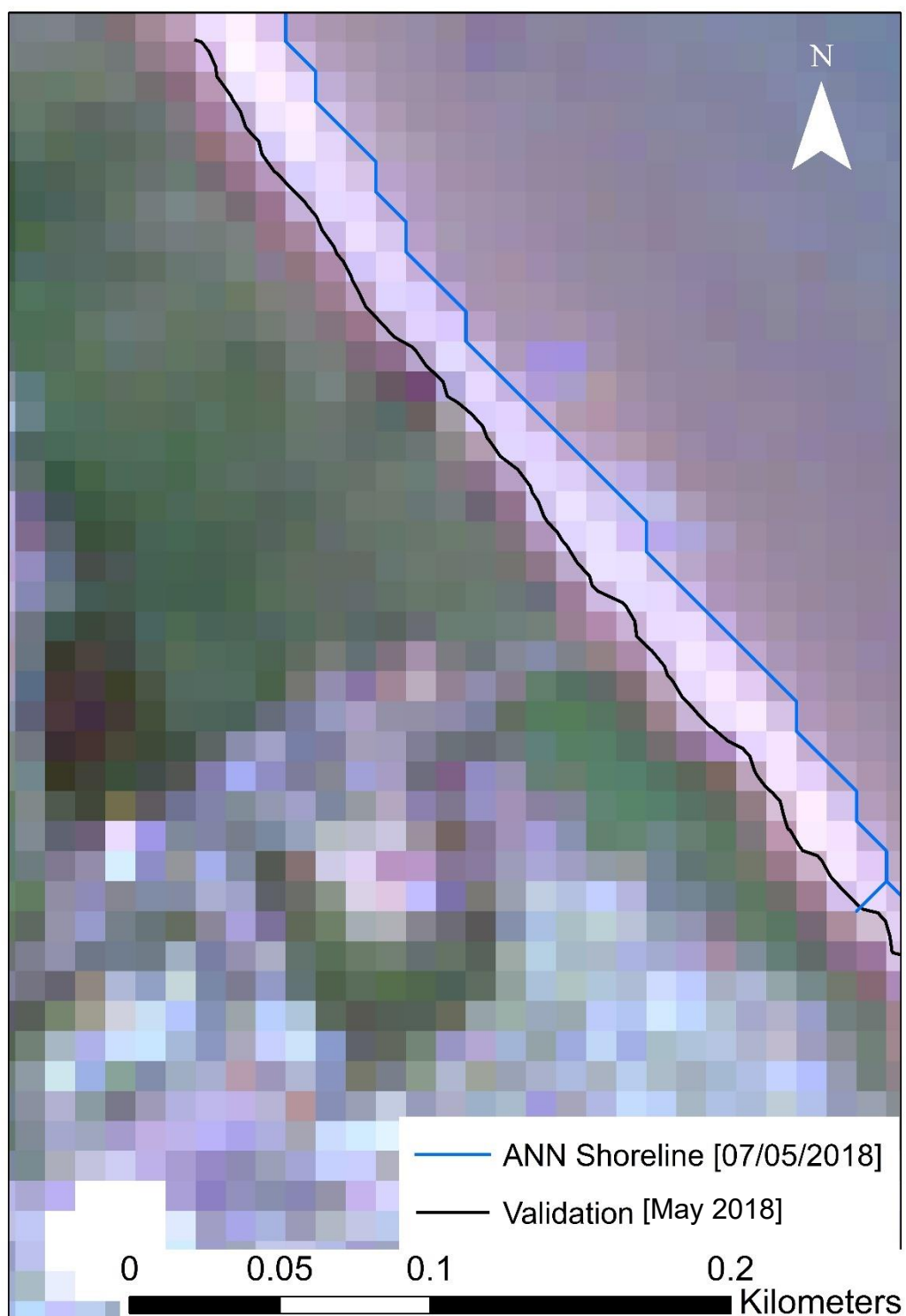


Figure 38: Comparison of ANN-derived shoreline (blue line) and validation shoreline (black line) at Aldbrough on 07/05/2018. The validation shoreline, obtained from LiDAR data on May-2018, is tidally corrected to align with the date of the captured shoreline.



Figure 39: Comparison of ANN-derived shoreline (blue line) and validation shoreline (black line) at Aldbrough on 17/10/2019. The validation shoreline, obtained from LiDAR data on Sept-2019, is tidally corrected to align with the date of the captured shoreline.



Figure 40: Comparison of ANN-derived shoreline (blue line) and validation shoreline (black line) at Aldbrough on 29/05/2020. The validation shoreline, obtained from LiDAR data on Jun-2020, is tidally corrected to align with the date of the captured shoreline.

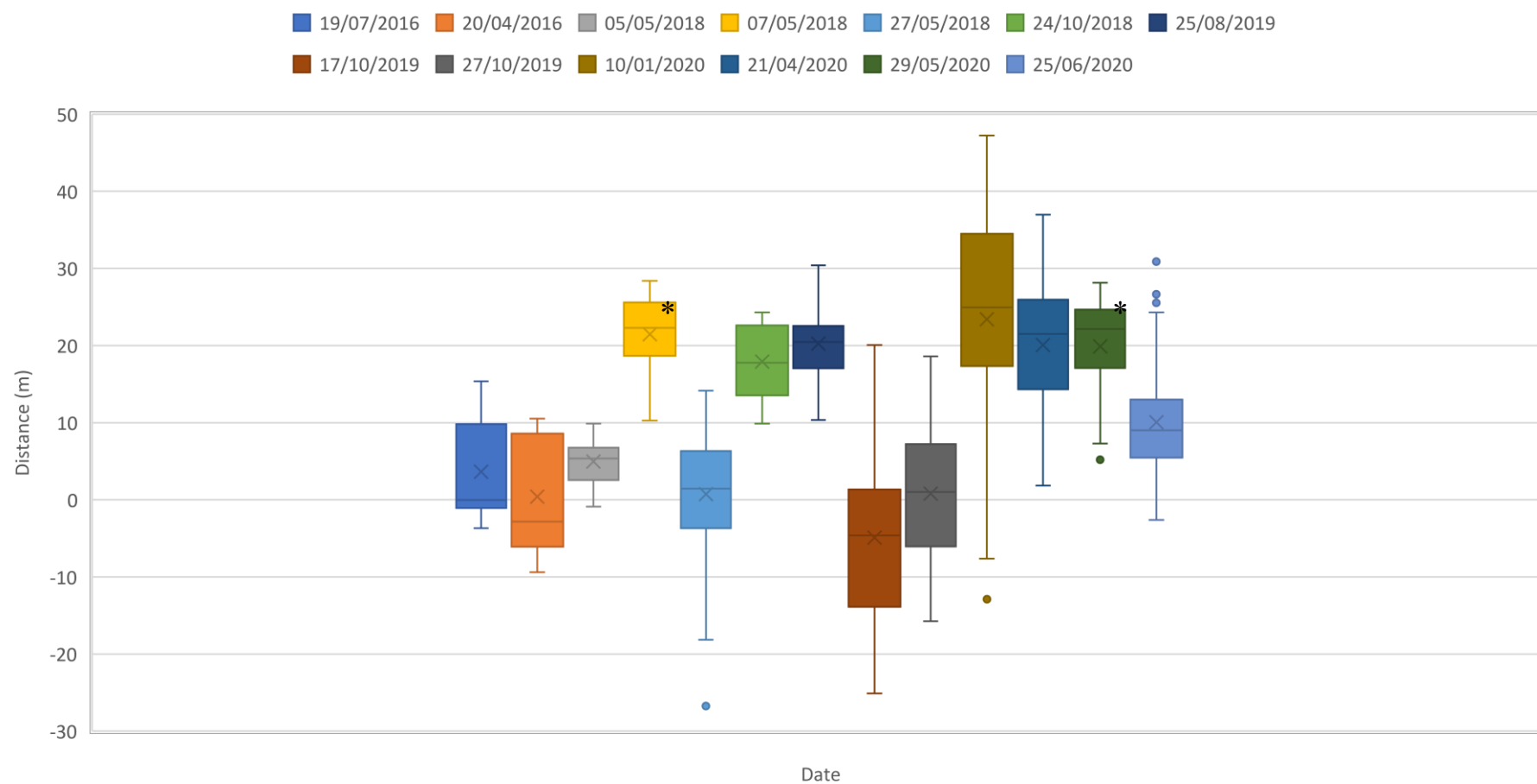


Figure 41: Box plot illustrating the distances between the ANN shorelines and the validation shorelines at Aldbrough. A positive skew indicates a seaward bias, while a negative skew indicates a landward bias. Plots marked “\*” indicate whitewater from breaking waves being present in the images.

### 4.3.3 Sizewell

At Sizewell (Figure 42 - Figure 45), 56% of shorelines had errors of less than 10 m, and all estimates were within 20 m of the actual shoreline. The results for Sizewell (Figure 46) however exhibit considerable variability. The most significant variations are observed on 07/05/2018, 31/07/2018, 17/01/2019, 04/04/2019, 30/07/2020, and 31/05/2021, where the differences range from 30 m to -40 m. This is mainly due to the algorithm differentiating between the sand and gravel instead of the wet/dry sand (Figure 45). Conversely, for the 17/05/2018 (Figure 42), 22/05/2018, 05/03/2019 (Figure 43), and 18/09/2020, the differences between the upper and lower quartiles are within 10 m. In Figure 46, the shorelines which were extracted at Sizewell with breaking waves visible in the image are marked with an Asterix (\*). These shorelines exhibit the smallest distribution of extracted shorelines, with much of the variation being attributed to differences in the validation data and the interpretation of the wet/dry boundary.

While the results shown variability it is important to note the ANN was able to delineate and understand the difference in the pixel values better than the CART algorithm and that it was able to understand the differences without the sand and gravel composition having a major impact on most shorelines (e.g., Figure 43). Additionally, the ANN's ability to handle non-linear relationships, perform feature extraction, adapt to diverse patterns in training data, and accommodate more complex decision boundaries might have contributed to its superior performance in distinguishing between gravel and sand.

Overall, the algorithm was able to accurately predict the waterline location, and factors such as beach slope or composition had less influence compared to the CART algorithm.





Figure 42: Comparison of ANN-derived shoreline (blue line) and validation shoreline (black line) at Sizewell on 17/05/2018. The validation shoreline, obtained from drone-based shorelines on 08/06/2018, is tidally corrected to align with the date of the captured shoreline.



Figure 43: Comparison of ANN-derived shoreline (blue line) and validation shoreline (black line) at Sizewell on 05/03/2019. The validation shoreline, obtained drone-based shorelines on 17/04/2019, is tidally corrected to align with the date of the captured shoreline.



Figure 44: Comparison of ANN-derived shoreline (blue line) and validation shoreline (black line) at Sizewell on 19/01/2020. The validation shoreline, obtained from drone-based shorelines on 07/05/2020, is tidally corrected to align with the date of the captured shoreline.





Figure 45: Comparison of ANN-derived shoreline (blue line) and validation shoreline (black line) at Sizewell on 31/05/2021. The validation shoreline, obtained from drone-based shorelines on 14/05/2021, is tidally corrected to align with the date of the captured shoreline.

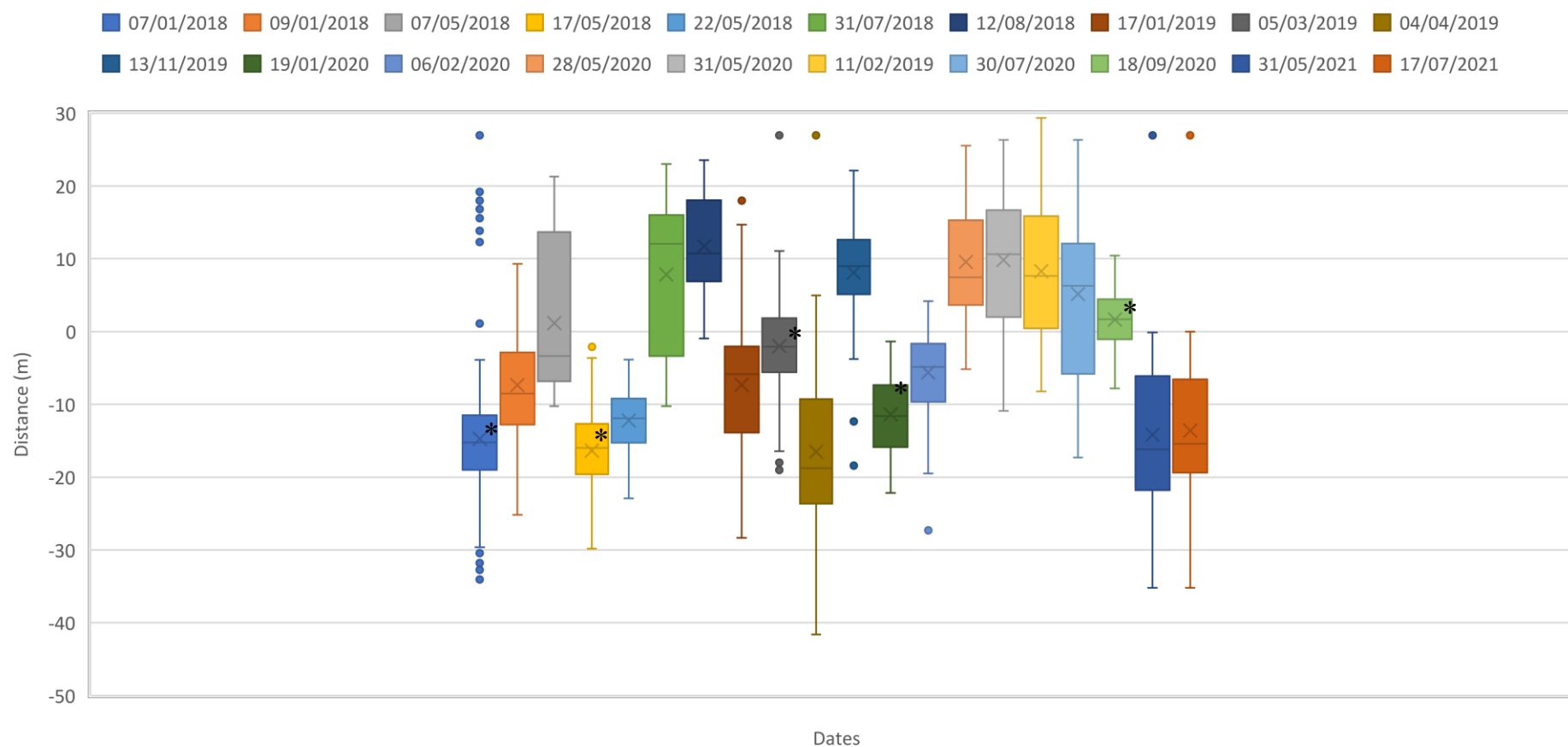


Figure 46: Box plot illustrating the distances between the ANN shorelines and the validation shorelines at Sizewell. A positive skew indicates a seaward bias, while a negative skew indicates a landward bias. Plots marked “\*” indicate whitewater from breaking waves being present in the images.

#### 4.4 CART, ANN, and Validation Visualisation

The shorelines generated by the CART algorithm were compared to those produced by an ANN in order to assess the difference in results for both algorithms. In this analysis the distance of the CART results from the ANN results is used to calculate the difference between them. As there were less shorelines extracted for the CART algorithm due to the algorithm struggling, the ANN results which matched the date of the CART results were used in this section. The outcomes of this comparison are depicted in Figure 47 to Figure 49.

At Start Bay, the CART algorithm exhibited larger errors, with a RMSE of 32.16 m, MAE of 30.71 m and a SD of 9.33 m. The results obtained at Sizewell also contained large errors, with an RMSE of 22.91 m, MAE of 20.3 m and SD of 9.39 m. Conversely, the smallest errors were observed at Aldbrough, with a RMSE of 13.22 m, MAE of 8.38 m and a SD of 11.40 m. The errors between the results obtained from both algorithms, as depicted in Table 11.

The boxplots showing the difference between the ANN shorelines and CART shorelines are shown in Figure 50 - Figure 52. In Figure 50, the boxplot illustrates the difference in shorelines for Start Bay. In these results, there is a mix of positive and negative differences, although the majority are negative, indicating that the CART shorelines are more landward than the ANN shorelines. Notably, the results for 25/01/2017, 05/05/2018, 27/09/2018, and 23/06/2020 all exhibit a similar distribution pattern, with the upper and lower quartiles being identical. This suggests that the differences between CART and ANN shorelines on these dates are consistent and relatively stable. A particularly significant date is 25/03/2020, where the median value of the difference is 0, indicating that, on this date, the CART and ANN shorelines are nearly identical. The distribution of

differences is minimal, signifying a high level of agreement between the two methods for shoreline extraction on this specific date.

In Figure 51 the boxplot illustrates the difference between the CART shorelines and the ANN shorelines at Aldbrough. A notable pattern emerges from this figure, where the lower quartile consistently sits at 0 for all plots. This consistent lower quartile value signifies that, across all dates, the CART and ANN shorelines exhibit minimal differences, and all have a seaward bias in their extraction at Aldbrough. While the lower quartile values are similar, the upper quartile values show varying distributions, and there are numerous outliers across all dates. Specifically, the results for 17/10/2019 and 27/10/2019 exhibit the highest distribution and the longest whiskers. This pattern aligns with the observations from the boxplots derived for the CART and validation shorelines, indicating that these two dates have particularly high variability in shoreline extraction results when compared to the validation data.

The results at Sizewell (Figure 52) show four of the plots consistently showing a lower quartile value of 0. However, despite this consistent lower quartile, there is notable variation in the distribution of results. Specifically, the plots for 03/05/2019 and 29/05/2020 display boxplots with high variability, indicating that the differences between the CART and the ANN shoreline are more pronounced during these periods. Conversely, the plots for 04/04/2019 and 19/01/2020 are shorter, suggesting less variation in shoreline extraction results on these dates. This implies that the CART and ANN shorelines fall within a range of 10 m of each other. The plot for 07/05/2018 exhibits a higher upper quartile, indicating a more seaward result and higher agreement between the CART and ANN shorelines. The shoreline for 31/05/2021 stands out, showing a large distribution and a tall boxplot. In this case, the upper and lower percentile values are 60 and 40 meters,

suggesting substantial variation and differences in shoreline extraction results on this date, while both shorelines exhibit a large seaward bias.

These results highlight the substantial variation observed between the two shoreline datasets, while concurrently emphasising the persisting errors produced by the CART algorithm when compared to the ANN shorelines.

Notably, Figure 50 visually illustrates the landward bias (8.52 m) of the CART algorithm compared to the ANN at Start Bay, indicating that the CART algorithm consistently underestimated the shoreline position. Conversely, at Aldbrough, a slight seaward bias of 3.13 m was observed in the results (Figure 51) whilst at Sizewell a seaward bias of 10.53 m was evident (Figure 52).

Table 11: Table illustrating the Average Difference, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Standard Deviation (SD) to depict shoreline uncertainties between CART-derived shorelines and ANN shorelines at each site.

| <b>Site</b> | <b>Average<br/>(m)</b> | <b>RMSE (m)</b> | <b>MAE (m)</b> | <b>Standard<br/>Deviation<br/>(SD)</b> | <b>Bias (m)</b> |
|-------------|------------------------|-----------------|----------------|----------------------------------------|-----------------|
| Start Bay   | 30                     | 32.16           | 30.71          | 9.33                                   | -8.52           |
| Aldbrough   | 6.27                   | 13.22           | 8.38           | 11.40                                  | 3.13            |
| Sizewell    | -3.11                  | 12.91           | 11.01          | 9.39                                   | 10.53           |





Figure 47: Comparison between the extracted CART shoreline (red), the ANN shoreline (blue) and the validation shoreline (black) observed at Start Bay on 12/09/2018.



Figure 48: Comparison between the extracted CART shoreline (red), the ANN shoreline (blue) and the validation shoreline (black) observed at Aldbrough in May 2018.



Figure 49: Comparison between the extracted CART shoreline (red), the ANN shoreline (blue) and the validation shoreline (black) observed at Sizewell on 08/06/2018.

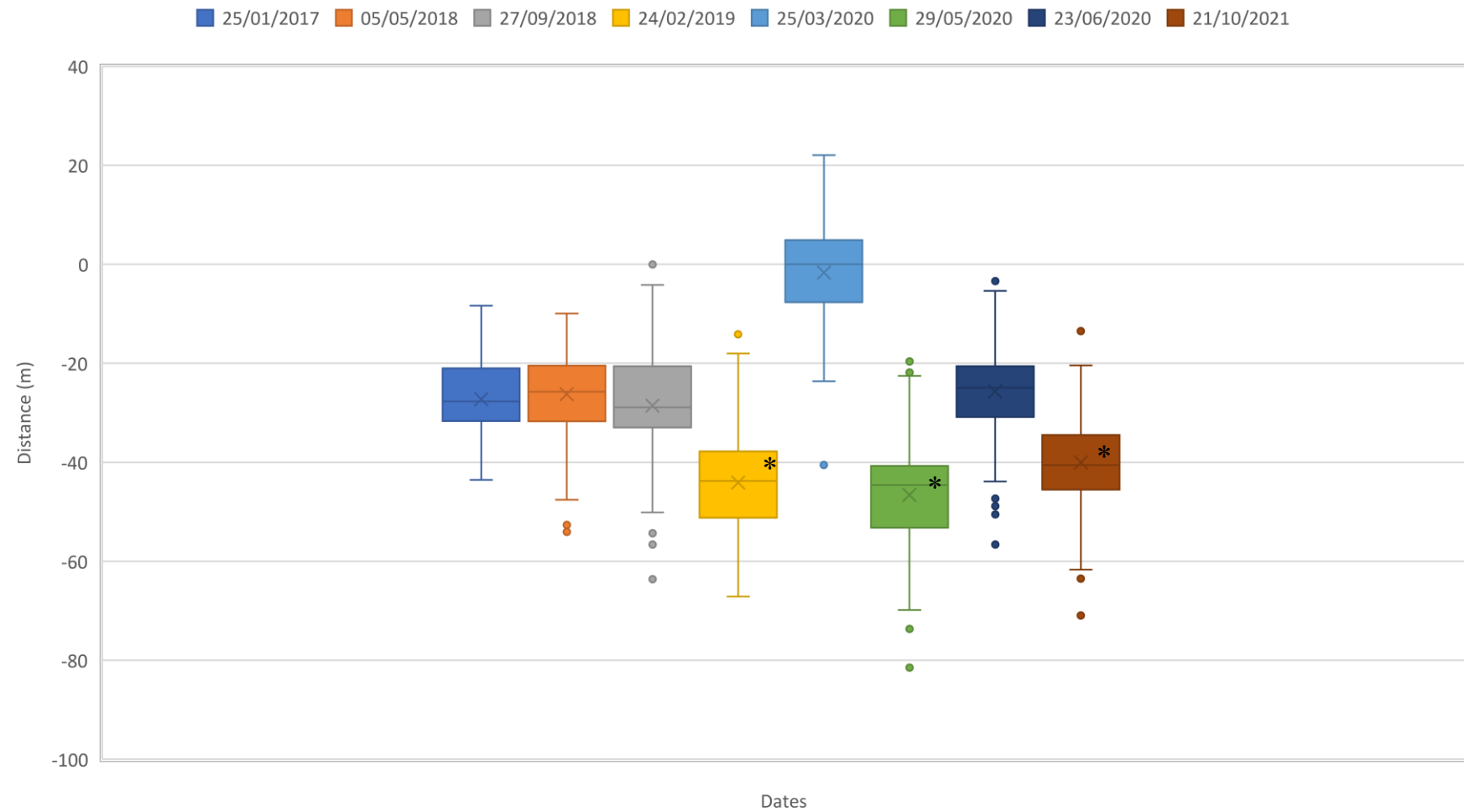


Figure 50: Boxplot depicting the deviation of the CART shoreline from the ANN shoreline in Start Bay. A positive skew indicates a seaward bias, while a negative skew indicates a landward bias. Plots marked “\*” indicate whitewater from breaking waves being present in the images.



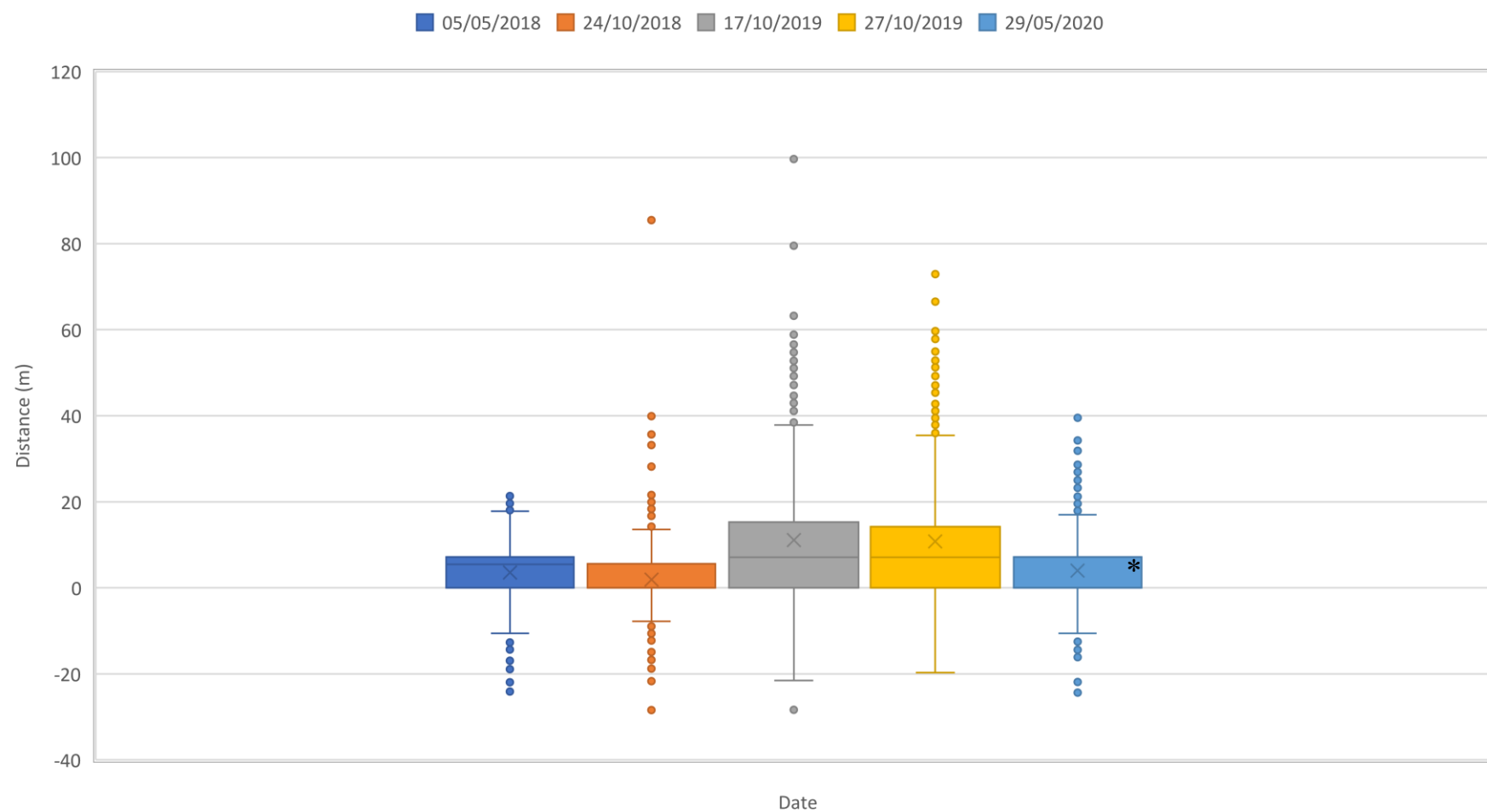


Figure 51: Boxplot depicting the deviation of the CART shoreline from the ANN shoreline at Aldbrough. A positive skew indicates a seaward bias, while a negative skew indicates a landward bias. Plots marked “\*” indicate whitewater from breaking waves being present in the images.

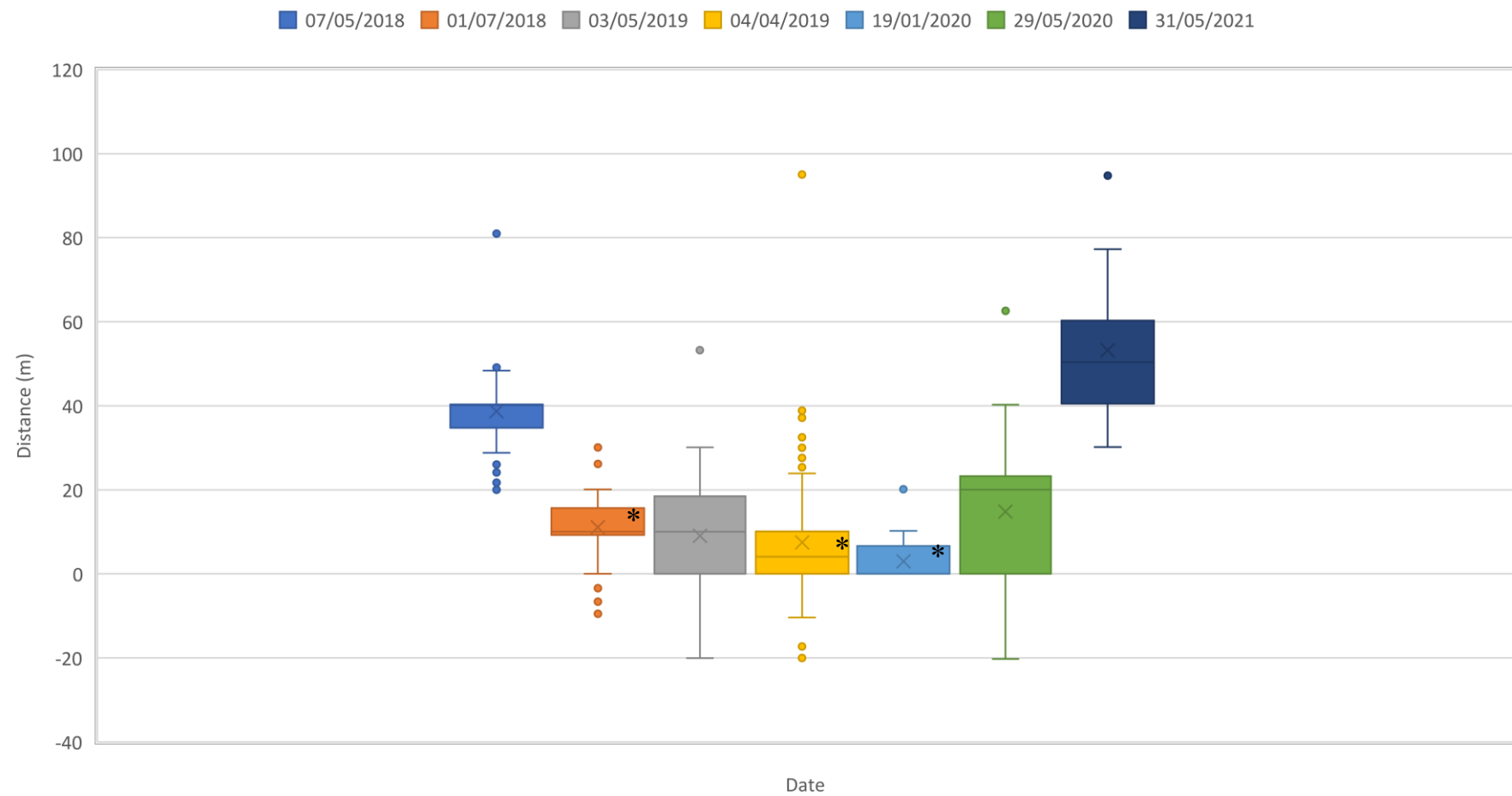


Figure 52: Boxplot depicting the deviation of the CART shoreline from the ANN shoreline at Sizewell. A positive skew indicates a seaward bias, while a negative skew indicates a landward bias. Plots marked “\*” indicate whitewater from breaking waves being present in the images.

## **4.5 Discussion**

This chapter focuses on the analysis of two supervised ML algorithms to determine their respective performance in achieving accurate shoreline delineations of the wet/dry boundary line from Sentinel-2 satellite imagery. A comparative analysis was conducted between the satellite derived shorelines and validation waterlines from LiDAR and drone-based shorelines. It was found that the ANN algorithm produced better shoreline results than the CART algorithm, as discussed in previous sections. The following discussion explores the obtained results and provides insights into potential factors influencing their outcomes.

### **4.5.1 Wet/Dry Boundary Line Extraction**

The results from both the CART and ANN algorithms demonstrated the ability of identifying the wet/dry boundary from Sentinel-2 satellite data through the use of supervised ML techniques, facilitating the successful determination of shoreline positions. Employing a two-step classification process for wet/dry boundary extraction was beneficial, as it allowed for a more precise classification of each of the classes. If a single classification step and training dataset were used, the presence of pixels belonging to other classes within the image could influence and contribute to misclassifications, resulting in gaps within the wet/dry boundary. The implementation of the two-step process was beneficial in mitigating misclassifications and ensuring accurate extraction of the wet/dry boundary, especially for the ANN algorithm.

As indicated in the Chapter 2, the majority of studies primarily focus on shoreline extraction exclusively for sandy beaches, often neglecting those with diverse compositions and varying spectral values, such as pebble beaches. Notably, the successful extraction of the wet/dry boundary across the three distinct shoreline types using an ANN

in this chapter highlights the potential for its application on various shorelines characterised by different compositions.

While the algorithms successfully extracted the wet/dry boundary it is important to consider if the extracted shorelines are represented correctly and are stable under different tidal levels, which depends on the specific time the satellite image is captured. Due to the variations in the results, it cannot be assumed that the wet/dry boundary consistently represents the high waterline in satellite images adding uncertainties into the results. However, for shoreline settings with low tidal range and steep beaches, the error will be minimal and significantly less than image resolution. Only with post-processing, including tidal analysis, can this association between tidal level and shoreline be established. Despite successful classification results, it is crucial to verify the extracted shorelines against the tidal cycle to ensure they are aligned with the same time frame. For automated shoreline extraction, having readily available tidal data to download or use within Python/Google Colab would be highly beneficial. Additionally, it would be useful to indicate the tidal phase at which the shoreline was extracted. Although this would require human input each time the model is executed and for the specific time period, implementing an automatic system would greatly simplify the post processing and analysis process. This would then be beneficial for applying the wet/dry boundary for larger scale applications.

#### **4.5.2 Sentinel-2**

Sentinel-2 data was chosen due to its free availability and a resolution of 10 m. Although Sentinel-2 imagery has been widely used in various shoreline studies, its application for wet/dry boundary extraction has been relatively limited. Despite the coarser nature of this



data, the utilisation of the ANN algorithm demonstrated the ability to produce accurate results with Sentinel-2.

The improved accuracy achieved with the ANN algorithm and Sentinel-2 data can be attributed to findings highlighted by Chen *et al.* (2010), indicating that higher-resolution satellite data may enhance visibility but not necessarily improve image classification. In cases where the spectral values are similar, the high resolution can lead to a speckle effect in the classification process, as the pixel values for different class types may exhibit spectral similarities that are challenging to differentiate.

In order to address the challenge of further enhancing accuracy when working with Sentinel-2 data, the sub-pixel method, developed by Pardo-Pascual *et al.* (2012) and Almonacid-Caballer *et al.* (2016), and subsequently utilised by Bishop-Taylor *et al.* (2019) and Vos *et al.* (2019), could potentially offer improvement. This method leverages the neighbourhood information of a pixel to optimise the positioning of the waterline, enhancing the accuracy of shoreline extraction.

### **4.5.3 Uncertainties**

Coastal environments undergo continuous and complex transformations, including tidal fluctuations, changes in wave characteristics (such as height and direction), and shifts in beach slope. These inherent variabilities introduce challenges when attempting to quantify and define shorelines. In the pursuit of shoreline studies, the prevalence of uncertainties needs thorough consideration across various dimensions, spanning both the natural environment and the methodologies employed.

Uncertainties extend to both the extraction and validation of shorelines within the scope of this thesis. While the aim of the methodology was to extract shorelines without the

need for tidal correction, errors will still exist and need to be considered. The extracted shorelines, which seek to portray the outermost boundary of tidal influence over a specific period, can produce errors due to the changes of tidal cycles, as well as the differences between spring and neap tides.

The temporal difference between the LiDAR data acquisition and image capture can produce errors, due to the changing topography between the two periods. In this chapter, the accuracy assessment involved deriving shorelines from LiDAR data and drone-based shorelines, which often differed in timing (of up to 6 months) from the image acquisition, leading to potential inaccuracies. This was evident in the case of Sekar *et al.* (2022) who faced challenges in validating their Landsat 7 (30 m) shoreline due to a two-week time difference between the validation data and image acquisition. Despite this, they discovered that the results, compared to the high-resolution ResourceSat-2 shorelines, fell within one pixel (30 m).

An important factor to also consider is the resolution of both the satellite data and the validation data (1 m). If the satellite imagery had a higher resolution ( $<10$  m) and the algorithm was applied to it, the results might have been more accurate, as they would fall within a 10 m range. Similarly, if the resolution of the validation data was coarser (e.g.,  $\sim 10$  m), the likelihood of accurate shoreline classification would increase. This would be particularly evident in sites where accuracies were within the 10 m pixel size.

Another source of uncertainty comes from the methodology employed, training data, model structures and parameters. The quality, quantity, and representativeness of the training data can impact the model's ability to generalize to new, unseen data. Incomplete

or biased training data may lead to limited applicability and accuracy of the model's predictions.

Model structures and parameters further contribute to uncertainty. The architecture of the chosen model, along with parameters like learning rates or regularization strengths, can greatly influence its performance. Selecting an appropriate model architecture and optimizing parameters can be challenging, and making suboptimal choices may lead to decreased predictive accuracy. Hence, this thesis employs the testing of two distinct models, a deliberate approach undertaken to address the multifaceted nature of uncertainty. The iterative refinement of these models aims to optimize accuracy while minimizing noise and errors within the obtained results.

## **4.6 Conclusion**

In conclusion, this chapter focused on the analysis of two supervised ML algorithms, CART and ANN, for accurate shoreline delineation of the wet/dry boundary using Sentinel-2 satellite imagery. The performance of these algorithms was evaluated through a comparative analysis with validation waterlines derived from LiDAR, drone-based shorelines, and sea level data.

The results demonstrate that the ANN algorithm consistently outperforms the CART algorithm across all sites. A crucial challenge in this context lies in accurately identifying the wet/dry boundary without encountering issues of overfitting or underfitting the model. The CART algorithm faced significant difficulties in this regard, as slight variations in the chosen depth level resulted in either overfitting or underfitting, depending on the specific value. Conversely, the ANN algorithm exhibited more stable performance without any visible signs of overfitting. The low error values achieved by the ANN

algorithm emphasise its effectiveness in detecting and delineating the wet/dry boundary. This further confirms the superior capability of the ANN algorithm compared to CART.

A limitation encountered in this chapter originates from the validation data and the uncertainties arising from temporal misalignment between the validation data and the extracted shorelines. This issue arises at times because the shorelines produced were correctly interpreted as the wet/dry boundary. However, discrepancies between the extracted shorelines and the validation data sometimes occurred, leading to larger errors, even when they weren't necessarily warranted.

In the future, it would be beneficial to explore whether the wet/dry boundary can be utilised to represent shoreline geomorphology and detect changes in the shoreline. This aspect will be further investigated in the subsequent chapter.

# **Chapter. 5 Assessing Shoreline Changes: A Comparative Study of Diverse Coastal Sites**

Chapter 4 demonstrates that the wet/dry boundary line can be extracted using Sentinel-2 MSI. Here, the thesis explores whether shoreline changes over short- and long-term timescales can be identified using the wet/dry boundary for the three different shoreline settings.

The study sites used throughout the thesis are in three diverse locations, characterised by different compositions and coastal geomorphology (see Table 1, Chapter 3). It is important to examine how the shoreline changes at these areas to determine if they can be quantified using the wet/dry boundary SI.

If the wet/dry boundary proves to be a reliable quantifier of change at the three geomorphically different sites, it builds confidence on the methodology being able to be applied to the whole of the UK or for larger or global applications, opening up more possibilities for broader coastal research and management.

This chapter is a follow on of Research Question 2, “Is there a SI representative of all shoreline types that can be extracted using medium-resolution MSI as a data source?”. In this chapter, the ANN algorithm introduced in Chapter 3 and validated in Chapter 4 is utilised to automatically detect the wet/dry boundary at Start Bay, Aldbrough, and Sizewell, using Sentinel-2 satellite imagery. The three locations are chosen based on their characteristics. Start Bay experiences beach rotation, where the beach shifts along the coastline over time. The Aldbrough cliff line is identified as one of the fastest eroding cliff lines in the UK. Here, the aim is to assess whether the rate of erosion correlates with changes in the adjacent beach. At Sizewell, the goal is to determine whether the relatively stable nature of the area is reflected in the shoreline dynamics. Shoreline change rates are calculated at these locations, and a comparison is made with the corresponding wave conditions during the same time period.

## **5.1 Methods**

### **5.1.1 Shoreline Extraction**

Images between 2016 and 2022 were collected for all three study sites using MSI from the Sentinel-2. For each image, an automated process was carried out. The images were input into the trained ANN algorithm. This algorithm produced a binary image representing wet and dry sand areas, which was further processed to extract its contours, which were then converted to real-world coordinates. This process is detailed in Chapter 3.

### **5.1.2 Shoreline Change Analysis**

Shoreline Change analysis was conducted using the DSAS within ArcGIS (see Chapter 2). The analysis involved calculating the Net Shoreline Movement (NSM) and End Point Rate (EPR) for each time step (Figure 16, Chapter 3). In the following analysis, positive values indicate movement toward the sea, while negative values indicate movement toward the land.

### **5.1.3 Shoreline Selection**

Both seasonal and multi-year analysis was carried out using the extracted shorelines. The multi-year shorelines were selected with the focus on achieving proximity in both season and tidal cycle. In order to comprehend the changes occurring over several years, two specific dates were chosen (the earliest and the most recent) to calculate the temporal difference (Table 12). For seasonal shorelines, preference was given to shorelines within the winter/early spring (October to March) period and early spring to early autumn image (April to September) period. Although this could not always be fully achieved, the shorelines closest to the start or end of these time periods were prioritised for seasonal analysis.

The selection of shorelines was influenced by the timing of the image acquisition during the tidal cycle. In Start Bay, all shorelines used were captured during high tide, while the multi-year images were taken during low tide. For Aldbrough, the chosen shorelines were acquired during low tide. At Sizewell, with the exception of two images from 2019, all other shorelines were chosen during high tide, and the remaining two were taken during low tide. These shorelines were chosen for each site based on the availability of extracted shorelines to maintain consistency in analysis. The chosen shorelines are shown in Table 12.

Table 12: Satellite images used for analysis for both long term and seasonal changes at Start Bay, Aldbrough and Sizewell.

|            | <b>Start Bay</b>                                                   | <b>Aldbrough</b>                                                                 | <b>Sizewell</b>                                                                  |
|------------|--------------------------------------------------------------------|----------------------------------------------------------------------------------|----------------------------------------------------------------------------------|
| Multi-year | 19/07/2016 - 25/11/2021                                            | 20/04/2016 - 19/04/2020                                                          | 01/07/2018 - 21/04/2021                                                          |
| Seasonal   | 05/05/2018<br>27/09/2018<br>24/02/2019<br>04/07/2019<br>25/03/2020 | 05/05/2018<br>24/10/2018<br>26/02/2019<br>17/10/2019<br>29/05/2020<br>21/09/2020 | 17/05/2018<br>01/09/2018<br>17/01/2019<br>25/08/2019<br>27/03/2020<br>18/09/2020 |

#### 5.1.4 Wave Data

Wave data is incorporated to understand coastal erosion dynamics, which are primarily influenced by higher waves during storms (Reeve *et al.* 2018). While long-term erosion may be driven by factors like climate change or variations in sediment supply, waves play a crucial role in the short-term erosion process. Depending on the intensity of environmental conditions, the effect of waves can shift rapidly from depositing sediment under mild wave conditions to eroding coastlines during storms. Storm events can lead to rapid and dramatic erosion, while fluctuations in water levels, including tides and surges, also contribute to erosion potential on beaches (Coco *et al.*, 2014; Splinter *et al.*, 2014).

Wave data was acquired through the Channel Coast Observatory (CCO) for the study sites (Dhoop. 2017; Dhoop. 2018; Dhoop. 2019; Dhoop. 2020; Warwick-Champion. 2022).



The Start Bay buoy (Latitude: 50° 17.53' N Longitude: 03° 36.99' W) was used for Start Bay, the Hornsea buoy (Latitude: 53° 55.02' N Longitude: 00° 03.95' W) used for Aldbrough, and the Lowestoft buoy (Latitude: 52° 28.55' N Longitude: 01° 49.03' E) was used for Sizewell.

Monthly averages for each site were extracted from the CCO's wave reports, containing relevant data on wave height and wave direction. These factors play a significant role as higher wave height is often associated with increased erosion and winter storms, while wave direction contributes to the generation of longshore currents, leading to sediment transport along the coast and resulting changes in shoreline shape and position. To identify storms at all sites, data was assessed from CCO to identify instances when wave heights exceeded storm thresholds. The storm threshold is defined when the height of waves surpasses what would typically be expected within a 0.25-year period. If wave heights are above the 0.25-year return period, they are categorised as a storm event. The values are provided within the discussion in Section 5.2. Wave direction rose diagrams were obtained to gain insights into the direction of waves at the sites. These diagrams provide valuable information about the prevailing wave directions and distribution of wave energy.

## **5.2 Results & Discussion**

### **5.2.1 Start Bay**

#### **5.2.1.1 Multi-year Net Shoreline Movement (NSM) and End Point Rate (EPR) at Start Bay**

Between 2016 and 2021, the Net Shoreline Movement (NSM) and End Point Rate (EPR) was assessed across all five beaches in Start Bay. The spatially averaged NSM at Start Bay between 2016 - 2021 was -15.92 m and with an average EPR of -3.88 m/ year.

The results revealed varying amounts of shoreline change, with the highest section of landward movement of -110 m found at Hallsands, located in the southern end of the embayment, highlighted by the red arrow in Figure 53. Stokes and Masselink. (2017) highlight the entire stretch of Hallsands beach as a vulnerable area and an erosional hotspot indicating that there is limited sediment available to provide resilience against erosion. However, while erosion is evident at Hallsands, a NSM of -110 m is substantial. This high rate of movement could be attributed to the extracted shoreline positions. Although these shorelines were extracted at high tide, there was more variation in the 2016 shoreline, which led to an increased shoreline movement. At Blackpool Sands, located in the north of the embayment, there was a NSM in the seaward direction 14.86 m, highlighted by the green arrow in Figure 53.

Over the 5-year period, the highest rates of retreat were observed at Hallsands, highlighted by the red arrow in Figure 54, with an average EPR of -10.72 m/year, corresponding to an average NSM of -32.32 m. At Beesands, the average rate of retreat was -3.56 m/year, accompanied by an NSM of -18.9 m, which is primarily concentrated in the northern section of the embayed beach. Both the northern and southern ends of Beesands beach

serve as erosional hotspots (Stokes and Masselink, 2017), aligning with the findings found here.

At Slapton Sands, the average NSM was -8.35 m, with an EPR of -1.56 m/year. This movement was predominantly observed along Slapton Ley and in the south of Slapton Sands, in front of Torcross village, both of which are highlighted as erosional hotspots (Stokes and Masselink, 2017), as shown in Figure 54. The northern section of Slapton Sands also experiences a landward movement, opposite to expectations, based on the rotational nature of the bay. Typically, a decrease in sediment in the south would correlate with an increase in sediment in the north. However, this pattern was not observed in this instance.

Forest Cove exhibited an NSM of -14.69 m, coupled with an EPR of -2.75 m/year. This contradicts the anticipated trend, given that for the past 18 years, both Forest Cove and Blackpool Sands have experienced net accretion (Stokes and Masselink., 2017). However, this deviation could potentially be linked to the methodology used for shoreline position extraction. Where the variance observed in the 2016 shoreline data may have contributed to the high shoreline retreat measurement. Blackpool Sands had the lowest NSM and EPR values of -2.35 m and -0.46 m/year, respectively. The green arrows in Figure 53 illustrate the seaward movement of areas along shoreline in the northern sections of the beach.

During this period, it was expected that beach rotation would be observed, as indicated by Wiggins *et al.* (2019). They suggested that embayment rotation may occur under the dominance of a particular wave direction, where southerly waves (from the Atlantic) lead to alongshore sediment transport to the north, resulting in beach narrowing in the south and widening in the north, while easterly waves (towards the Atlantic) result in more

accretion in the south and narrowing in the north (Figure 61) (Stokes and Masselink, 2017). Between 2016 and 2021, the prevailing wave direction was predominantly towards the south/southeast direction. During this period, sediment primarily moved landward, which was particularly evident in Slapton Sands and the northern regions of Beesands and Hallsands. With minimal accretion observed in the northern area of Blackpool Sands.



Figure 53: NSM at Start Bay ( $50^{\circ}17'0.76''\text{N}$ ,  $3^{\circ}38'46.44''\text{W}$ ) between 2016 - 2021. Arrows indicate the areas of erosion (red and orange) and accretion (green) based on the rate of change during the study period. The red arrows highlight significant NSM of the shorelines in Hallsands and Beesands. The orange arrows highlight the NSM of the shorelines in Slapton Sands and the green arrow indicates the area with net accretion in Blackpool Sands.



Figure 54: EPR at Start Bay (50°17'0.76"N, 3°38'46.44"W) between 2016-2021. Arrows indicate the areas of erosion (red and orange) and accretion (green) based on the rate of change during the study period. The orange arrows highlight the negative EPR in Beesands and Slapton Sands. The green arrows show significant positive EPR in areas of Slapton Sands and Blackpool Sands.



### 5.2.1.2 Seasonal Change at Start Bay

Seasonal shoreline changes between 2018 and 2020 are shown in Figure 55 to Figure 58 with NSM and EPR for each period depicted in Table 13.

From 05/05/2018 to 27/09/2018, there was an average seaward movement of the shoreline measuring 19.64 m (Figure 55). All beaches along Start Bay had a net seaward movement during this period, with Hallsands exhibiting the most pronounced movement of 19.8 m. When examining wave conditions, which significantly impact erosion, accretion, and sediment transport along the coastline (Reeve *et al.*, 2017), it's important to note that during this period, the prevailing wave direction consistently shifted southeastwardly (Figure 59), with average wave heights below 0.60 m. Typically, during summer months, with milder wave conditions, a net stability or positive NSM is expected, however the large NSM of 19.64 m is an unexpected observation, especially within a relatively short timeframe. It is very unlikely that factors such as wave height and direction may influence this sort of behaviour on shoreline dynamics, and it is more likely that the shorelines used for the analysis for this period may not be as accurate as required for the analysis.

From 27/09/2018 to 24/02/2019, the shoreline experienced an overall landward movement with an average displacement of 8.02 m (Figure 56). Hallsands had the highest landward movement (NSM = -15.50 m), whilst Blackpool Sands had the largest seaward movement (NSM = 10.21 m). At Slapton Sands, the north of Slapton Lay experienced significant landward changes with a displacement of -12.34 m. During this period, there was a shift in wave direction, towards the south, along with an increase in wave height ranging from 0.56 m to 0.89 m. The seaward movement of sediment visible south of the sub-embayed beaches at Blackpool Sands and Forest Cove could be attributed to the rotation of the shoreline (Figure 61) (discussed further in Section 5.2.1.3), where a

southwards wave direction transports sediment to the south of each beach, leading to an accumulation of sediment forming at the headland (Stokes and Masselink, 2017).

From 24/02/2019 to 04/07/2019, the shoreline continued to exhibit a consistent landward pattern (Figure 57), with an average overall movement of -9.8 m. All the beaches displayed landward movement during this period (Table 13). Hallsands recorded the largest negative NSM of -16.62 m, while Forest Cove showed the least movement (NSM = -2.37 m). Figure 57 highlights that during this period, there was a noticeable seaward movement of sediment in the northern sections of Forest Cove and Slapton Sands. This suggests a sediment transport direction towards the north. However, during this period, the wave direction remained in a southerly direction. There was also a decline in wave height from 0.89 m to 0.38 m, which could be facilitating beach recovery, potentially enabling sediment previously situated in the southern areas of Blackpool Sands and Forest Cove during the previous winter period to shift southward. As a result, this sediment movement may be contributing to the accumulation of sediment in the northern sections of the neighbouring beaches.

Between 04/07/2019 and 25/03/2020, landward movement was primarily concentrated in the northern section of Slapton Sands (NSM = -13.31 m), as shown in Figure 58. The northern region of Start Bay, including Forest Cove (NSM = -11.87 m) and Blackpool Sands (NSM = -16.65 m) also experienced substantial landward shifts, with Hallsands being the only beach to exhibit seaward movement during this period (NSM = 5.81 m). It is also important to note that while Forest Cove encountered considerable landward movement in the south, there was minor seaward movement in the north of the beach. As mentioned previously, this movement could potentially be attributed to sediment leaving Blackpool Sands, located north of Forest Cove, adding sediment to its neighbouring



beach. During this period, there was also an increase in wave height, rising to 1.06 m, which could have increased the amount of NSM occurring along the shoreline. Additionally, the wave direction reverted more towards the southeast and the storm threshold was surpassed twice during this timeframe, which could have increased the landward movement.

In Figure 60, the extent of NSM for each transect for the different seasonal changes are visualised. It primarily highlights the accretion during the initial period, followed by notable erosion in the subsequent periods.

Table 13: Seasonal and Multi-Year Net shoreline movement (NSM) along the five beaches at Start Bay. The movements of each beach are visualised further in Figure 60.

|                               | Net Shoreline Movement (m) |          |               |             |                 |         | EPR<br>(m/ year) |
|-------------------------------|----------------------------|----------|---------------|-------------|-----------------|---------|------------------|
|                               | Hallsands                  | Beesands | Slapton Sands | Forest Cove | Blackpool Sands | Average |                  |
| 05/05/2018<br>-<br>27/09/2018 | 19.80                      | 19.07    | 19.96         | 18.80       | 9.27            | 19.7    | 49.87            |
| 27/09/2018<br>-<br>24/02/2019 | -16.50                     | -8.78    | -8.75         | -2.37       | 10.21           | -8.03   | -19.51           |
| 24/02/2019<br>-<br>04/07/2019 | -16.62                     | -8.87    | -8.60         | -6.38       | -9.65           | -9.80   | -27.54           |
| 04/07/2019<br>-<br>25/03/2020 | 5.81                       | -9.61    | -8.15         | -11.87      | -16.65          | -6.87   | -9.46            |
| 2018 - 2020                   | -16.80                     | -19.10   | -11.0         | -15.18      | -1.64           | -32.32  | -10.72           |



Figure 55: NSM at Start Bay (50°17'0.76"N, 3°38'46.44"W) between 05/05/2018 and 27/09/2018.



Figure 56: NSM at Start Bay (50°17'0.76"N, 3°38'46.44"W) between 27/09/2018 and 24/02/2019.





Figure 57: NSM at Start Bay (50°17'0.76"N, 3°38'46.44"W) between 24/02/2019 - 04/09/2019.



Figure 58: NSM at Start Bay (50°17'0.76"N, 3°38'46.44"W) between 04/07/2019 and 25/03/2020.

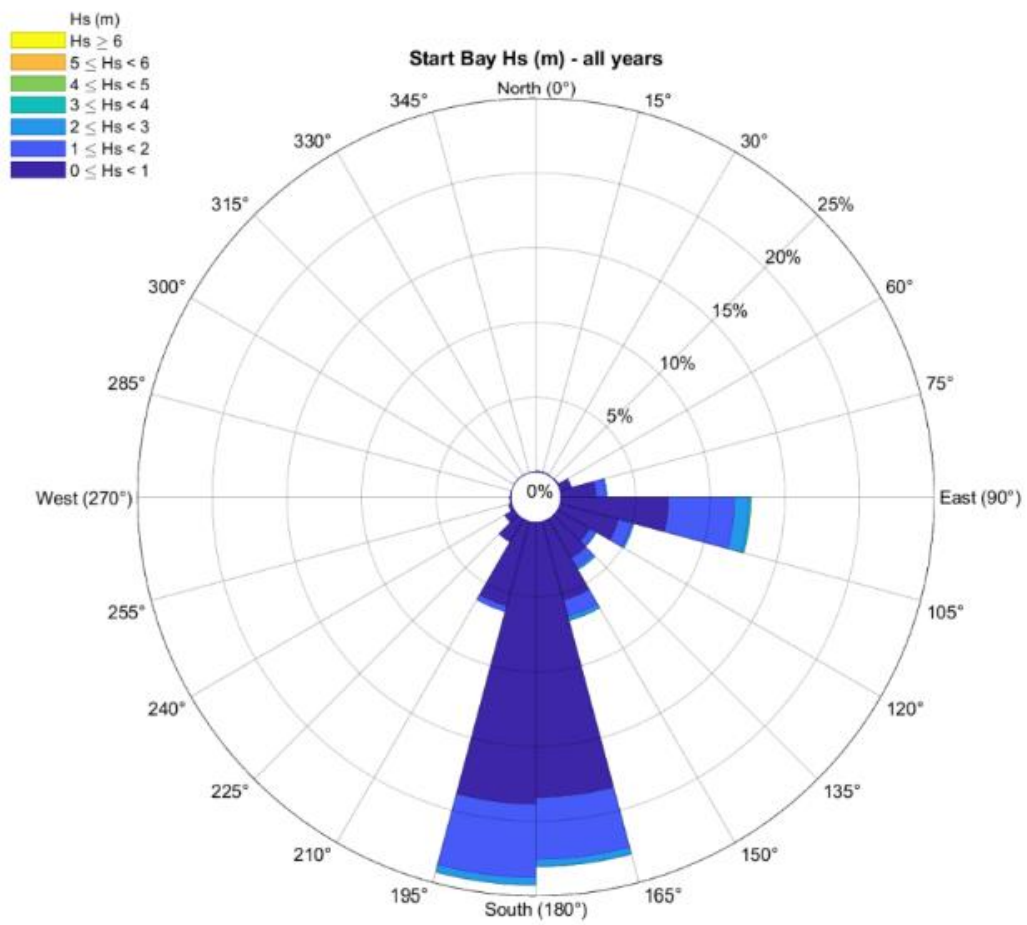


Figure 59: Wave direction rose for Start Bay between 2007- 2022 (Source: CCO)

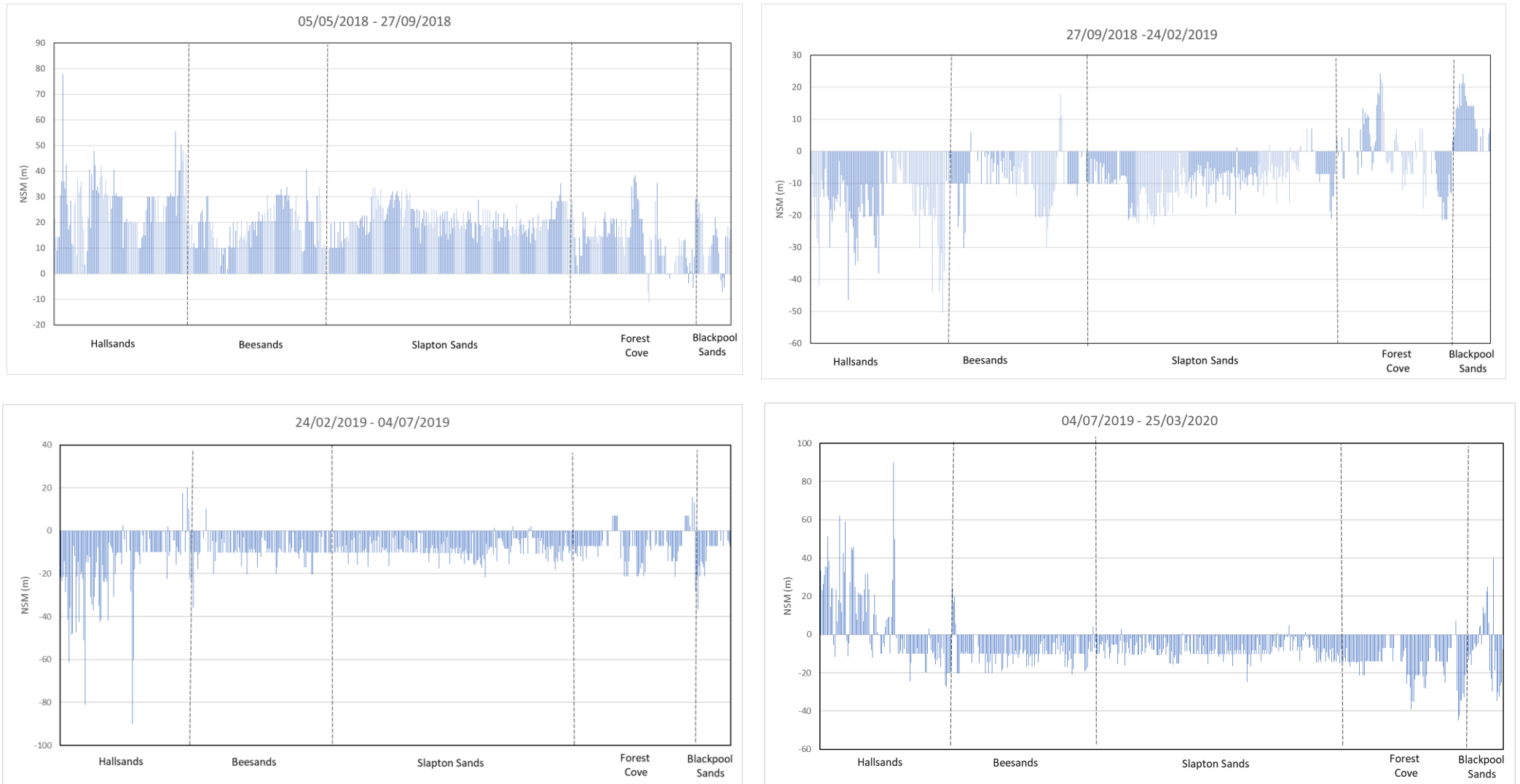


Figure 60: NSM of the extracted shorelines along Start Bay for each of the seasonal time periods discussed in Section 5.2.1.2



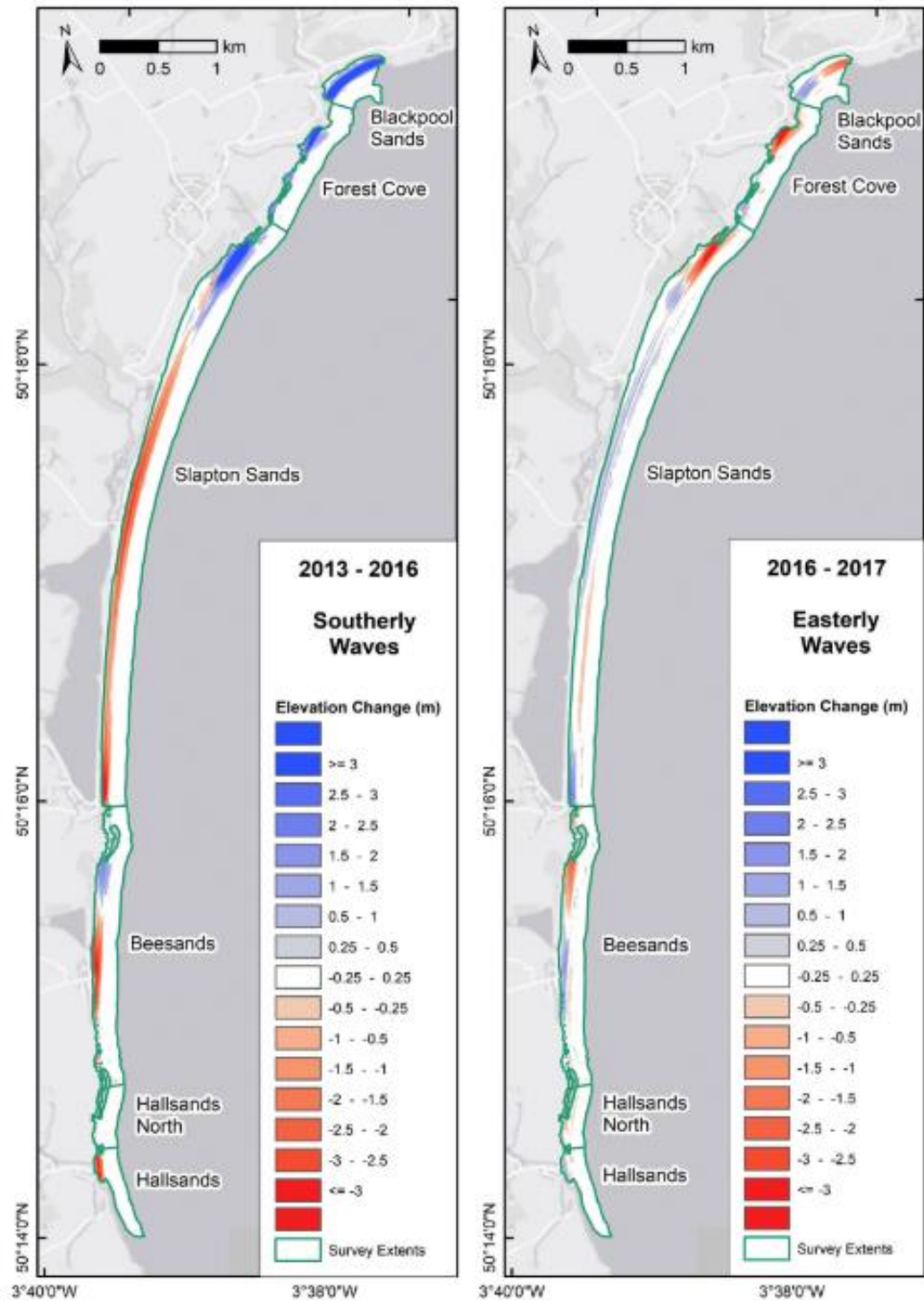


Figure 61: Vertical elevation difference for the southerly waves between 2013 and 2016 (Left) and easterly waves between 2016 and 2017 (Right). Elevation changes represented as colour intensity from red (erosion) to blue (accretion), with no detectable change represented as a lack of colour (Source: Wiggins et al. 2019).



### 5.2.1.3 Comparison to Volume Changes

Shoreline data from 2016 to 2017 was collected for Start Bay (illustrated in Figure 62b) to perform a comparative analysis with the volume change findings of Wiggins *et al.* (2019) (depicted in Figure 62a). The objective was to determine if the shoreline position could effectively highlight the changes taking place along Start Bay due to beach rotation, a phenomenon previously observed in volume changes by Wiggins *et al.* (2019). This investigation is based on the understanding that alongshore sediment transport and beach rotation are closely linked to the magnitude and direction of incident wave power.

At Start Bay, wave patterns are influenced by both southerly and easterly directions. Southerly waves originate in the Atlantic Ocean and refract into Start Bay as they move along the English Channel. Conversely, easterly waves originate from local storms within the Channel itself.

Typically, alongshore sediment transport in Start Bay is driven by Atlantic waves, leading to a net movement of sediment from south to north. However, during periods like 2016/2017 drift reversal occurs, where sediment shifts from north to south due to the influence of easterly waves from the English Channel. The interaction between sediment transport and beach rotation highlights the importance of comprehending the magnitude and direction of incident wave power in shaping coastal dynamics.

Wiggins *et al.* (2019) examined volume changes in Start Bay, as depicted in Figure 62a. During 2016 - 2017, the impact of easterly waves became evident. At Hallsands, there was an overall increase in sediment volume across the beach. Beesands exhibited varied volume changes, including a slight reduction in the south, an increase in the centre, and a reduction in the north. Slapton Sands showed a volume increase in the south, followed by a reduction around Slapton Ley. Beyond Slapton Ley, there was a volume increase moving north, but a significant reduction was observed at the northern point. Forest Cove experienced a slight volume increase in the southern section and a substantial decrease in the north. Blackpool Sands displayed a

volume increase in the south and a decrease in the north. These changes align with the influence of easterly winds driving sediment southwards within the embayment, consistent with current knowledge of beach rotation dynamics in Start Bay.

Horizontal shoreline positions at Start Bay were investigated due to the connection between the volume changes and beach rotation. Transects for Start Bay are depicted in Figure 62b. Drawing on insights from previous research by Stokes and Masselink. (2017) and the findings of Wiggins *et al.* (2019), it was anticipated that shoreline position would shift in response to sediment transport. Observations showed that at Hallsands, sediment moved seaward in the south and landward in the north. At Beesands, there was an overall seaward movement in the south and landward movement in the north. At Slapton Sands, seaward movement was observed in the south, followed by landward movement along Slapton Ley. This pattern continued with small sections of the beach showing seaward movement, while significant landward movement was recorded in the north. Forest Cove exhibited seaward sediment movement followed by two patches of landward movement. Blackpool Sands experienced a landward movement in the south and a seaward movement in the north. These findings align with expectations during periods of predominantly easterly waves.

When comparing the volume changes reported by Wiggins *et al.* (2019) with the shoreline position results, similar patterns of change emerge, characterised by consistent positive shoreline movement/volume in the southern sections of each beach and negative shoreline movement/volume in the north, influenced by wave direction and longshore sediment transport. However, there are some differences between the two. There are more results available for Hallsands for the shoreline position, indicating seaward movement in the south and landward movement in the north, consistent with existing literature. In contrast, these patterns were not as evident in the volume change data. This suggests that the increased number of transects used in this study's analysis may have enhanced sensitivity to such patterns. At

Beesands, a slight seaward movement is observed in the north section of the beach in the shoreline position results, while the volume changes gradually decrease further north towards the headland. This variation could be attributed to differences in the shorelines from the extraction process compared to the actual morphological changes occurring. A significant difference is noted at Slapton Sands, where increasing volume changes coincide with a landward movement of sediment. This may be explained by sediment primarily accumulating on the backshore before being transported southward, especially given the narrowness of the area along Slapton Ley, which is commonly over washed (Stokes and Masselink., (2017)). Finally, the shoreline position results at Forest Cove display two peaks, whereas only one is evident in the volume changes. This could be attributed to differences in the shorelines from the extraction process and the increased number of transects used for the shoreline change analysis.

While vertical volume changes and horizontal shoreline changes may not directly correlate, discernible patterns emerge from the data. An anticipated relationship between volume loss and a reduction in beach width was observed, reflecting the dynamics of Start Bay where sediment lost from one beach section migrates either north or south. This trend was evident in both sets of results. However, it is essential to note that comparing the magnitudes of these changes is challenging due to differences in data resolution. Shoreline change measurements, with a resolution of 10 m, exhibit larger magnitudes compared to volume changes, which rely on very high-resolution data from UAVs (1 m), bathymetry (1 m), and Digital Elevation Models (DEMs) (1 m). The higher resolution of volume change data allows for more precise measurement of changes in volume, such as erosion or deposition, at smaller spatial scales.

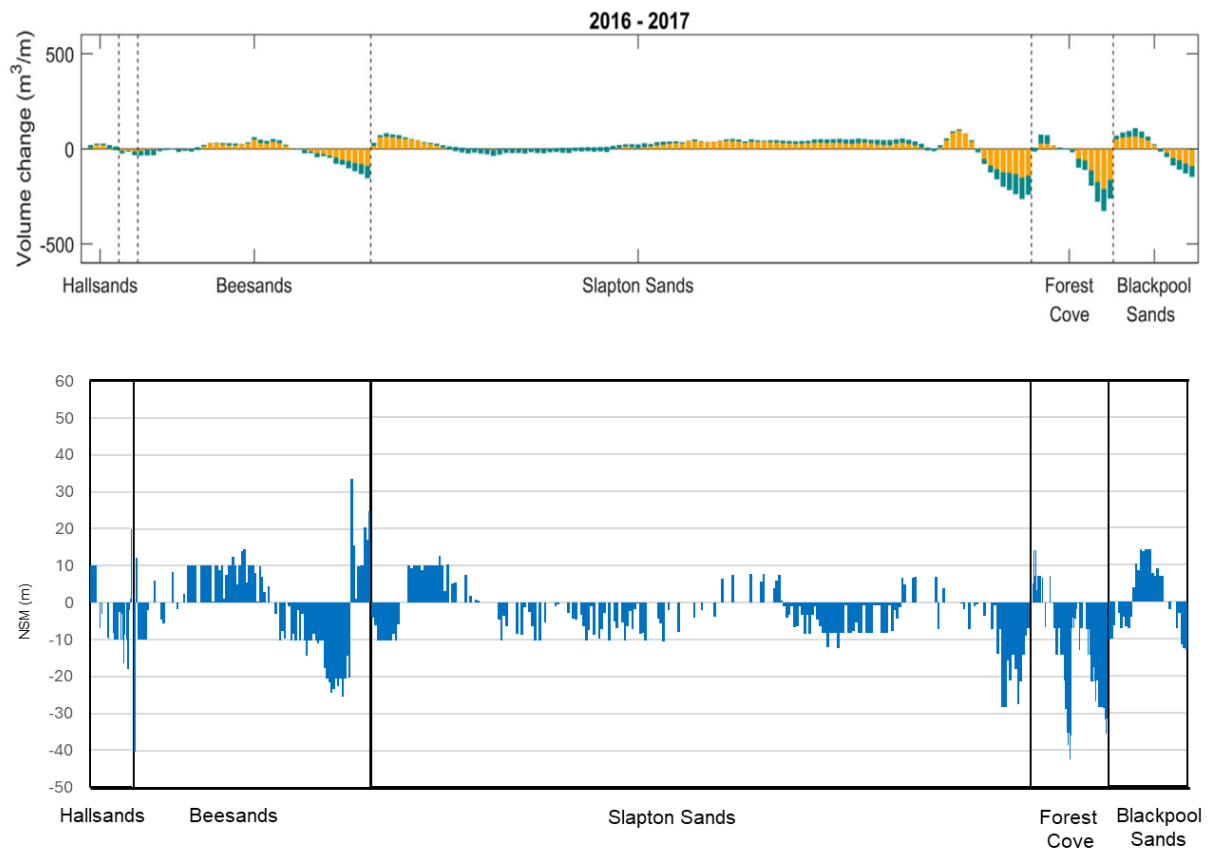


Figure 62: a) Volume changes at Start Bay between 2016-2017. Orange bars represent sub-aerial areas and green bars represent sub-tidal areas (Source: Wiggins *et al.* 2019). b) Shoreline movement between 2016-2017 at Start Bay derived from the ANN algorithm. Hallsands can be found in the southern region of Start Bay, while Blackpool Sands is situated in the northern region. Dashed/vertical lines represent headlands between sub-embayments.

## 5.2.2 Aldbrough

### 5.2.2.1 Multi-year Net Shoreline Movement (NSM) and End Point Rate (EPR) at Aldbrough

Table 14 and Figure 63 - Figure 64 show the NSM and EPR along the Aldbrough coastline between 2016 and 2020. For the entire coastline during this period, the spatially averaged NSM was found to be 7.23 m, and the EPR was measured at 1.81 m/year, indicating overall accretion, however the signal is spatially patchy.

Figure 64 shows several distinct sections of shoreline behaviour, denoted as a to g. Sections a, c, e, and g demonstrate seaward movements of the shoreline (accretion), while sections b, d, and f indicate landward movements (erosion). Notably, the results exhibit a consistent pattern of alternating landward and seaward movements (Figure 63). As highlighted by Pye and Blott. (2015) the Holderness coast exhibits a pattern of beach 'highs' and 'lows' that migrate along the shore, which may be highlighted in Figure 64. Alternatively, the increase and decrease of sediment along the coast could be influenced by both the input of sediment onto the beach from the erosion of cliffs in the region and the removal of sediment due to longshore drift.

At times, sand may accumulate in front of the cliffs, providing a buffer against direct wave erosion. However, as this sediment is gradually transported southwards, it may give the appearance of erosion along the coastline. In reality, the cliffs are no longer protected by the accumulating sand, making them more vulnerable to erosion. This process can amplify the overall impact of erosion in the area. This could be further explained by the 'low' sections of the beach described by Pye and Blott. (2015) which typically feature minimal to no sand, leaving the cliffs vulnerable to erosion. In contrast, the 'high' sand banks serve as protective barriers, shielding the cliffs from additional erosion.

During the period from 2016 to 2020, the section with the highest landward movement was section g, located near East Newton, where the NSM measured 33.50 m, with an EPR of 8.31 m/year. Both section a and section e, displayed NSM values of 22.25 m and 22.34 m, respectively. While section c had the least seaward movement, recording an NSM of 5.33 m.

Comparing the landward movements, the largest change was observed in section b, with an NSM of -16.70 m (EPR = -4.18 m/ year). Section f, exhibited an NSM of -11.67 m, and section d had an NSM of -8.38 m.

Table 14: NSM and EPR along section a-g (refer to Figure 64) along the Hull Coastline

|                |   | <b>NSM<br/>(m)</b> | <b>EPR<br/>(m/ year)</b> |
|----------------|---|--------------------|--------------------------|
| <b>Section</b> | a | 22.25              | 5.57                     |
|                | b | -16.70             | -4.18                    |
|                | c | 5.33               | 1.33                     |
|                | d | -8.38              | -2.10                    |
|                | e | 22.34              | 5.59                     |
|                | f | -11.67             | -2.92                    |
|                | g | 33.50              | 8.31                     |

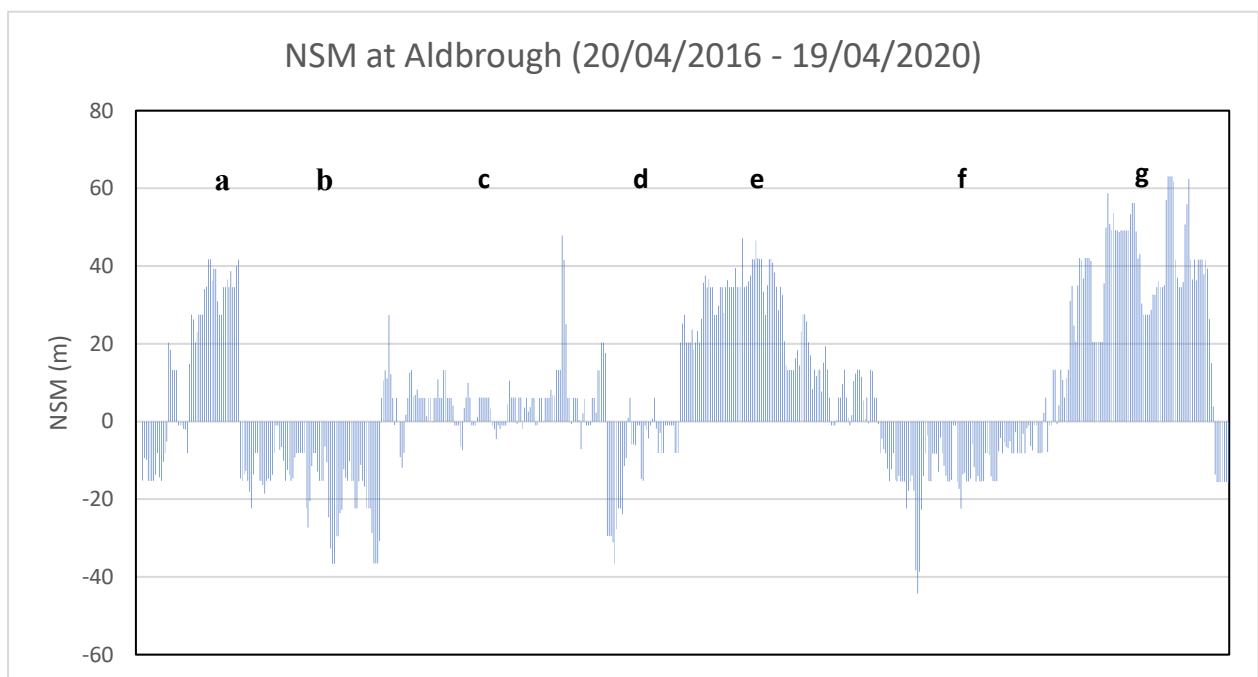


Figure 63: NSM for every transect from 2016 - 2020, along the Hull coastline. Letters a-g correspond to Table 14 and Figure 64.



Figure 64: NSM and EPR along the Hull coastline near Aldbrough between 2016 and 2020. Sections a-g highlight the seaward and landward pattern of change over the time period.

### 5.2.2.2 Seasonal Changes at Aldbrough

Seasonal shoreline changes between 2018 and 2020 are shown in Figure 65 to Figure 69.

Between 05/05/2018 – 24/10/2018, there was an overall seaward movement of the entire coastline with a NSM of 18.93 m (EPR = 40.20 m/year), shown in Figure 65. While there are sections which show landward movement (Red arrow in Figure 65), these do not have an impact on the overall net seaward movement, however they do have high rates of change (illustrated in Figure 65). The magnitude of the seawards results shown here tend to be unlikely due to the erosive nature of Aldbrough and the surrounding environment (Pye and Blott. 2015). Considering the influence of wave conditions during this period, no storms were recorded over the storm threshold (3.44m), and the wave height was between 0.39 m and 0.95 m, which may be linked with low erosion levels.

Between 24/10/2018 - 26/02/2019, there is a major amount of landward movement with a NSM of -19.92 m and an EPR of -58.10 m/year, illustrated in Figure 66. With only one section of the shoreline (highlighted by green arrows in Figure 66), moving seaward in the northwestern section near Cowden (NSM = 16.60 m; EPR = 48.42 m/year). When compared to the results from the previous season, they tend to negate the seaward movement of the shoreline observed. Instead, the overall seaward results may have been due to the extracted shoreline position, where the 24/10/2018 shoreline was more seaward from the extraction process. Considering the influence of wave conditions during this period the storm threshold (4.25 m) was exceeded four times, which may have increased the movement of sediment offshore or further southwards down the coast.

Between 26/02/2019 – 17/10/2019, there was a net seaward movement of 0.88 m (EPR = 1.37 m/year). During this period there is a section with significant landward movement in the same location as the seaward movement in the last seasonal period (NSM = -26.27 m; EPR =



-41.18 m/year), highlighted by the orange arrow in Figure 67. This area of landward movement could be due to the removal of sediment due to longshore drift as area south of the location has a seaward movement. Overall, minimal changes were observed along the shoreline during this period, which could also be attributed to the absence of storms.

Between 17/10/2019 - 29/05/2020, there is a continuation of seaward shoreline movement with a NSM of 5.22 m (EPR = 8.47 m/year). Although there is a positive NSM, there are areas where there is a negative EPR (highlighted by orange arrows in Figure 68), in both the northwest near Cowden, north of Aldbrough caravan park and in the southeast near East Newton. These consistent and larger erosional spots highlight areas along the Hull coastline which have continued removal of sediment, while the surrounding areas appear to remain stable. This pattern may be attributed to the presence of 'low' sediment areas on the beach, which could serve as sources of sediment input into the more stable areas. The erosion could also be more pronounced in these areas due to storms removing sediment from the shoreline as sediment transport rates tend to be highest during major storm events (HR Wallingford et al. 2002) as during this period the storm threshold (3.09 m) was exceeded twice.

Between 29/05/2020 – 21/09/2020 there is landward movement at Aldbrough with a NSM of -13.63 m (EPR = -43.29 m/year) (Figure 69). There is one location showing seaward movement, which is illustrated in Figure 69 (green arrow), with a NSM of 2.96 m, which was predominantly landwards in the previous seasons.

It is important to acknowledge the influence of tides and waves (Figure 70) on the shoreline at Aldbrough, as these forces are responsible for moving sediment offshore and southwards (Pye and Blott, 2015). It is also important to consider the quality of the shorelines used in analysing seasonal changes at Aldbrough. As demonstrated in Chapter 4, these shorelines show considerable variability, where making comparisons over short time scales may falsely indicate

shoreline changes. However, it is worth noting that areas exhibiting alternating landward and seaward movements may warrant further investigation, as they consistently show opposing directions compared to the overall shoreline during each period.

Table 15: NSM and EPR values for each seasonal period at Aldbrough

|                         | <b>NSM (m)</b> | <b>EPR (m/year)</b> |
|-------------------------|----------------|---------------------|
| 05/05/2018 – 24/10/2018 | 18.93          | 40.20               |
| 24/10/2018 - 26/02/2019 | -19.92         | -58.10              |
| 26/02/2019 – 17/10/2019 | 0.88           | 1.37                |
| 17/10/2019 - 29/05/2020 | 5.22           | 8.47                |
| 29/05/2020 – 21/09/2020 | -13.63         | -43.29              |
| 2016 - 2020             | 7.23           | 1.81                |

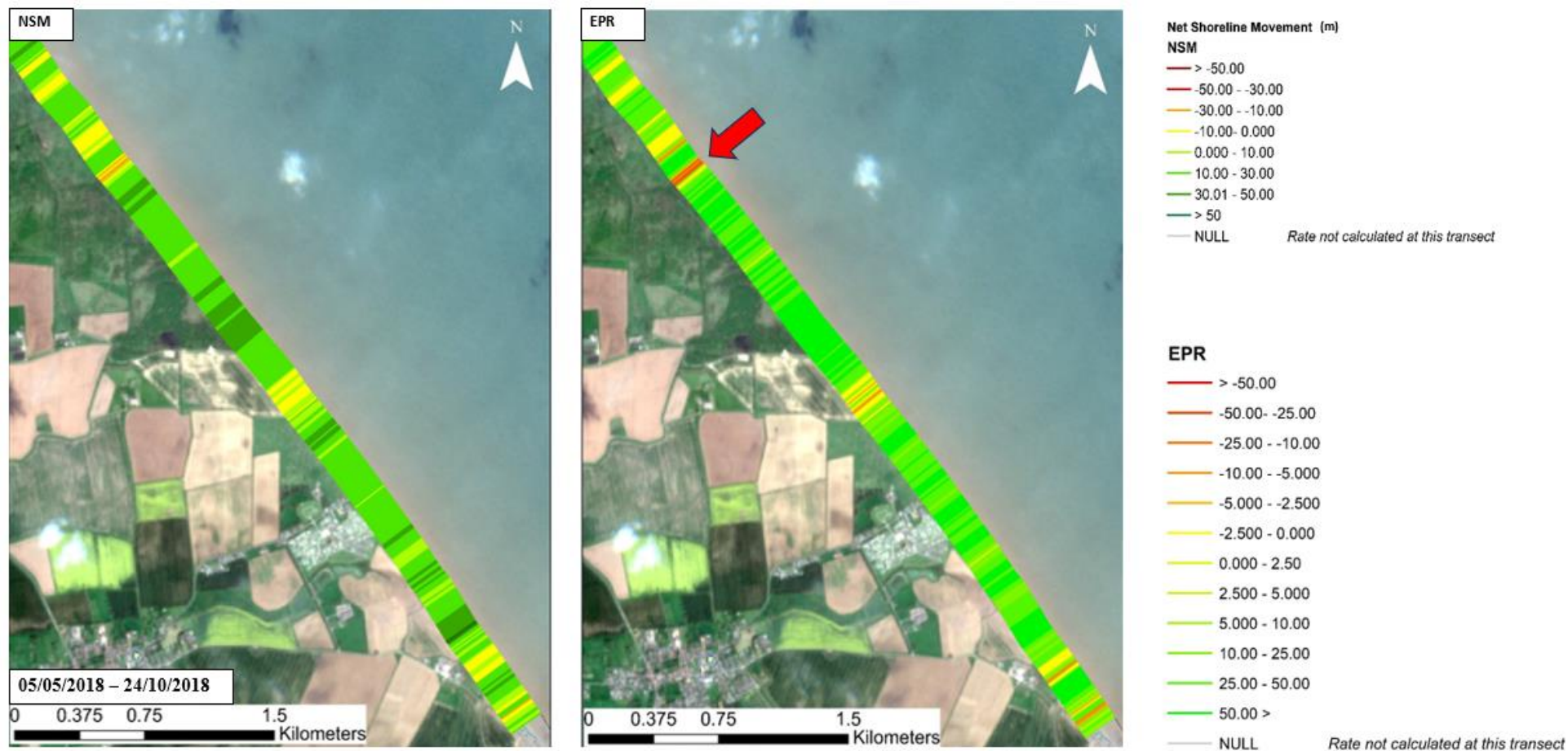


Figure 65: NSM and EPR between 05/05/2018 – 24/10/2018 at Aldbrough (53°50'9.23"N, 0° 5'22.91"W) and its surrounding coastline.

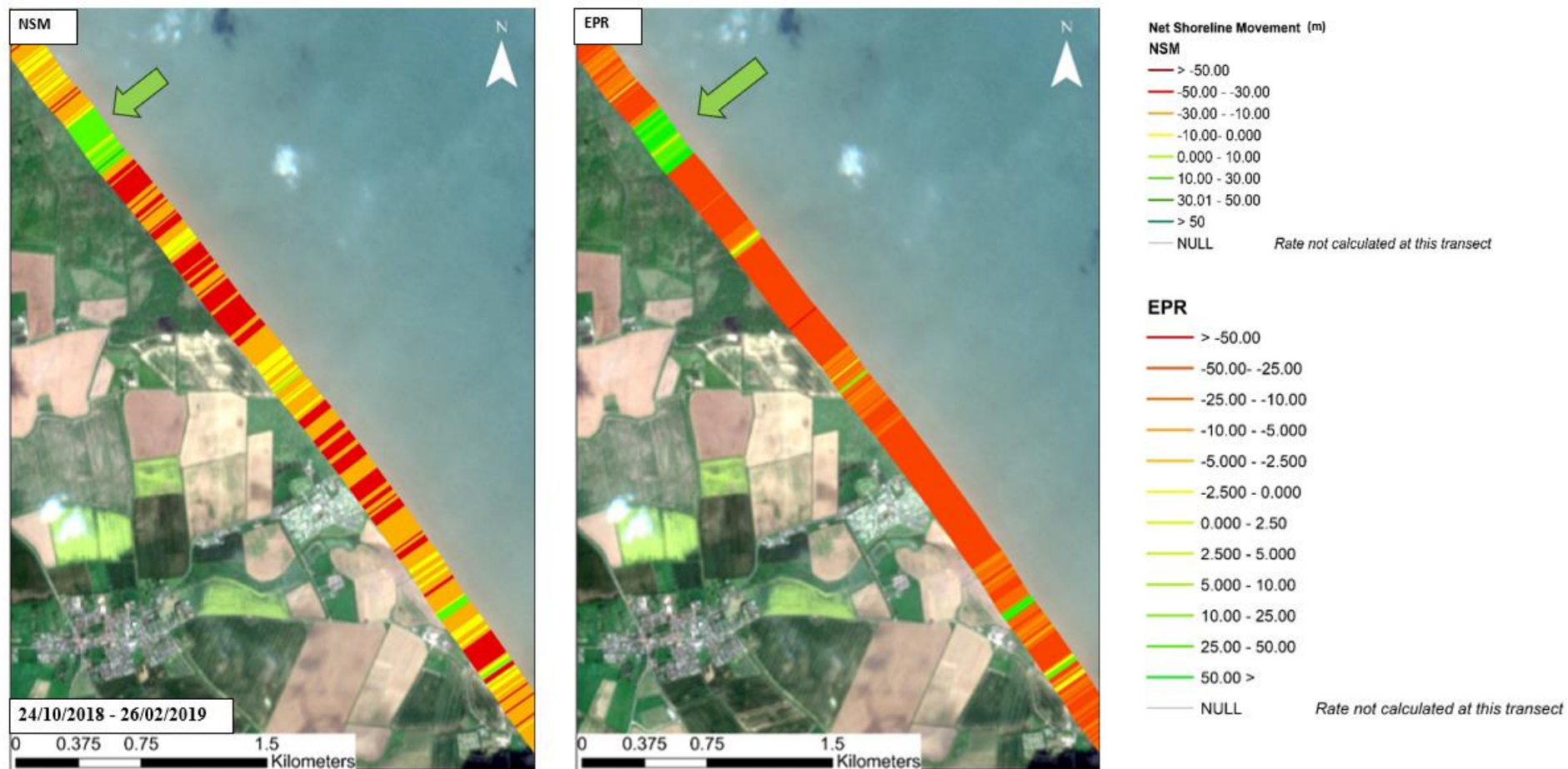


Figure 66: NSM and EPR between 24/10/2018 - 26/02/2019 at Aldbrough (53°50'9.23"N, 0° 5'22.91"W) and its surrounding coastline. The images show the overall negative NSM and EPR along the shoreline with the green arrows highlighting the only area showing seaward movement.



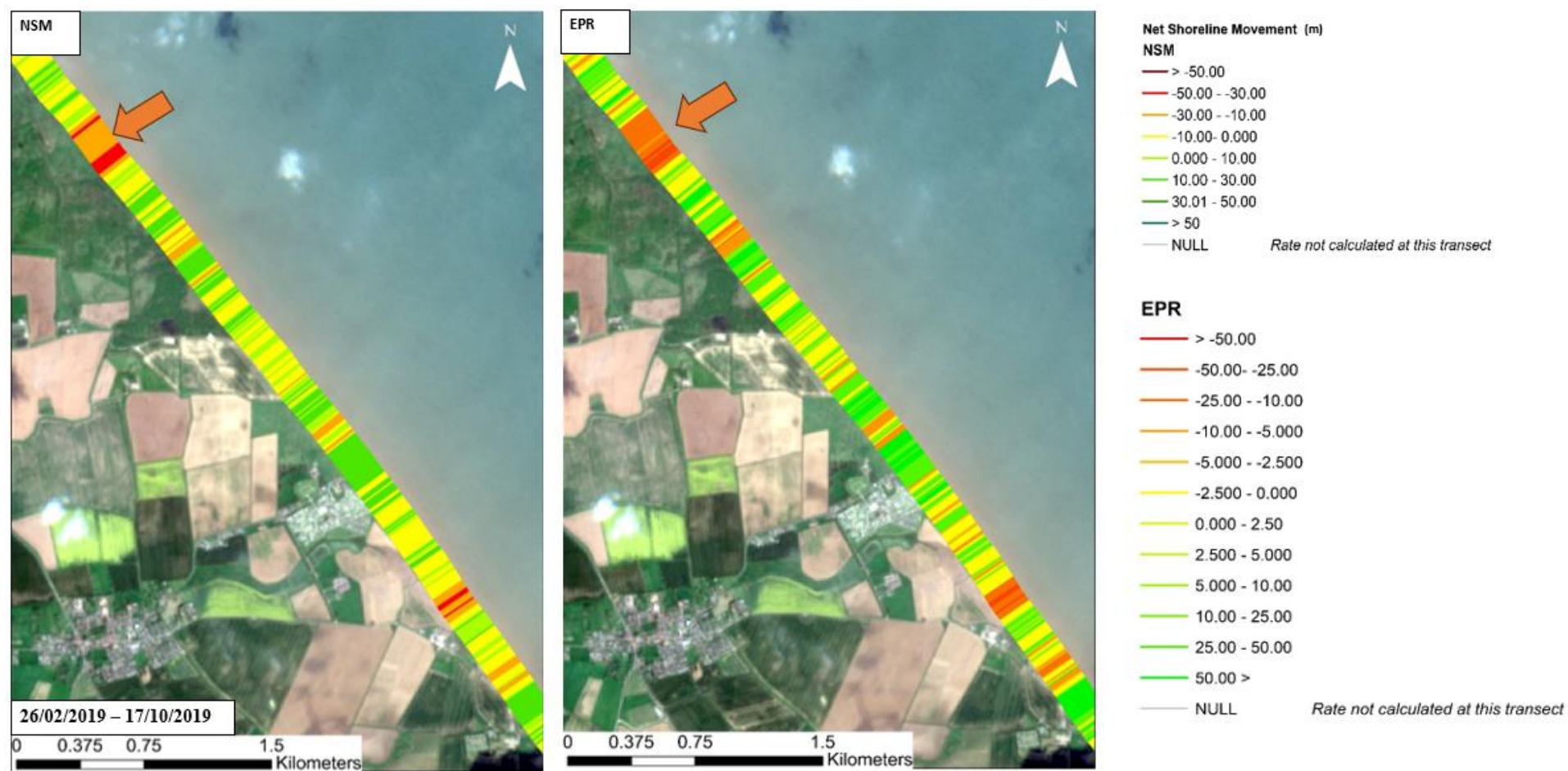


Figure 67: NSM and EPR between 26/02/2019 – 17/10/2019 at Aldbrough (53°50'9.23"N, 0° 5'22.91"W) and its surrounding coastline. The images show the overall positive NSM and EPR along the shoreline with the orange arrows highlighting the area showing landward movement.

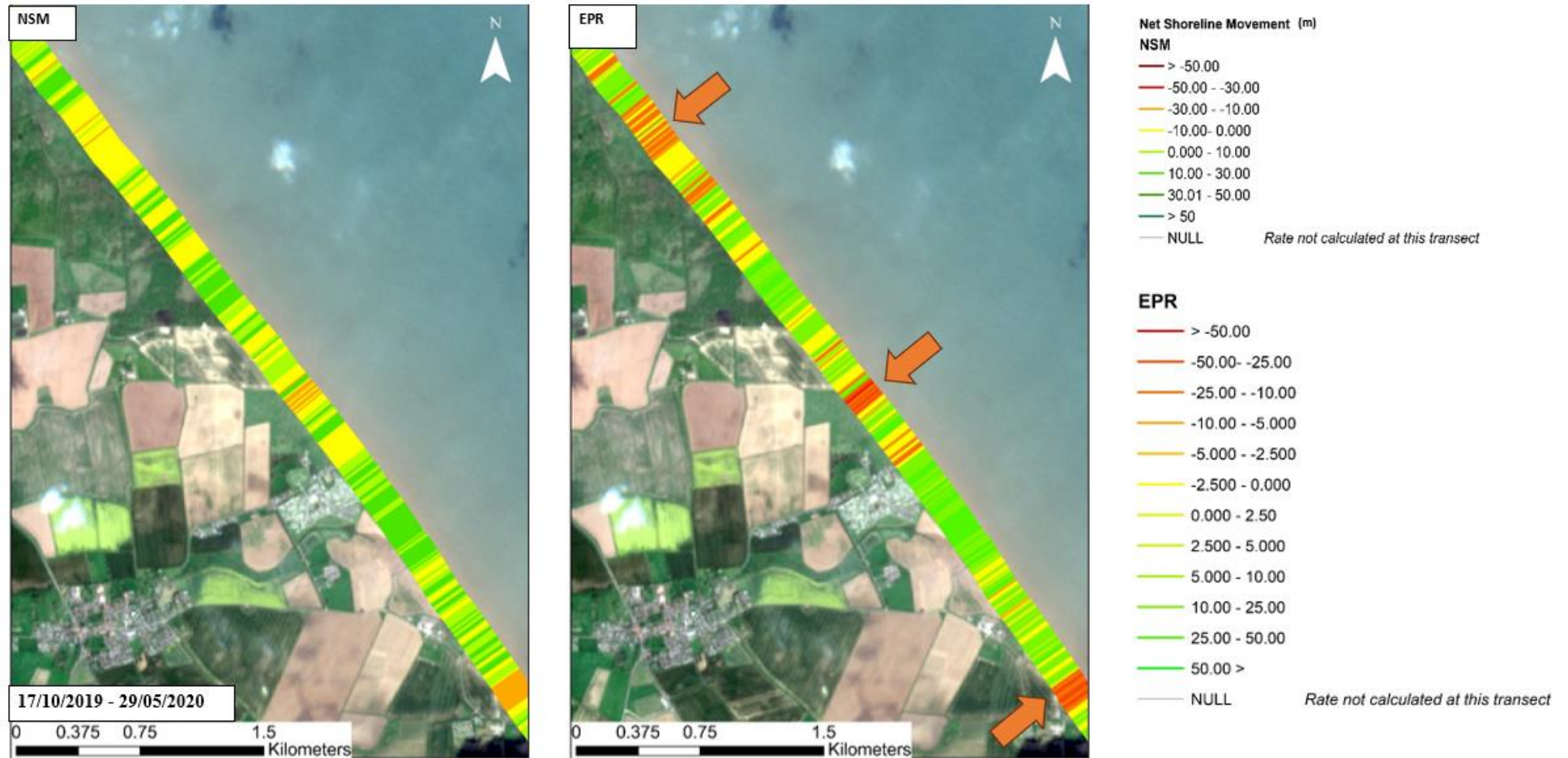


Figure 68: NSM and EPR between 17/10/2019 - 29/05/2020 at Aldbrough (53°50'9.23"N, 0° 5'22.91"W) and its surrounding coastline. The images show the overall positive NSM and EPR along the shoreline with the orange arrows highlighting the area showing landward movement.



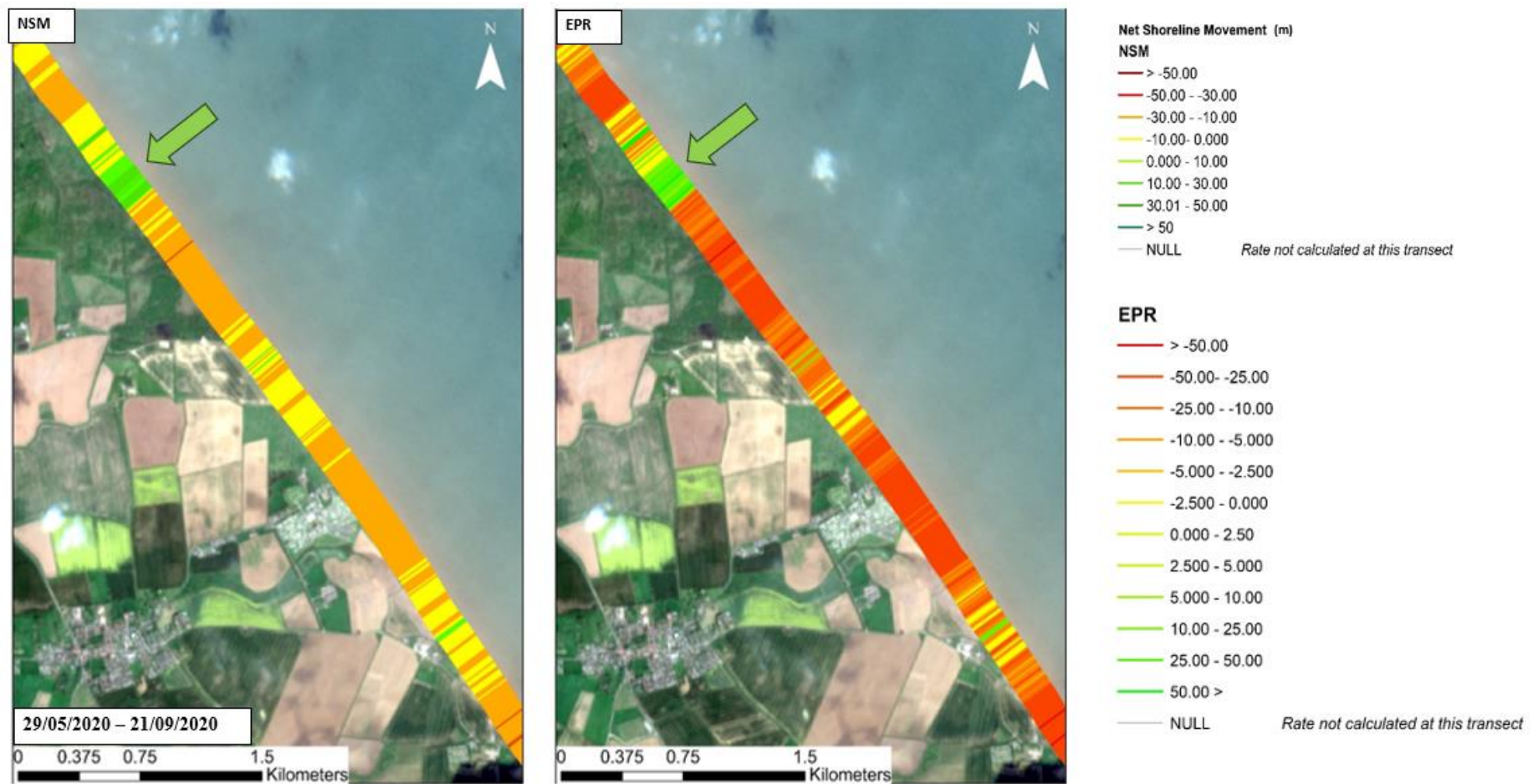


Figure 69: NSM and EPR between 29/05/2020 – 21/09/2020 at Aldbrough (53°50'9.23"N, 0° 5'22.91"W) and its surrounding coastline. The images show the overall negative NSM and EPR along the shoreline with the green arrows highlighting the area showing seaward movement.

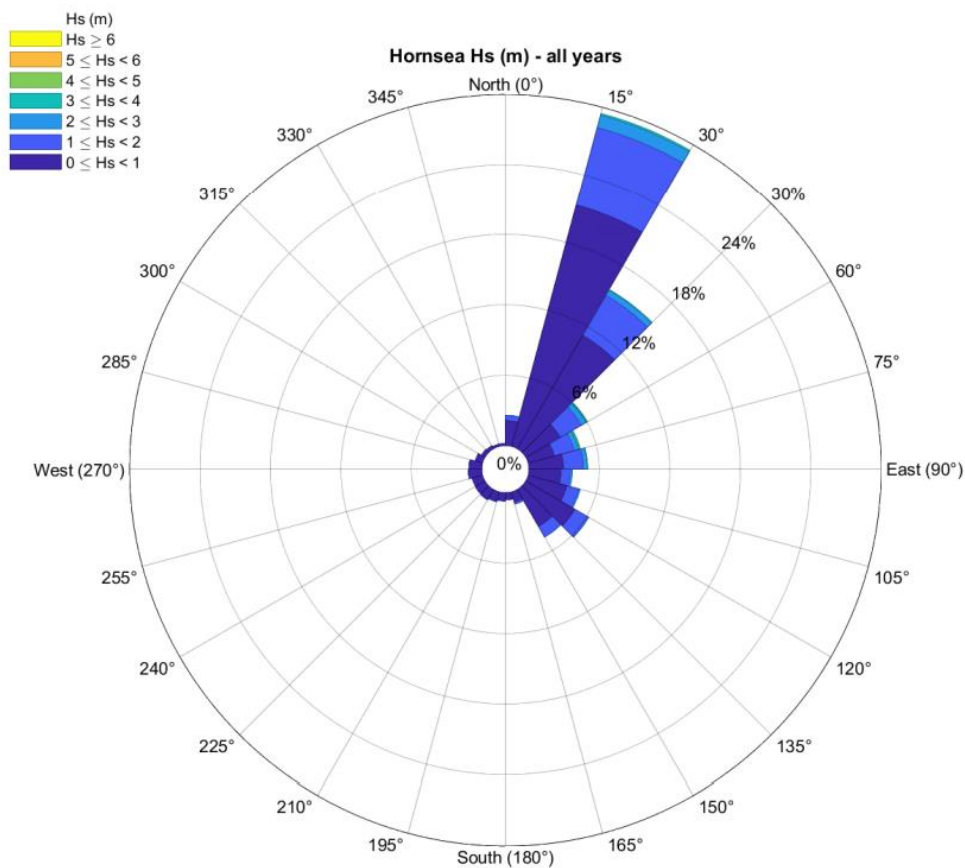


Figure 70: Wave Direction Rose for the Hornsea Buoy between 2007 -2022 (Source: CCO)

## 5.2.3 Sizewell

### 5.2.3.1 Multi-year Net Shoreline Movement (NSM) and End Point Rate (EPR) at Sizewell

Between 01/07/2018 and 21/04/2021, shoreline movement along Minsmere – Sizewell frontage was analysed (Figure 71). Over this four-year period, the spatially averaged NSM was seaward at 11.42 m, whilst the EPR was recorded at 4.07 m/ year. Within the averaged seaward movement along most of the coastline, there are alternating bands of landward and seaward movement, which are typical of this shoreline (Wallbridge *et al.* (2019) and Dolphin *et al.* (2020)). It is hypothesised that these patchy behavioural observations are the result of disruptions to longshore sediment transport caused by the



Minsmere Outfall, which blocks shingle transport, except when storms coincide with extreme water levels (Dolphin and Wallbridge, pers comm.). Furthermore, a salient-like feature at Sizewell B, considered to be formed and linked to deviation in longshore bars around the station's cooling water outfall, is known to move locally and result in shoreline change envelopes<sup>8</sup> of up to 58 m (NNB Generation Company (Sizewell C) Limited (2020)). The result is a dynamic coast with localised erosion and accretion patterns that reverse and result in overall low rates of net change (accretion for the study period; see Figure 71), which is seen both in the validation and satellite shorelines.

Adjacent to the Sizewell B station, however, a band of slight landward movement of -0.92 m (EPR = -3.3 m/year) was observed, between 2018-2021. Isolated bands of landward movement are typically up to 10 m and seaward movement of up to 50 m.

#### **5.2.3.2 Seasonal Changes at Sizewell**

Seasonal shoreline changes were analysed for Sizewell between 2018 and 2020 (Table 16). During the period 17/05/2018 to 01/09/2018, an overall seaward movement was observed, with a spatially averaged NSM of 5.94 m and an EPR of 20.27 m/ year. However, as shown in Figure 72 much of the Sizewell B frontage experienced landward movement during this period, with an NSM of -4.86 m and an EPR of -16.59 m/year.

In the subsequent autumn and early winter (01/09/2018 – 17/01/2019) this behaviour was reversed (Figure 73). Regions that were previously undergoing landward movement shifted towards the sea, and vice versa. The overall average NSM during this period was -2.15 m (EPR = -5.67 m/year). Notably, along the Sizewell B frontage there was a distinct seaward movement with a local NSM of 9.24 m (EPR = 24.41 m/year).

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<sup>8</sup> The most seaward shoreline position minus its landward-most position.

From 17/01/2019 to 25/08/2019, the shoreline movement underwent further changes. The southern section of the shoreline displayed seaward movement with an NSM of 28.83 m and an EPR of 47.86 m/year. Conversely, the northern section showed landward movement, with an NSM of -5.63 m and an EPR of -9.35 m/year (shown in Figure 74). During this period, a large NSM of 10.51 m was recorded, indicating a net recovery phase. However, this specific time step used low tide imagery, which could have influenced the results by contributing to the higher NSM value, however it is also worth recalling that Sizewell is microtidal and the sand-gravel beach face is relatively steep (circa 8°; NNB Generation Company (Sizewell C) Limited, (2021b)), so tidal errors will be relatively small.

Based on Figure 72 - Figure 74 a noticeable pattern emerges, suggesting a southward movement of sediment (which is in agreement with the net southerly transport direction) (Figure 78). In 2018, there was an increase in sediment in the north, and with each time step, this positive movement gradually extends further down the coast. The evidence suggests that there may not be an overall erosion; instead, it appears to be more of an alongshore sediment movement phenomenon.

Between 25/08/2019 and 27/03/2020, the shoreline exhibited an overall landward movement with small, isolated patches of seaward movement, as shown in Figure 75. The total movement during this period was -10.10 m, with an EPR of -17.10 m/year. The southern accretion pattern reversed, whilst the northern eroding area showed patches of reversal and continued landward movement. The northern region with seaward movement in front Sizewell B had an average NSM of 6.67 m.

From 27/03/2020 to 18/09/2020, a continued landward movement was observed (Figure 76), although at a lower rate ( $EPR = -10.13$  m/year), with the shoreline moving a total of -4.85 m during this period. Bands of seaward movement were observed, but not in the same locations as the previous period.

Between 18/09/2020 and 31/05/2021 (Figure 77) there was a NSM of 2.63 m and an EPR of 3.77 m/year. While there was still a landward movement in front of the powerplant (NSM = -1.56 m;  $EPR = -2.19$  m/year), south of it there was areas of seaward movement (NSM = 7.86 m;  $EPR = -11.29$  m/year).

The results for Sizewell reveal shoreline movement (both landward and seaward) set on a backdrop of overall net shoreline advance for the period examined (a positive NSM of 11.42 m), which is similar to the long-term pattern of net shoreline stability in this area, as demonstrated for the last three decades by NNB Generation Company (Sizewell C) Limited (2020). The observed changes in the region are alternating (spatially and temporally) and are likely to be due to the movement of a beach salient feature, although this feature has not been widely reported.

Several factors contribute to the shoreline change at Sizewell, including sand supply from longshore sediment transport originating from the Easton and Covehithe Cliffs, and historically pebble supply from the Dunwich Cliffs, located north of Sizewell, as discussed in the NNB Generation Company (Sizewell C) Limited (2020). Additionally, man-made erosion resistant features like the Walberswick harbour jetties and the Minsmere sluice outfall, interfere with longshore sediment transport and therefore play a role in the shoreline position.

Monitoring wave conditions is important for understanding shoreline changes, however Dolphin *et al.* (2020) examined the effect of the Beast from the East storms and established that spatial patterns in the driving wave conditions did not correlate to the observed shoreline response, leading them to conclude that antecedent morphology and particle-size arrangement within the mixed sand and gravel beach may be a controlling factor to observed shoreline change. As for the wave conditions during the examined seasons here, there was no correlation between the wave direction (which was predominantly east/southeast) and the changing landwards and seawards movements.

The wave results reported are not sufficient to account for the degree of spatial variation shown in the satellite-based shorelines, but the shorelines do align with behaviours measured by the validation shorelines. In particular, the interpretation of mobile, alternating bands of erosion and accretion, on the backdrop of a shoreline with low net accretion, aligns with ground measurements.

Table 16: Spatially averaged NSM and EPR for Sizewell between 2018 - 2020

|                          | <b>NSM (m)</b> | <b>EPR (m/ year)</b> |
|--------------------------|----------------|----------------------|
| 17/05/2018 - 01/09/2018  | 5.94           | 20.27                |
| 01/09/2018 - 17/01/2019  | -2.15          | -5.67                |
| 17/01/2019 to 25/08/2019 | 10.51          | 17.45                |
| 25/08/2019 - 27/03/2020  | -10.10         | -17.10               |
| 27/03/2020 - 18/09/2020  | -4.85          | -10.13               |
| 18/09/2020 – 31/05/2021  | 2.63           | 3.77                 |
| 2018-2021                | 11.42          | 4.07                 |

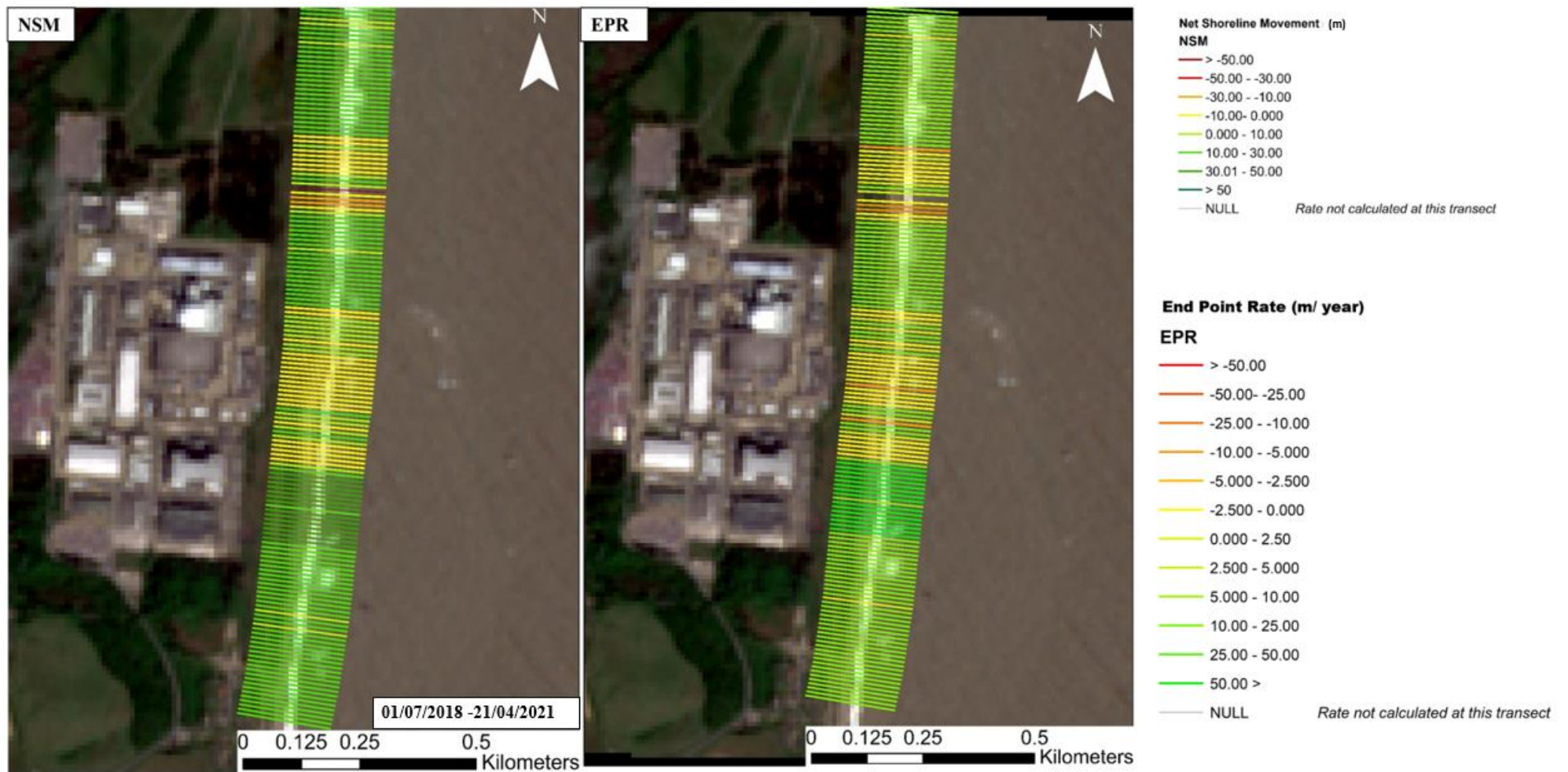


Figure 71: NSM and EPR at Sizewell (52°12'51.11"N, 1°37'26.02"E) between 01/07/2018 - 21/04/2021.

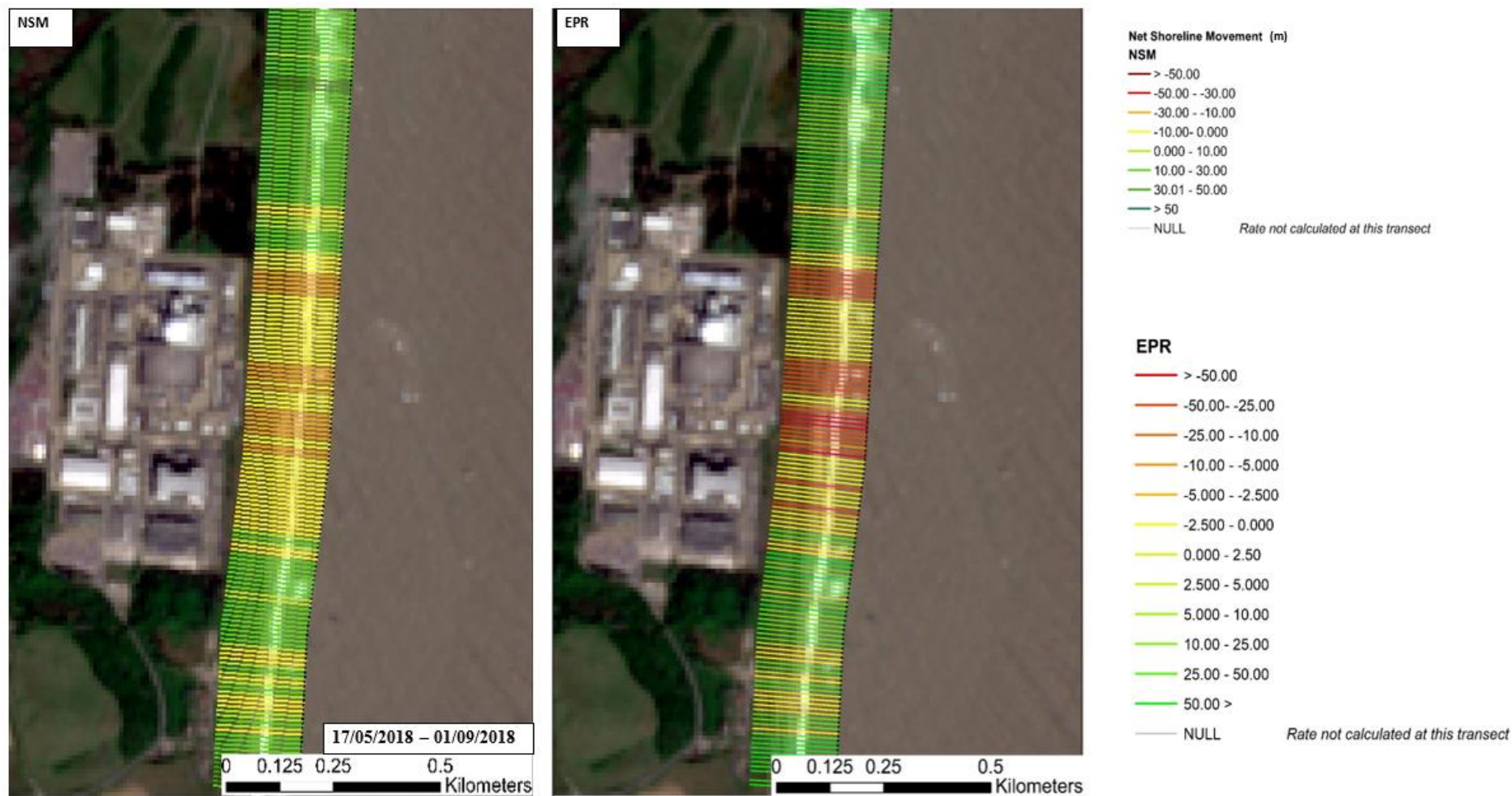


Figure 72: Seasonal NSM at Sizewell (52°12'51.11"N, 1°37'26.02"E) between 17/05/2018 - 01/09/2018.



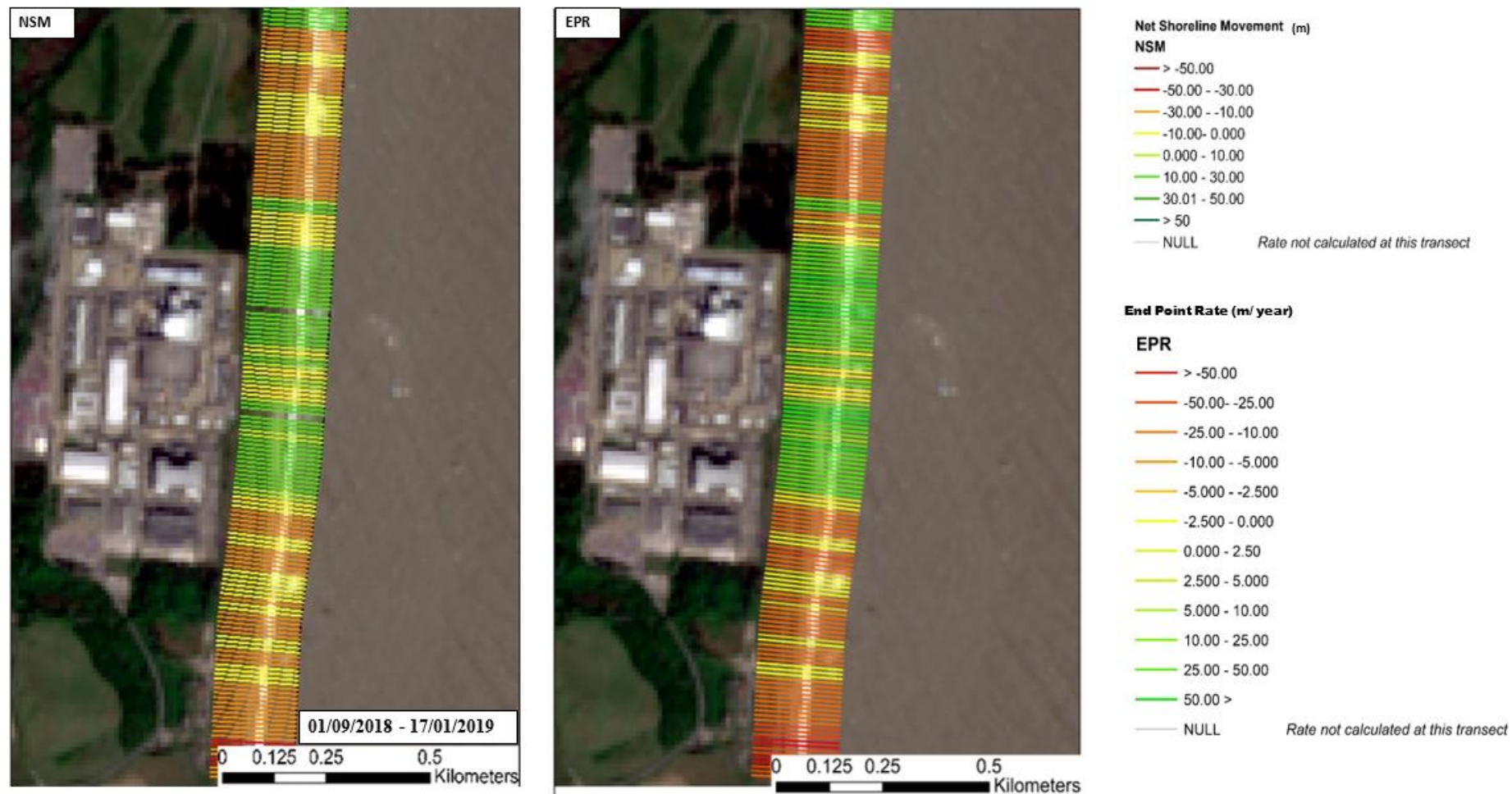


Figure 73: Seasonal NSM at Sizewell (52°12'51.11"N, 1°37'26.02"E) between 01/09/2018 and 17/01/2019.

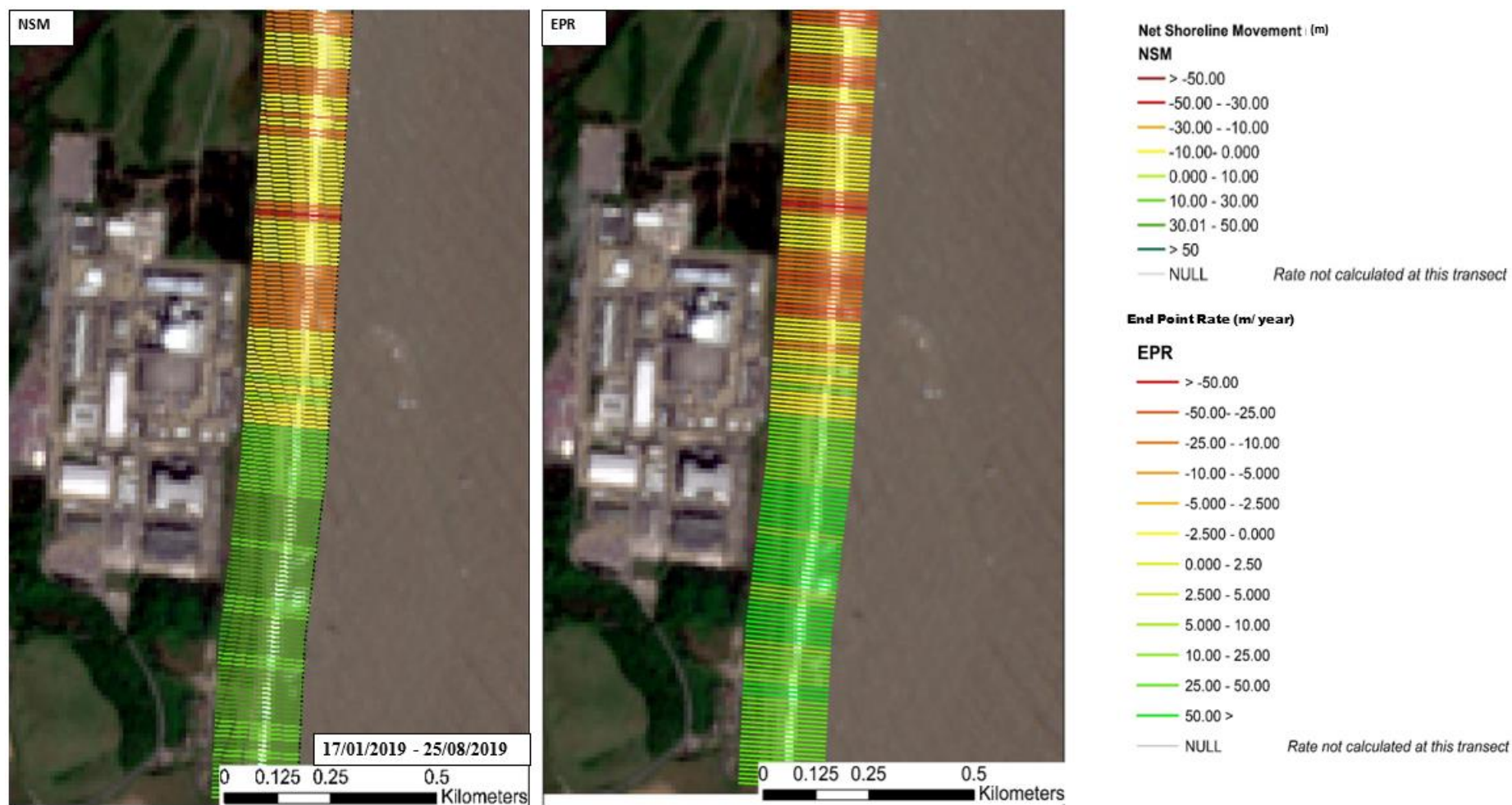


Figure 74: Seasonal NSM at Sizewell (52°12'51.11"N, 1°37'26.02"E) between 17/01/2019 and 25/08/2019.



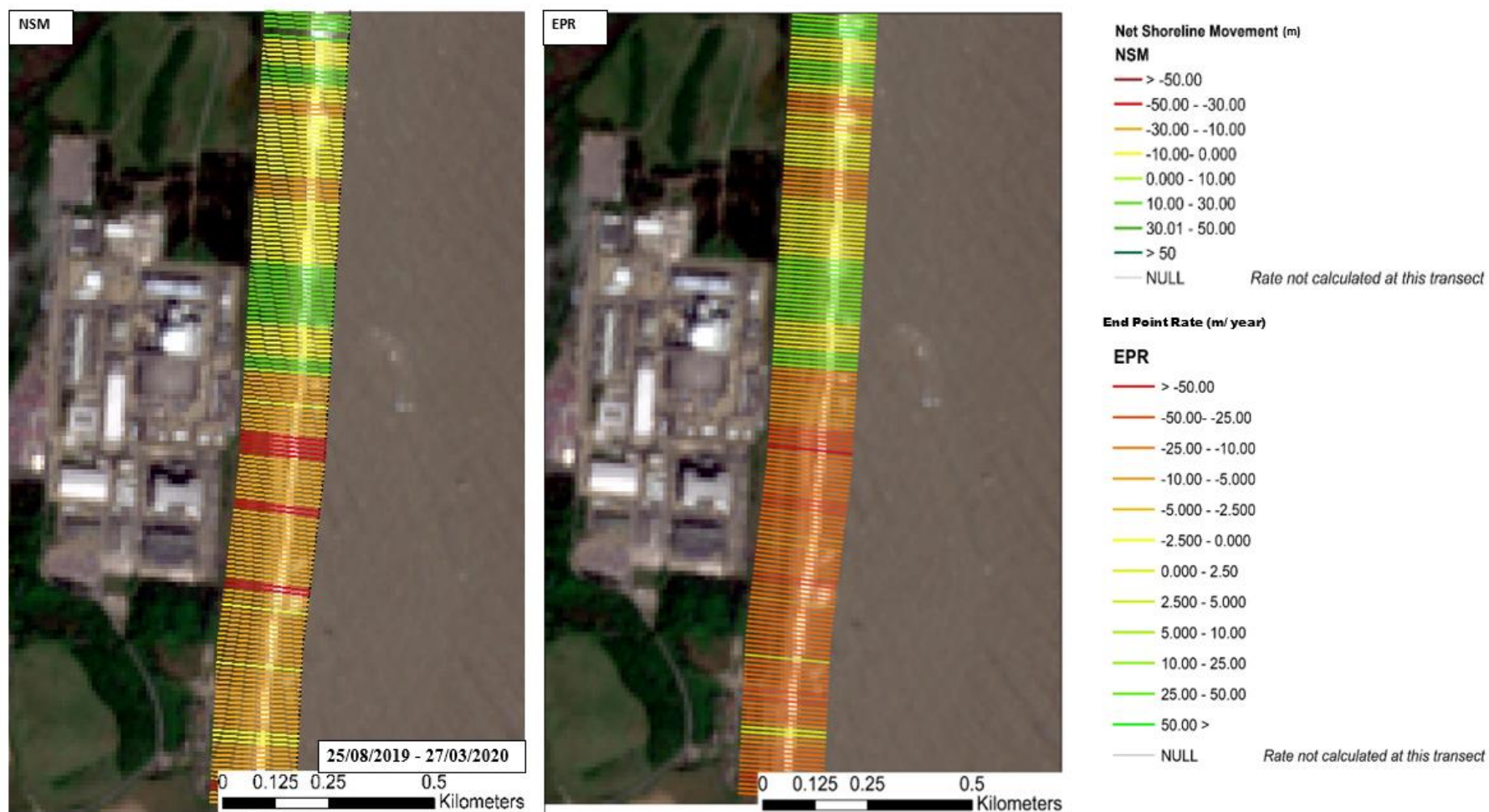


Figure 75: NSM at Sizewell (52°12'51.11"N, 1°37'26.02"E) between 25/08/2019 and 27/03/2020.

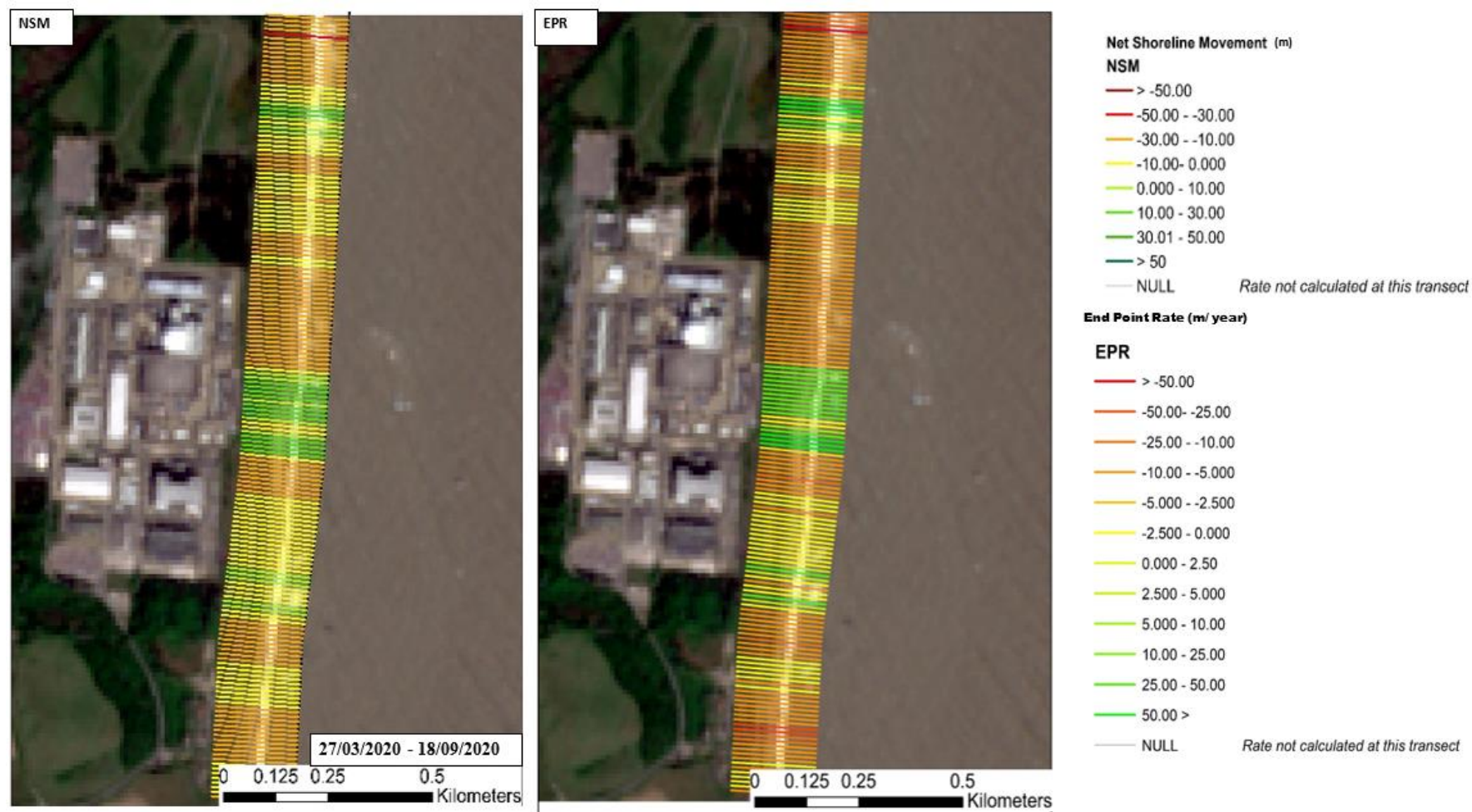


Figure 76: Seasonal NSM at Sizewell (52°12'51.11"N, 1°37'26.02"E) between 27/03/2020 and 18/09/2020.

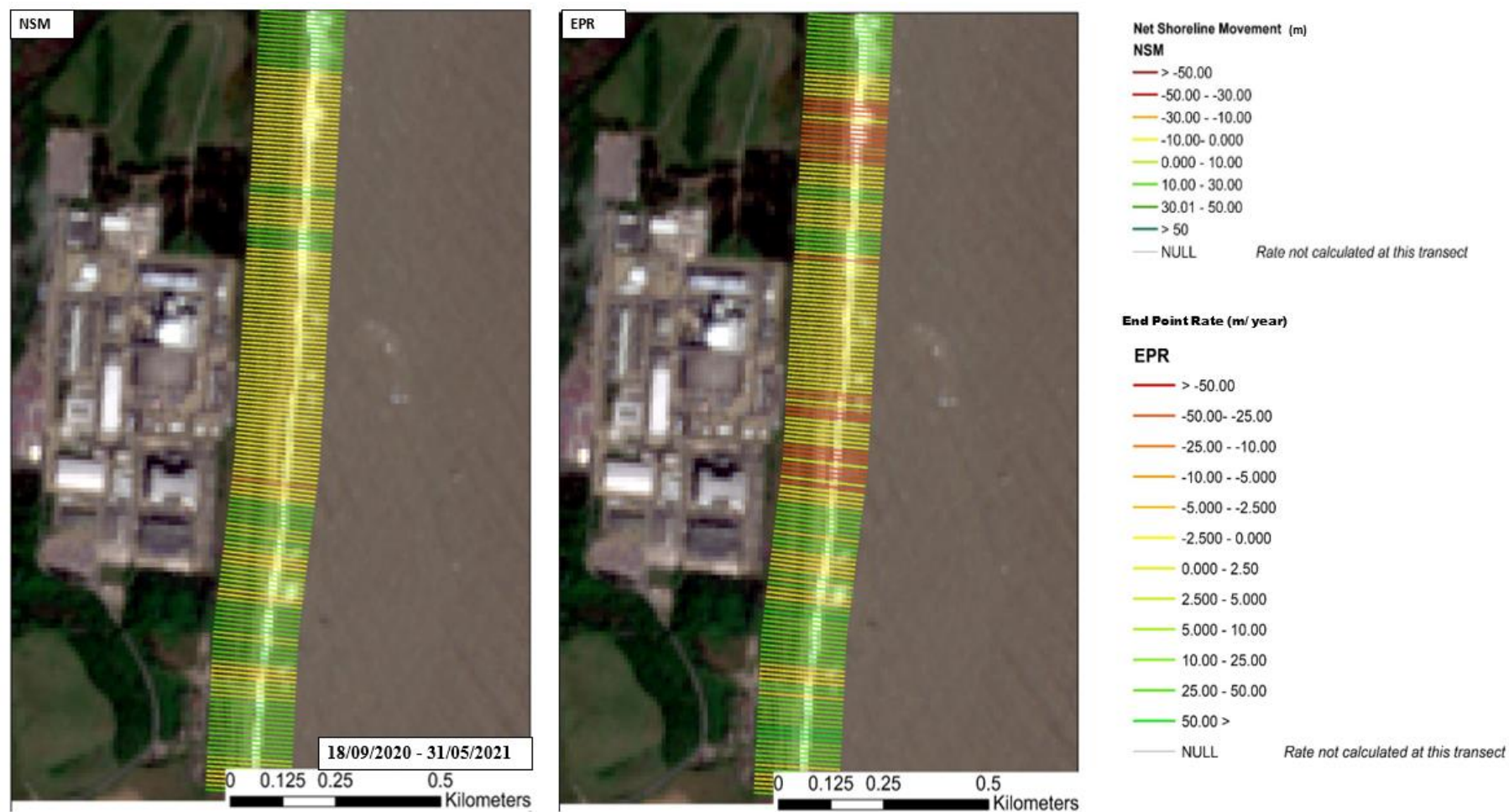


Figure 77: Seasonal NSM and EPR for Sizewell (52°12'51.11"N, 1°37'26.02"E) between 18/09/2020 and 31/05/2021.



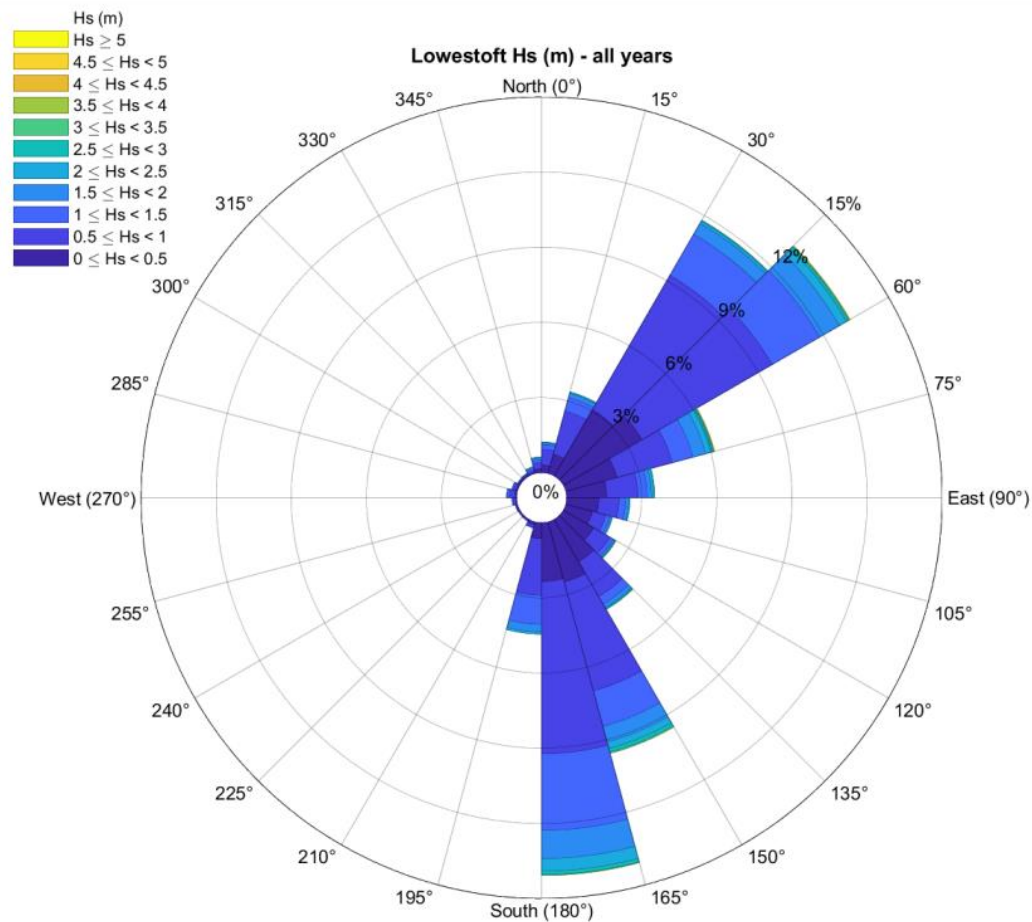


Figure 78: Wave direction rose for the Lowestoft buoy between 2007 - 2022 (Source: CCO).

### 5.3 Conclusion

In this study, shoreline changes at three diverse coastal locations, Start Bay, Aldbrough, and Sizewell, were examined using high-resolution satellite imagery and wave data. The objective was to investigate whether the wet/dry boundary line could serve as a reliable indicator of shoreline changes over short- and long-term periods.

At Start Bay, a 5-year analysis revealed that sediment movement occurred in a landward direction at Slapton Sands and the northern parts of Beesands and Hallsands, while Blackpool Sands experienced accretion. These observed changes were influenced by the prevailing wave

direction in the south-southeast direction. Seasonal analysis demonstrated the impact of wave direction on shoreline changes during specific time frames, in line with the findings of Wiggins *et al.* (2019).

Aldbrough exhibited a consistent pattern of longshore sediment movement towards the southeast, resulting in recurring cycles of erosion and accretion. The shoreline dynamics at this location were possibly influenced by natural cliff erosion and the transport of sediment along the coast. Conducting further analysis to compare cliff erosion with sediment input on the beach would be highly beneficial in establishing a potential relationship between these factors and gaining a deeper understanding of the geomorphology at the shoreline in Aldbrough.

Sizewell exhibited a continually shifting shoreline position over the years, resulting in an overall NSM of 11.42 m, which is in line with current literature by NNB Generation Company (Sizewell C) Limited (2020). As discussed, the fluctuations might be attributed to sediment movement over time rather than the occurrence of net erosion or accretion. To gain a deeper understanding of the interannual changes, further observations over an extended time scale and possibly involving more shorelines would be necessary rather than relying solely on data between two seasons.

The potential of the wet/dry boundary line as a SI for monitoring shoreline changes was demonstrated. However, it is essential to conduct post-processing and verify the data against tidal cycles to ensure a correct understanding of the shoreline before undergoing analysis. Incorporating readily available tidal data and implementing an automatic system for identifying high and low tide periods would enhance the applicability of the wet/dry boundary for larger scale applications.

Overall, this chapter contributes to the understanding of coastal dynamics at three different study sites, and the application of the wet/dry boundary line as a SI presents exciting

possibilities for coastal research and management on broader scales. Further investigations and refinements in this methodology will advance our understanding of coastal processes and enable better decision-making for coastal protection and management strategies.

# **Chapter. 6 Future Shoreline Prediction using Satellite Derived Shorelines and Machine Learning.**

This chapter addresses Research Question 3: “Can future shorelines be predicted using past shorelines and other environmental data?”. To address this question, the historical methods employed for predicting future shorelines are reviewed, with a primary focus on empirical-based models. Furthermore, the potential integration of ML techniques for predicting future shorelines over short time scales, with satellite imagery as a resource, is explored. The performance of four ML models (GAN, CGAN, LSTM, and ConvLSTM) (discussed in Section 6.2.4) on a dynamic study site known for its rapid changes over short periods, Kessingland, UK, is assessed. Limitations found within this chapter are discussed including the need for larger datasets for training. Subsequently, consideration is given to methods for enhancing these models in the future and exploring avenues for incorporating additional data into their framework.

## 6.1 Introduction

Coastlines are highly dynamic areas and are subject to shifts in shoreline position resulting from both natural processes and human activities. The prediction of future shorelines has emerged as a crucial component of coastal management and planning, with the aim of predicting the behaviour and location of shorelines in the years and decades ahead. Given the challenges posed by climate change, coastal erosion, rising sea levels, and human interventions, the significance of shoreline forecasting cannot be overstated. It has become a necessary tool for understanding and mitigating the potential impacts on coastal regions.

The prediction of future shorelines can be particularly challenging due to the dynamic nature of physical coastal processes. Shoreline erosion and accretion can be influenced by numerous factors, including coastal geomorphology, sediment dynamics, wave patterns, tidal fluctuations, and human interventions.

Shoreline prediction can be approached through two general methods. First, through physical based process models, such as CoSMoS-COAST (Coastal One-line Assimilated Simulation Tool) (Vitousek *et al.* (2017)), ShoreFor (Davidson *et al.* (2012)), or LX-shore (Robinet *et al.* (2020)), which simulate coastal processes. Second, through empirical based, data-driven statistical methods that do not rely on process models. This type of prediction uses historical observations of erosion/accretion rates to forecast future scenarios. This is commonly seen in time series forecasting (Calkoen *et al.* (2021); Farris *et al.* (2023); Gomez-De La Peña *et al.* (2023); Zeinali *et al.* (2021)), GIS-based techniques (Laksono *et al.* (2022); Dewidar and Bayoumi (2021); Abd-Elhamid *et al.* (2023); Yan *et al.* (2021) Nijamir *et al.* (2023); Islam and Crawford (2022); Ahammed and Pandey (2022)), and Machine Learning based prediction (Peponi *et al.* (2019); Kumar *et al.* (2020)) including Bayesian models (Mao *et al.* (2021); Gutierrez *et al.* (2015); Beuzen *et al.* (2018); Sahin *et al.* (2019)).



Important factors regarding our ability to fully comprehend coastal change have been highlighted by Splinter and Coco (2021), with one major limitation being the absence of long-term, large-scale, high-resolution (both in time and space) coastal datasets. Consequently, many studies on coastal shoreline dynamics have relied on data from only a few selected sites and covered specific timeframes, which has restricted their findings. This has been improved due to publicly available satellite imagery, which now provides opportunities for conducting large-scale coastal change studies based on shoreline observations.

## **6.2 Review of Empirical Models and Machine Learning Approaches for Shoreline Prediction**

This section briefly reviews, for context, the traditional empirical methods for shoreline prediction and machine learning approaches that have been applied to date.

### **6.2.1 Digital Shoreline Analysis System (DSAS)**

Among the empirical methods are the GIS based techniques using the DSAS, one of the most used toolkits in detecting shoreline movement. The toolkit uses historical change rates to predict future shorelines by applying statistical extrapolation. DSAS includes the Kalman filtering-based approach that is employed for shoreline prediction. Based on the historical shoreline location data, this tool enables future estimates to be created for the next 10 and 20 years. This calculation is done by using the Kalman filter (Kalman (1960)) to combine observed shoreline positions with model-derived positions to forecast a future shoreline position as developed by Long and Plant. (2012). The Kalman filter approach is initialised with the Linear Regression Rate (LRR) calculated by DSAS. It then estimates the shoreline position and rate every 10th of a year and provides an estimate of positional uncertainty at each time step.

In their study, Islam and Crawford (2022) used Landsat imagery spanning from 1988 to 2021 to quantify the rates of shoreline movement during different time periods. They applied various

prediction methods, including simple extrapolation of the end point rate (EPR), linear regression rate (LRR), weighted linear regression rate (WLR), and the Kalman filter method, to predict future shoreline positions. The findings of their study revealed that the predictive performance improved as the number of shorelines used in calculating and predicting shoreline change rates increased. In terms of the time scale, the prediction accuracies were, expectedly, significantly higher for the immediate future years compared to the more distant future.

Shoreline position forecasting for the years 2019 and 2020 was conducted by Yan *et al.* (2021) using the Kalman filter, based on historical shoreline position data spanning 1983 to 2009 and 1983 to 2010. The study highlights that while the DSAS forecasting tool offers forecasting capabilities, it may not be suitable for all locations, data types, and shoreline change patterns. Several specifications and limitations related to the data must be considered when utilising this tool to determine forecasted shoreline positions. Since the DSAS forecasting tool cannot be modified, highlighting that users are responsible for carefully considering the specifications and limitations of their data when employing this tool to predict shoreline positions.

Careful consideration is necessary when utilizing the DSAS Kalman filter for shoreline prediction due to potential challenges in its implementation. These challenges stem from the model's complexity, reliance on linear assumptions, sensitivity to parameters, and data requirements. Effectively using the Kalman filter for shoreline prediction and obtaining reliable results hinges on a thorough understanding of these factors.

### **6.2.2 Bayesian Networks (BNs)**

An alternative approach to predict shorelines involves the utilisation Bayesian Networks (BNs). BNs are probabilistic graphical models using Bayesian statistics to represent and infer relationships between variables. Through the integration of diverse data sources, such as remote sensing data, historical shoreline data, meteorological data, and coastal surveys,

Bayesian networks demonstrate their ability to effectively capture complex relationships influencing shoreline changes.

Mao *et al.* (2021) demonstrated the application of Bayesian networks in their work where inputs including Tidal Range, Sea Level Rise Rate, Coastal Geomorphology, Backshore Profile, Distance to Inlets, Mean Wave Height, Longshore Wave Power Gradient, and Coastal Slope, as well as Shoreline Change Rate Data, was used to develop their Bayesian network. Their findings revealed that the model could reflect the impact of various factors on coastal evolution and successfully predict future shoreline changes by analysing historical data. Beuzen *et al.* (2018) used 10 years of daily shoreline and storm data to construct a BN. The model was able to effectively predict shoreline recession caused by unexpected storm events and provide insights into modelling storm events. Gutierrez *et al.* (2015) used a Bayesian network to assess the significance of multiple interactions among barrier island geomorphic variables. The model was employed to predict dune height, beach width, and beach height variables, incorporating inputs encompassing longer-term, larger-scale, and external variables. These studies highlight benefits of using Bayesian networks in shoreline forecasting. The model's capacity to represent complex relationships among variables allows it to accommodate diverse factors influencing shoreline changes. The capability to integrate various data types, such as remote sensing, historical records, and survey data, facilitates a comprehensive analysis of shoreline behaviour. The resulting data integration enhances the predictive capabilities of the Bayesian networks, making them more reliable tools for accurate shoreline forecasting.

In their work, Mao *et al.* (2021) highlights that the accuracy of data-driven models for large scale research (continental) is significantly affected by the quality of data sets. The presence of local-scale errors within data sets contribute to increased uncertainties in the model results. Both Mao *et al.* (2021) and Beuzen *et al.* (2018) highlight the limited availability of data sets

on such a large scale, restricting the inclusion of more representative variables for the physical processes of coastal evolution. Furthermore, Beuzen *et al.* (2018) highlights that the challenges related to data requirements that BNs may not be suited to all coastal applications.

### **6.2.3 Time Series Analysis**

Time series analysis is another prominent approach in future shoreline prediction. This method involves the examination of shoreline data over a continuous sequence of time. Researchers use statistical techniques to identify patterns, trends, and cyclic behaviours in shoreline changes. By analysing the temporal patterns of shoreline fluctuations, time series analysis allows for the identification of seasonality, long-term trends, and short-term variations.

Traditionally, statistical methods such as Error Trend Seasonality (ETS), Extrapolated Linear Regression (ELR), Ordinary Least Squares (OLS) and Autoregressive Integrated Moving Average (ARIMA) (Farris *et al.* 2023) have been widely used for time-series forecasting due to their simplicity, robustness, and effectiveness on various problems. Recently, the implementation of ML models for time series analysis has gained popularity. ML models excel at identifying patterns from complex and irregular collections of time series, surpassing the capabilities of traditional statistical approaches. Recent studies (e.g., Zeinali *et al.* (2021); Gomez-De La Peña *et al.* (2023)) have highlighted that Neural Networks (NNs) are particularly well-suited for leveraging datasets with extensive time-series information. The versatility and adaptability of NNs make them highly effective in capturing intricate patterns and relationships within the data, thus offering a powerful alternative for time-series forecasting tasks.

An important study comparing time series analysis predictions was conducted by Calkoen *et al.* (2021). In this study, eight different time-series forecasting methods were evaluated. These methods comprised three statistical approaches (OLS, ETS, ARIMA) and five ML-based approaches (SimpleFFN (Simple Feed Forward Network), SimpleLSTM (Simple Long Short-

Term Memory), DeepAR (Depp Auto Regressive), MQCNN (Multi-Horizon Quantile CNN), DeepSSM (Deep Statistical Shape Modelling)). The objective was to predict future shorelines derived from historic satellite-derived shorelines by analysing over 37,000 transects globally. The findings revealed that the statistical forecast approaches, specifically ETS and ARIMA, along with ML models such as SimpleFFN, DeepAR, and MQCNN, exhibited greater skill than OLS regression (skill refers to the measure of how effectively a model or method is able to accurately forecast or estimate future outcomes, patterns, or events). Interestingly, the tests indicated that ML models did not generate significantly superior predictions compared to traditional methods. The relatively weak performance of the ML algorithms was attributed to the absence of shoreline-dynamics forcing data and the coarseness of the SDS data. The results emphasised two noteworthy advantages of ML approaches over classic time-series forecast methods which is their ability to consider additional variables and their capacity to learn across time-series of shorelines.

#### **6.2.4 Machine Learning**

ML-based predictive models using satellite imagery for future change prediction have seen recent development. ANNs, CNNs, LSTMs, and Generative Adversarial Networks (GANs/CGANs) have been employed for this purpose. Reasons for the application of these models include their ability to capturing spatial patterns and features for image classification, object detection, and segmentation, handle sequential data, making them valuable for image captioning (e.g., CNN), capturing temporal dependencies within images (e.g., LSTM) and generate realistic images by learning from training data, enabling applications like image synthesis, style transfer, and image-to-image translation (e.g., GANs/ CGANs).

In a study by Kumar *et al.* (2020), a comparison was made between KNN, SVM, and ANN models to predict shoreline realignment along the eastern Indian coast of Orissa. The modelling process involved analysing satellite images, between 1985 and 2015 and corresponding

reanalysis data of the coastline from the Modern-Era Retrospective analysis for Research and Applications (MERRA-2) and the European Centre for Medium-Range Weather Forecast (ECMWF). The results of the comparison revealed that the ANN model, demonstrated superior accuracy compared to the other models, achieving an accuracy of 86.2%, with the monthly forecasting significantly improving at each point location when using the ANN model. It was concluded that ML techniques, particularly the ANN model, enabled the precise and accurate prediction of shoreline changes, making them valuable tools for such forecasting tasks.

A study by Peponi *et al.* (2019) integrated GIS and an ANN to develop a model capable of forecasting erosion changes in Costa da Caparica, Lisbon, Portugal. Data including social/demographic and environmental information from the 2001 and 2011 census, land cover data for 2000 and 2006, and records of coastal erosion changes between the years 1967, 1980, 1995, and 2008 were used. This combined approach enables the model to provide insights into both the spatial distribution and the underlying reasons behind the erosion changes that have occurred or are expected to happen in the future.

There have been multiple studies combining CNNs and LSTM models. The reason behind this is that CNNs are excellent at extracting spatial features from images. In shoreline prediction, satellite imagery often serves as a fundamental data source and CNNs can analyse the images to identify patterns, shapes, and textures related to the coastline. These extracted spatial features provide valuable information for predicting shoreline positions and changes. LSTMs are a type of recurrent neural network (RNN) designed to handle sequential data. Satellite imagery provides a time-series of images, where each image corresponds to a specific time point. LSTMs can effectively capture the temporal dependencies and patterns present in these sequential images, making them ideal for modelling shoreline changes over time.

A typhoon track prediction model named DeepTyphoon was created by Lu *et al.* (2022) by integrating a CNN and LSTM. The relationship between the satellite image and the typhoon centre was established by marking the typhoon centre on the satellite image for 513 typhoon sequences, and a total of 13400 satellite images. A hybrid dilated convolution was employed to extract the cloud features of the typhoon from the satellite images, and LSTM was used to predict these features. The location of the typhoon was able to be detected based on the predictive markers in the output image.

Boulila *et al.* (2021) used time-series satellite images (three sequences with 4 images per sequence) for predicting urban expansion. They applied a ConvLSTM network to prediction urban expansion. The results show that the proposed model produced better prediction results in terms of Mean Square Error, Root Mean Square Error, Peak Signal to Noise Ratio, Structural Similarity Index. In addition, the overall classification accuracy has been found to be better than Pix2Pix GAN and Dual GAN providing image classification with an overall accuracy of 92.19%. The ConvLSTM based model enabled the learning of global spatiotemporal information without reducing the size of spatial feature maps. Although focusing on urban expansion, this study's use of ConvLSTM networks to analyse time-series satellite imagery parallels methods for shoreline evolution research, highlighting the necessity to track dynamic changes over time.

GANs and LSTM have been used together to make future prediction from satellite imagery. A GAN consists of two neural networks: the generator and the discriminator. The generator's role is to create new data samples that resemble the training data. It takes random noise as input and tries to generate realistic samples. The discriminator, on the other hand, is like a binary classifier that aims to distinguish between real data from the training set and fake data generated by the generator. A CGAN is an extension of the GAN that incorporates additional information to condition the generation process. It introduces extra input, called a conditional variable,

which provides information to both the generator and the discriminator. This information guides the generation process to generate samples with specific characteristics. In the context of image generation, the conditional variable could be a class label or a specific attribute that the generated image should possess. By conditioning the generation process on this additional information, CGANs can generate samples that match certain criteria or have specific attributes, which is not possible with traditional GANs. While the application of these models has yet to be applied for shoreline change below are some examples of applications to remote sensing data.

Fang *et al.* (2020) implemented a prediction model using radar image data. The model used LSTM and Deep Convolutional Generative Adversarial Networks (DCGAN) for single-frame prediction and sequence prediction. The training process used 200 sets of data, each comprising radar sample data covering a 6-hour and 6-minute interval. The method enabled effective learning of image features and enhanced the generalisation capabilities of predictive models. Through experiments, it was demonstrated that the network model exhibited greater robustness and efficiency in timing prediction compared to 3DCNN and traditional ConvLSTM.

Xu *et al.* (2019) applied a GAN and LSTM to predict future images in image sequences captured from FY-2E satellite cloud maps. The results revealed that the proposed GAN-LSTM network efficiently captured the evolution rules of weather systems. The use of GAN contributed to reducing the dimension of the output data and improving the quality of the desired images. Additionally, the LSTM network successfully uncovered the complex cloud evolution rules.

A recurring consideration that is brought up in all of these studies refer to the amount of data available and how it affects the model's capacity to produce satisfactory results. For many ML techniques, particularly deep and generative models, a substantial amount of data is required



to train them effectively. The availability of data plays a crucial role in determining the model's performance and generalisation ability. Insufficient data can hinder the model's ability to learn complex patterns and can lead to overfitting, limiting its usefulness in practical applications. So, ensuring access to an adequate and diverse dataset is vital for enhancing the performance and reliability of these machine learning models.

The studies reviewed demonstrate the potential of ML-based models in accurate and efficient shoreline prediction. Whether it is using radar image data or satellite imagery, ML models offer valuable insights into coastal evolution and can serve as powerful tools for coastal engineering and management applications. However, careful consideration of data quality, model assumptions, and limitations is crucial for obtaining reliable and meaningful predictions.

In summary, the literature review highlights the diversity of methods available for shoreline prediction, each with its strengths and limitations. It underscores the significance of choosing the appropriate model based on specific data requirements and the objectives of the prediction task. The continuous advancements in ML and deep learning techniques hold great promise for future shoreline forecasting which has not been fully explored in this area yet and contribute to better coastal management and environmental conservation efforts.

### **6.3 Potential Applications of Satellite Imagery and Machine Learning for Shoreline Prediction**

As discussed earlier, applications of ML models for predicting shoreline change from satellite derived shorelines are yet to be fully explored. As highlighted, the recommendation is for a substantial amount of data to be utilised to train an ML model effectively in forecasting future shoreline change. However, data limitations can occur, particularly regarding commercial data availability (Chapter 2) or a short-term availability of data from a new satellite. Given this context, the objective is to investigate whether an ML model could successfully predict future

steps while employing a restricted set of short-term (2016-2022) annual data, where significant shoreline changes occur at each time step. To achieve this, Kessingland beach was chosen, as it undergoes large changes over a short period of time, which is easily identified on Sentinel-2 satellite imagery. The pattern of change enables the algorithm to effectively identify and track these changes as they occur.

This chapter then explores four different models, namely GAN, CGAN, LSTM, and ConvLSTM, for future image prediction. These four models are used as they cover a broad spectrum of image prediction tasks. GANs are commonly used in generating realistic images (e.g., Wen *et al.* (2018)). CGANs allow for controlled image generation by incorporating additional information (e.g., Fang *et al.* (2020)). LSTM networks are effective for sequential data prediction, useful for time-series image tasks (e.g., Xu *et al.* (2019)). ConvLSTM combines the power of CNNs (Convolutional Neural Networks) and LSTMs, ideal for spatiotemporal prediction tasks like video prediction (e.g., Boulila *et al.* (2021)).

### **6.3.1 Study Site**

Located on the Suffolk Coast, Kessingland beach (coordinates: 52.425133, 1.730522) is characterised by a mix of sand and shingle. Notably, its northern expansion is attributed to the northerly migration of Benacre Ness (coordinates: 52.385286, 1.716908). The area experienced a remarkable accretion rate, observed at North Kessingland, reaching 16.9 m/year, marking it as the most significant accretion on the Suffolk coast. This makes the site a good area to analyse the shoreline prediction models. A noteworthy trend of considerable accretion was evident from 1992 to 2005, with water levels shifting approximately 250 m offshore at an average rate of about 20 m/year. Subsequently, from 2005 to 2010, the trend levelled off and slightly turned erosional, attributed to the peak of the ness passing north of this profile in recent years (Environment Agency (2011)). The evolution of Kessingland Ness since 1945 is shown in Figure 79.



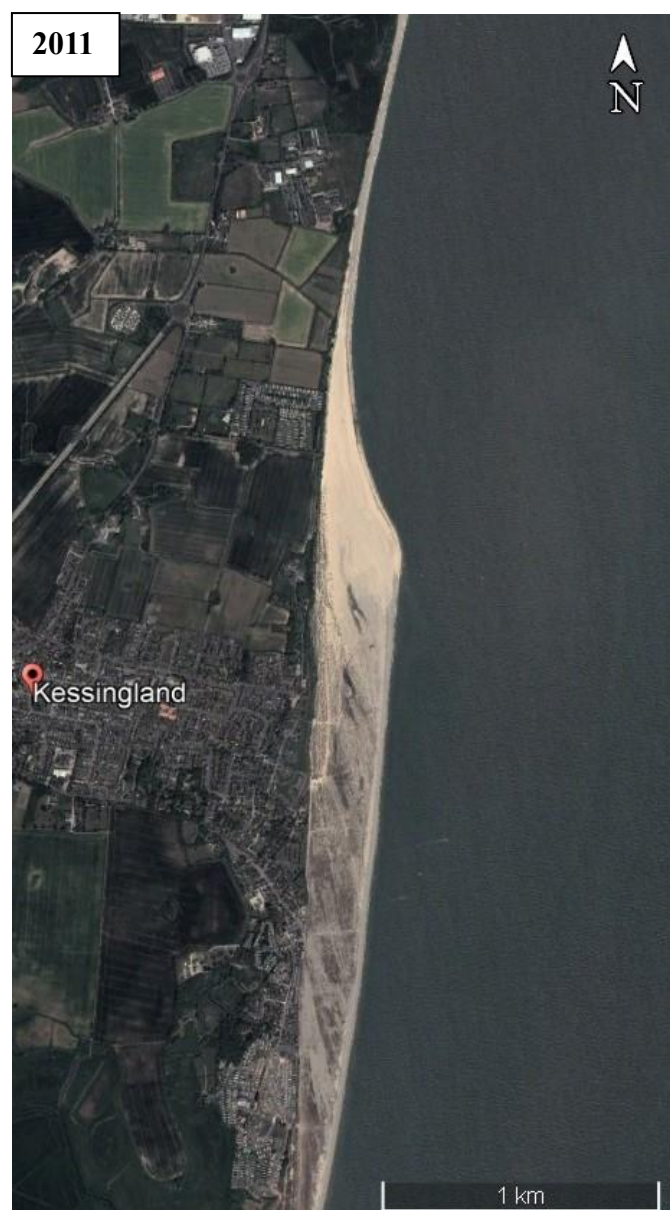
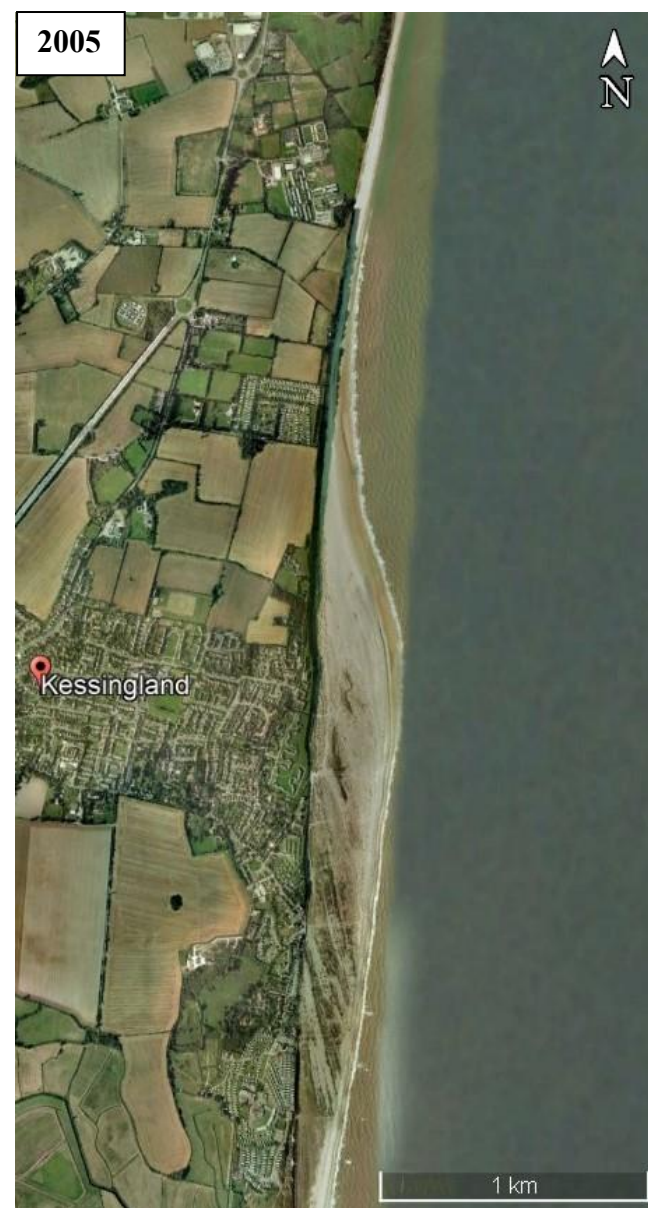
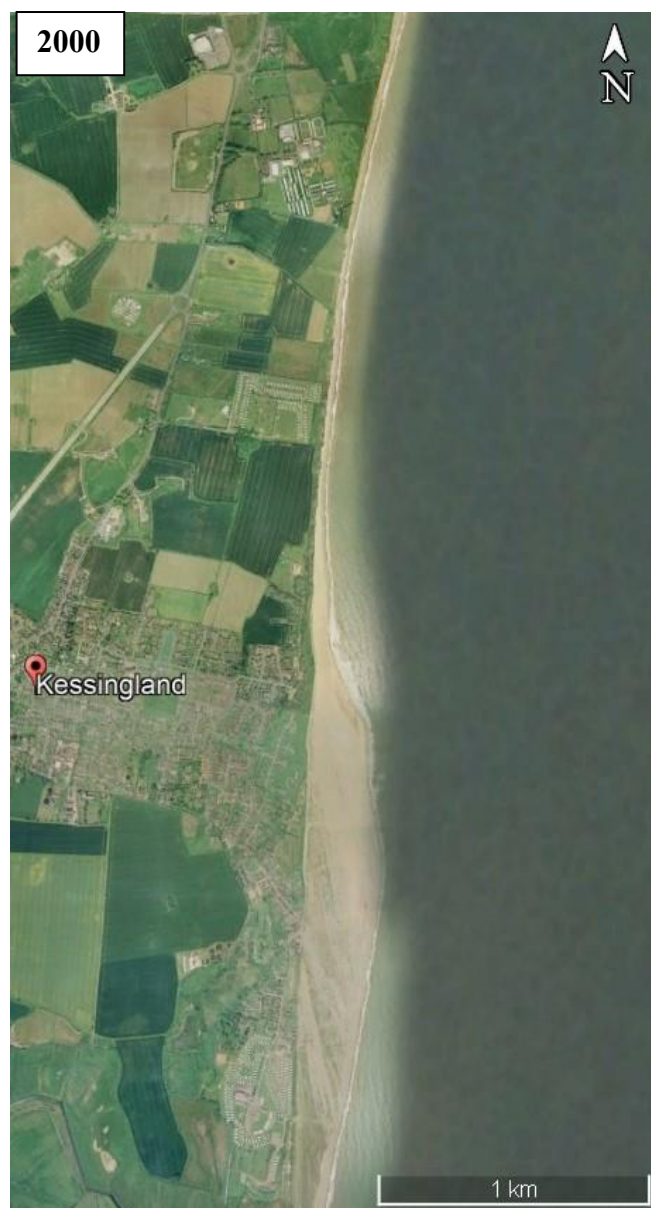


Figure 79: Evolution of Kessingland Ness between 1945 and 2021. The growth of the Ness is seen moving north, with the sediment input coming from the south from Benacre. Over the period shown, the beach has extended 3km northwards (Source: Google Earth).



### **6.3.2 Shoreline Methodology**

Shoreline extraction at Kessingland was carried out by using images obtained from Sentinel-2 for the period 2016 to 2022. The application of the methodology outlined in Chapter 3 served as the foundation for this study. Employing the established approach, the image classification process was conducted to delineate the wet/dry boundary line, resulting in the creation of a binary image. Furthermore, the corresponding date of each image was saved as an input and converted to represent the year when the image was taken. This procedure enabled the association of each extracted shoreline with its respective year, providing a temporal dimension for analysing shoreline changes over the study period. These were the data inputs for the analysis.

### **6.3.3 Data Inputs**

In the context of the GAN and CGAN models, the data inputs included images and labels, with labels being used exclusively in the CGAN setup. The images were of size (330px, 90px), and the dataset contained a total of 88 samples, representing images for the years 2016 to 2022. For the CGAN, the training labels had a shape of (88,1), encoding the corresponding year for each image.

The LSTM and ConvLSTM models used a different data input approach. The inputs were organised as 17 sequences, and each sequence consisted of 8 images spanning the temporal range from 2016 to 2022. The shape of the input data for both LSTM and ConvLSTM models were (17, 7, 330, 90). An example of the input data is shown in Figure 80.

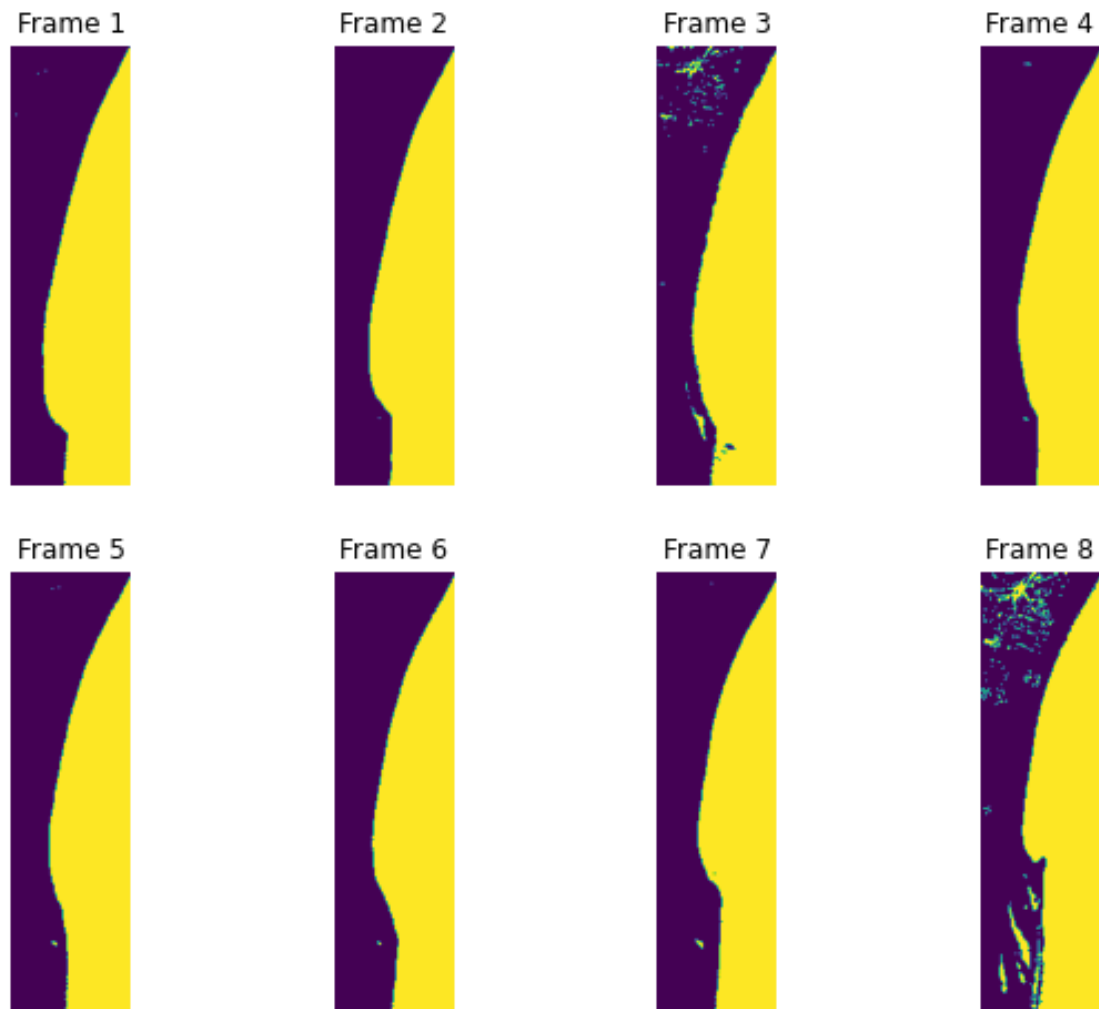


Figure 80: Example of training data between 2016-2022 used as inputs into the predictive models.

### 6.3.4 Predictive Models

In order to predict future shoreline change, four ML models are used for next image prediction. These models include GAN, CGAN, LSTM, and ConvLSTM, each chosen for its unique capabilities in image prediction and temporal change comprehension. Section 6.3.3 provides details of the utilised dataset, composed of labelled binary classified satellite images, acting as the training data for the four predictive models. The goal is to use ML to predict the next sequence of satellite images. The GAN model was tested to determine if it could generate shoreline images resembling the existing input data or potential future shorelines. The CGAN

model was tested to see if it could replicate 2016 and 2022 shorelines based on previously observed data. It was also assessed whether the CGAN model could forecast extended shorelines for future dates while following the natural movement patterns. The LSTM and ConvLSTM were tested to see if they could generate shorelines following the year 2022. These shorelines were compared to the projection of the previous historic shorelines to see if they follow the natural shoreline.

The performance of these four models were tested to determine their ability to predict changes within a short time frame using image data. The models used are discussed below.

#### **6.3.4.1 GAN**

A Generative Adversarial Network (GAN) is a type of deep learning model that consists of two neural networks, the generator, and the discriminator, trained together in a competitive process. GANs were introduced by Goodfellow *et al.* (2014) and has since become a powerful tool for generating realistic and high-quality synthetic data, including images, audio, and text.

The basic idea behind GANs is to have the generator network learn to generate fake data (e.g., images) that resembles real data, while the discriminator network is simultaneously trained to distinguish between real and fake data (process shown in Figure 81). Both the generator and the discriminator are neural networks. The generator's output is directly connected to the discriminator's input. By applying backpropagation, the discriminator's classification generates a signal that the generator uses to update its weights. This iterative process continues, with the generator improving its ability to create realistic data and the discriminator enhancing its capacity to distinguish between real and generated data. Through this adversarial training mechanism, the two networks gradually reach a dynamic equilibrium, resulting in a well-trained generator that can produce highly convincing data samples (Goodfellow *et al.* (2014)).

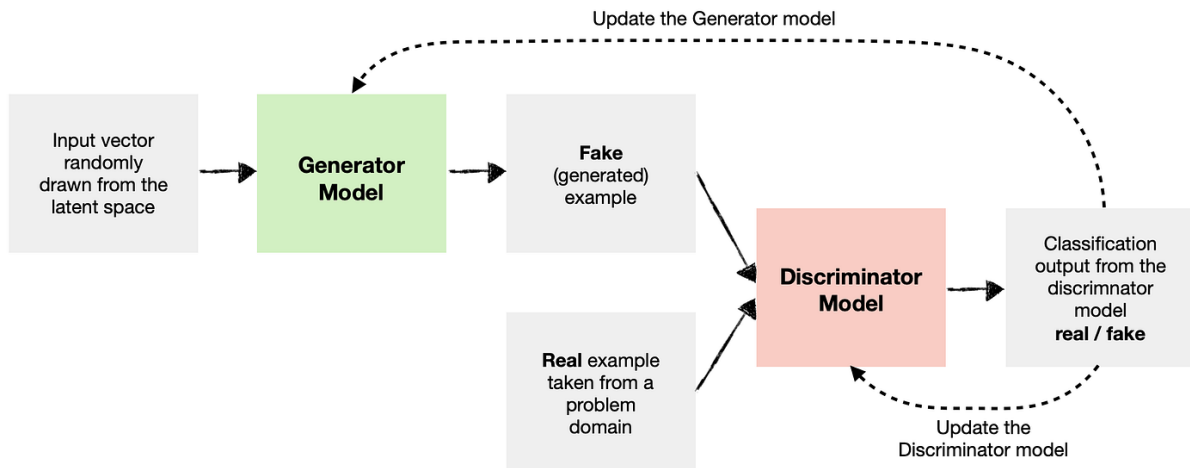


Figure 81: Structure of a GAN model.

The GAN network was implemented using TensorFlow libraries in Python. The architecture and training process of the discriminator and generator can be summarized as follows:

### ***Discriminator Network***

The discriminator is responsible for distinguishing between real and fake images. It was constructed using the Sequential model and comprised of convolutional layers, and dense layers. The model was compiled using the binary cross-entropy loss function and the Adam optimizer.

The model consists of three convolutional layers, each followed by LeakyReLU activation to introduce non-linearity and avoid the vanishing gradient problem (where the gradients of the loss function diminish significantly during backpropagation, hindering the training of lower layers and limiting the network's ability to learn complex representations and patterns). Each convolutional layer consists of 128 filters, however each kernel and stride length for each layer differs to maintain the shape of the image (Shown in Table 17). After the convolutional layers, the model flattens the output feature map and applies dropout regularization to reduce overfitting (dropout rate = 0.4). A dense layer is used to classify the input as real (output close to 1) or generated (output close to 0). The model is compiled with the Adam optimizer, which

is a popular choice for GANs, using a learning rate of 0.0002 and a beta1 value of 0.5. The binary cross-entropy loss function is used since it's suitable for binary classification tasks.

Table 17: Structure of the GAN discriminator

| Component             | Description                                                                                          |
|-----------------------|------------------------------------------------------------------------------------------------------|
| Input Shape           | (330, 90, 1)                                                                                         |
| <b>Discriminator</b>  |                                                                                                      |
| Convolutional Layer 1 | Filters: 128, Kernel Size: (5, 5), Stride: (5, 5), Activation: LeakyReLU(alpha=0.2), Padding: 'same' |
| Convolutional Layer 2 | Filters: 128, Kernel Size: (3, 3), Stride: (3, 3), Activation: LeakyReLU(alpha=0.2), Padding: 'same' |
| Convolutional Layer 3 | Filters: 128, Kernel Size: (2, 2), Stride: (2, 2), Activation: LeakyReLU(alpha=0.2), Padding: 'same' |
| Flatten               |                                                                                                      |
| Dropout               | Rate: 0.4                                                                                            |
| Dense Output Layer    | Activation: Sigmoid                                                                                  |
| <b>Compilation</b>    |                                                                                                      |
| Optimizer             | Adam, Learning Rate: 0.0002, Beta1: 0.5                                                              |
| Loss Function         | Binary Crossentropy                                                                                  |
| Metrics               | Accuracy                                                                                             |

### ***Generator Network***

The generator takes random latent space vectors as input and transforms them into generated images. It was constructed using the Sequential model and consisted of dense layers, activation functions, reshape layers, and transpose convolutional layers. The generator's architecture aimed to upsample the latent vectors into a high-resolution image.

The generator takes a random noise vector as input, and the dimension of this noise vector (latent dimension) is 100. The generator starts with a dense layer, generating a dense representation of the input noise. After the dense layer, the LeakyReLU activation function with an alpha value of 0.2 is applied. The generator uses a series of convolutional transpose



layers (also known as "deconvolution" or "upsampling" layers) to progressively upsample the feature map, increasing its spatial dimensions and generating more complex representations. The details on the convolutional transpose layers are shown in Table 18. The last Conv2D layer applies the "tanh" activation function to map the values between -1 and 1, generating the final output of the generator. This output represents a generated data sample with a shape of (330, 90, 1), where 330 is the width, 90 is the height, and 1 indicates a single-channel image.

Table 18: Structure of the GAN generator

| Component               | Description                                                                         |
|-------------------------|-------------------------------------------------------------------------------------|
| Input Dimension         | Random noise vector of size of 100 (latent_dim)                                     |
| <b>Generator</b>        |                                                                                     |
| Dense Layer             | Neurons: 100 (latent_dim), Activation: LeakyReLU(alpha=0.2)                         |
| Conv2DTranspose Layer 1 | Filters: 128, Kernel Size: (3, 3), Stride: (3, 3), Activation: LeakyReLU(alpha=0.2) |
| Conv2DTranspose Layer 2 | Filters: 128, Kernel Size: (2, 2), Stride: (2, 2), Activation: LeakyReLU(alpha=0.2) |
| Conv2DTranspose Layer 3 | Filters: 128, Kernel Size: (6, 6), Stride: (5, 5), Activation: LeakyReLU(alpha=0.2) |
| Conv2D Final Layer      | Filters: 1, Kernel Size: (11, 3), Activation: tanh, Output Shape: (330, 90, 1)      |

The discriminator and generator are then combined, forming the GAN model. During the training of the final GAN, the discriminator weights are set to “not trainable”, to ensure that the training process focuses solely on updating the generator, allowing it to learn.

The model is trained using the input images, with 10 epochs and batch size of 2.

### 6.3.4.2 CGAN

A Conditional Generative Adversarial Network (CGAN) is an extension of the traditional Generative Adversarial Network (GAN) that incorporates conditional information during the image generation process. Introduced by Mirza and Osindero (2014), CGANs enable more controlled and targeted image creation by conditioning the generator on additional input data.

In a CGAN, both the generator and discriminator networks receive an additional input, which acts as a conditional label or context vector. This additional information can be anything that provides context or constraints for image generation, such as class labels, attributes, or even other images (Shown in Figure 82).

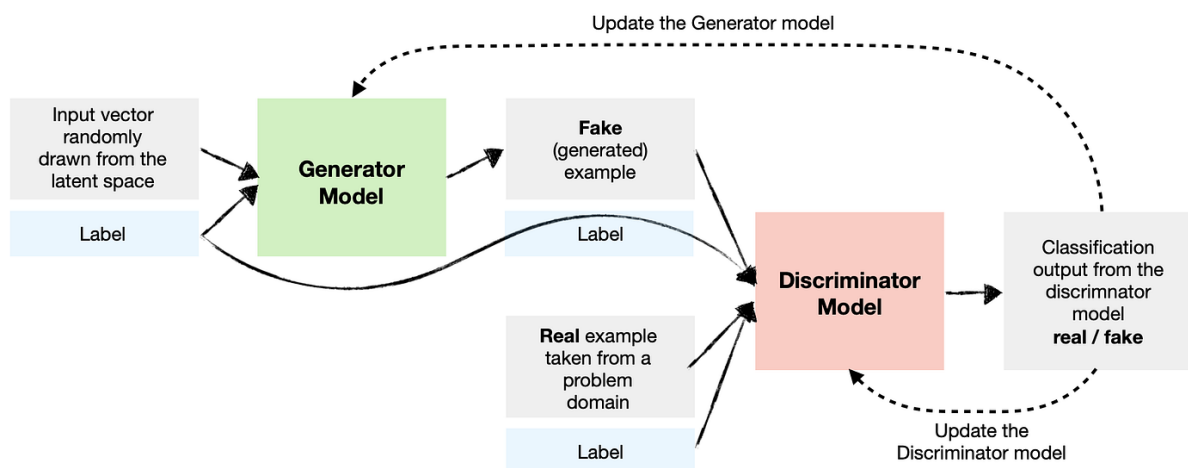


Figure 82: Structure of a CGAN model.

#### ***Discriminator***

The discriminator model has two inputs, the image and its corresponding label, representing the data. The label is embedded and scaled to match the spatial dimensions of the image. The scaled-up label is reshaped to create an additional channel and is then concatenated with the original image using the ‘Concatenate layer’. This process combines the image and label information, creating a single input that is used for further processing.

The concatenated input is passed through three convolutional layers (Conv2D) with 128 filters each (shown in Table 19). Each convolutional layer is followed by a LeakyReLU activation function with an alpha value of 0.2. These layers perform downsampling, reducing the spatial dimensions of the feature maps. The feature maps obtained from the convolutional layers are flattened into a 1D vector using the Flatten layer. A Dropout layer with a rate of 0.4 is applied to reduce the risk of overfitting by randomly setting a fraction of input units to zero during training. The flattened feature vector is passed through a final Dense layer with a single neuron and a sigmoid activation function. This layer performs binary classification, determining whether the input is real or generated. The model is compiled using the Adam optimizer with a learning rate of 0.0002 and a beta1 value of 0.5. The binary cross-entropy loss function is used as the discriminator's objective, and the model's performance is measured using accuracy as a metric, which is based on the model's ability to generate images and the validation images for the corresponding label and image.

Table 19: Structure of CGAN discriminator

| Component        | Description                                                                                                  |
|------------------|--------------------------------------------------------------------------------------------------------------|
| Input (in_image) | Input images of shape (330, 90, 1) representing grayscale images with height 330 pixels and width 90 pixels. |
| Input (in_label) | Input labels representing categories or classes.                                                             |
| Embedding        | Embedding layer with a dimension of 50 to embed the categorical input labels.                                |
| Dense            | Dense layer to scale up the embedded label to match the spatial dimensions of the input image.               |
| Reshape          | Reshape layer to add an additional channel to the scaled label.                                              |
| Concatenate      | The original image and the reshaped label are concatenated using the Concatenate layer.                      |

|                          |                                                                                                 |
|--------------------------|-------------------------------------------------------------------------------------------------|
| Conv2D<br>(Downsampling) | Conv2D layer with 128 filters and a (3,3) kernel, followed by LeakyReLU activation (alpha=0.2). |
| Conv2D<br>(Downsampling) | Conv2D layer with 128 filters and a (2,2) kernel, followed by LeakyReLU activation.             |
| Conv2D<br>(Downsampling) | Conv2D layer with 128 filters and a (6,6) kernel, followed by LeakyReLU activation.             |
| Flatten                  | Flatten layer to convert feature maps to a 1D vector.                                           |
| Dropout                  | Dropout layer with a rate of 0.4 to prevent overfitting.                                        |
| Dense                    | Dense layer with a single neuron and sigmoid activation for binary classification.              |

### ***Generator***

The generator takes a noise vector (latent\_dim) and corresponding labels as input and generates images accordingly. The generator consists of several layers, including embedding, dense, reshape, and convolutional transpose layers (Table 20). The generator labels are input, embedded, and linearly multiplied to prepare the labels for concatenation with the generated images. The noise vector (in\_lat) is passed through a Dense layer with 128 neurons, followed by a LeakyReLU activation function with an alpha value of 0.2. The tensors from the generated image foundation and the linearly transformed labels are concatenated and are then passed through a series of Conv2DTranspose layers, which perform upsampling to increase the spatial resolution of the tensor. Here, three Conv2DTranspose layers are used, each followed by a LeakyReLU activation function with an alpha value of 0.2. These layers successively upscale the tensor to produce the final generated image.

Table 20: Structure of CGAN generator

| Layer                           | Description                                                                                        |
|---------------------------------|----------------------------------------------------------------------------------------------------|
| Input (in_label)                | Input labels representing categories or classes.                                                   |
| Embedding                       | Embedding layer with the specified number of classes (n_classes) and an embedding dimension of 50. |
| Dense                           | Dense layer to linearly multiply the embedded labels, generating a tensor with shape (11, 3, 1).   |
| Reshape                         | Reshape layer to prepare the linearly transformed labels for concatenation.                        |
| Input (in_lat)                  | Input noise vector (latent_dim) representing the foundation for image generation.                  |
| Dense                           | Dense layer with 128 neurons, followed by a LeakyReLU activation function (alpha=0.2).             |
| Reshape                         | Reshape layer to prepare the generated image foundation for concatenation.                         |
| Concatenate                     | Concatenation of the generated image foundation and the transformed labels.                        |
| Conv2DTranspose<br>(Upsampling) | Conv2DTranspose layer with 128 filters, (5, 5) kernel, and LeakyReLU activation (alpha=0.2).       |
| Conv2DTranspose<br>(Upsampling) | Conv2DTranspose layer with 128 filters, (3, 3) kernel, and LeakyReLU activation (alpha=0.2).       |
| Conv2DTranspose<br>(Upsampling) | Conv2DTranspose layer with 128 filters, (2, 2) kernel, and LeakyReLU activation (alpha=0.2).       |
| Conv2D (Output)                 | Conv2D layer with (11, 3) kernel and tanh activation function for the generated image output.      |

The CGAN model was formed by combining the discriminator and generator. Throughout this training stage, 5 batches were used, and the model was run for 7 epochs to achieve the optimal results.

#### **6.3.4.3 LSTM**

A Long Short-Term Memory (LSTM) represents a recurrent neural network (RNN) architecture specially designed for handling sequential data with long-range dependencies (Hochreiter and Schmidhuber (1997)). Unlike conventional feedforward neural networks, LSTMs feature feedback connections, granting them the ability to process entire sequences, such as time series, while considering the interdependence of data points (Lipton *et al.* (2015)). This facilitates the retention of crucial information from previous data instances, thereby aiding the processing of subsequent data points.

At a particular time step, the output of an LSTM relies on three key factors: the current long-term memory (cell state), which holds valuable information about the sequence's context, the output from the previous time step (hidden state), which carries over relevant knowledge and the input data at the current time step, which brings new information for processing.

LSTMs use a series of 'gates' which control how the information in a sequence of data comes into, is stored in, and leaves the network (Chung *et al.* (2014)). There are three gates in a typical LSTM; forget gate, responsible for deciding which information to discard from the cell state. The input gate, determining which new information to incorporate into the cell state. and output gate, dictating how much of the updated cell state should be exposed as the final output. Each of these gates operates as its own neural network, ensuring that the LSTM efficiently captures and processes the relevant patterns and dependencies present in the sequential data (Figure 83).

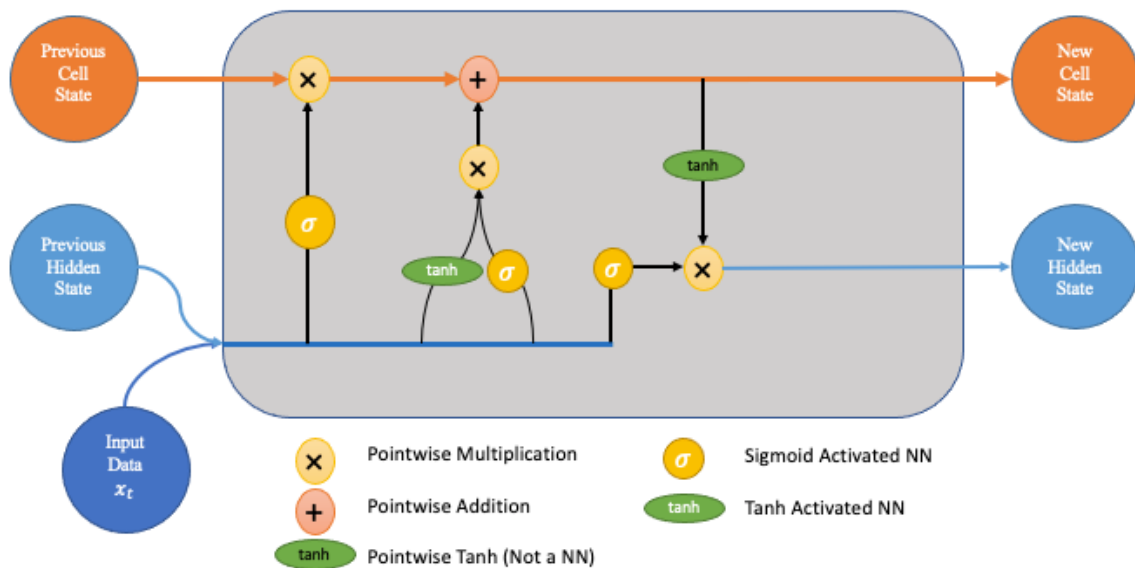


Figure 83: Structure of LSTM model.

### Training

The LSTM model is used for sequence-to-sequence prediction. The LSTM model was trained using sequences of images, with the model expected to output the next image in the sequence.

The LSTM model takes a sequence of data as input, processes it through LSTM units, and independently applies a Dense layer to each time step's output for predicting values at each time step. The model's compilation involves the Adam optimizer and the mean squared error loss function, making it suitable for sequence-to-sequence prediction tasks. Further detail is in Table 21.

Table 21: Structure and hyperparameters of LSTM model

| Layer                    | Parameters                                               |
|--------------------------|----------------------------------------------------------|
| Input                    | Shape: - (330, 90)                                       |
| LSTM                     | Units: 64, Return Sequences: True, Input Shape: (330,90) |
| TimeDistributed (Dense)  | Units: (number of features in input data)                |
| <b>Model Compilation</b> |                                                          |
| Optimizer                | Adam                                                     |

|               |                          |
|---------------|--------------------------|
| Loss Function | Mean Squared Error (MSE) |
|---------------|--------------------------|

#### 6.3.4.4 ConvLSTM

A ConvLSTM (Convolutional Long Short-Term Memory) is a type of recurrent neural network (RNN) that incorporates convolutional layers within the LSTM architecture (Shi *et al.* (2015)) (Figure 84). It is specifically designed for handling sequential data with spatial dependencies, such as video frames or time-series images (Ng *et al.* (2015); Perazzi *et al.* (2017)). ConvLSTM is an extension of the traditional LSTM that can effectively capture both temporal and spatial information in the input data.

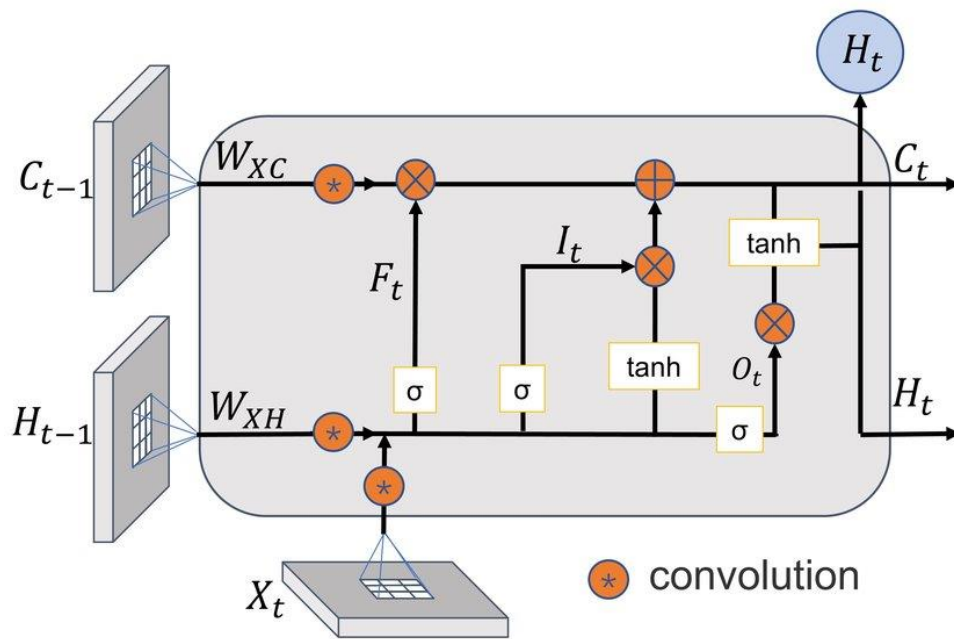


Figure 84: Structure of ConvLSTM model.

Convolutional Long Short-Term Memory (ConvLSTM) model is defined to handle spatiotemporal data. Three ConvLSTM2D layers are used in the model. Each ConvLSTM2D layer is followed by BatchNormalization, which normalizes the output of the previous layer, stabilizing the learning process. The ConvLSTM2D layers have 64 filters each, which means they have 64 memory cells to learn spatial-temporal patterns. A Conv3D layer is added to the



model after the three ConvLSTM2D layers (Table 22), the architecture of ConvLSTM2D followed by a Conv3D layer is designed to capture spatial-temporal dependencies within the input data, enabling the model to process and learn from both spatial and temporal features. The Conv3D layer combines the information learned from all time steps, resulting in an output volume that represents the final prediction or segmentation for the entire spatiotemporal sequence.

The ConvLSTM model is trained using various batch sizes and epochs to explore different configurations. After conducting experiments, it was observed that the best results were obtained when using a batch size of 5 and training the model for 10 epochs.

Table 22: Structure and hyperparameters of ConvLSTM

| Layer              | Parameters                                                                                              |
|--------------------|---------------------------------------------------------------------------------------------------------|
| Input              | Shape: (7, 330, 90, 1)                                                                                  |
| ConvLSTM2D         | Filters: 64, Kernel Size: (5, 5), Padding: 'same', Return Sequences: True, Input Shape: (7, 330, 90, 1) |
| BatchNormalization |                                                                                                         |
| ConvLSTM2D         | Filters: 64, Kernel Size: (3, 3), Padding: 'same', Return Sequences: True                               |
| BatchNormalization |                                                                                                         |
| ConvLSTM2D         | Filters: 64, Kernel Size: (2, 2), Padding: 'same', Return Sequences: True                               |
| BatchNormalization |                                                                                                         |
| Conv3D             | Filters: 1, Kernel Size: (3, 3, 3), Activation: 'sigmoid', Padding: 'same'                              |
| Reshape            | Output Shape: (7, 330, 90, 1)                                                                           |

|                    |                     |
|--------------------|---------------------|
| <b>Model</b>       |                     |
| <b>Compilation</b> |                     |
| Loss Function      | Binary Crossentropy |
| Optimizer          | Adam                |

## 6.4 Results and Discussion

### 6.4.1 GAN

The initial model tested was the GAN. GANs, by design, do not require any input other than an image. They are primarily designed for image generation rather than image prediction. In this context, a test was devised to assess whether the GAN could generate images that closely resembled the input images. As shown in Figure 85, images were created by the GAN which look similar to the input shorelines, however noise exists with these images (Figure 86). This can be due to various factors, including a potential shortage of training data or a lack of diversity in the dataset. (Salimans *et al.* 2016). Consequently, the GAN may encounter difficulties in generating high-quality images.

The results presented here were obtained through numerous iterations of hyperparameter tuning and adjustments to the model's architecture. The results displayed represent the most favourable outcomes achieved using the available training data. The smaller batch size was chosen as the dataset was limited and it allowed the model to see more unique samples during training. Increasing the batch size did not allow for the images to form, which could be due to noise in the gradient estimates during training, leading to less stable updates of the model's parameters. This noise could have impacted the generator's ability to learn meaningful patterns and details in the data distribution (Brock *et al.* (2018)).

Figure 87 shows the extracted boundary line of the shorelines for both the training image and the generated image. For the majority of output images, the shorelines produced were “landwards” and resembled shorelines between 2016 - 2019. It was not expected that the GAN could produce future predictions however it can be challenging to determine the specific time period that the output image represents if there is no accompanying labelled data for reference.

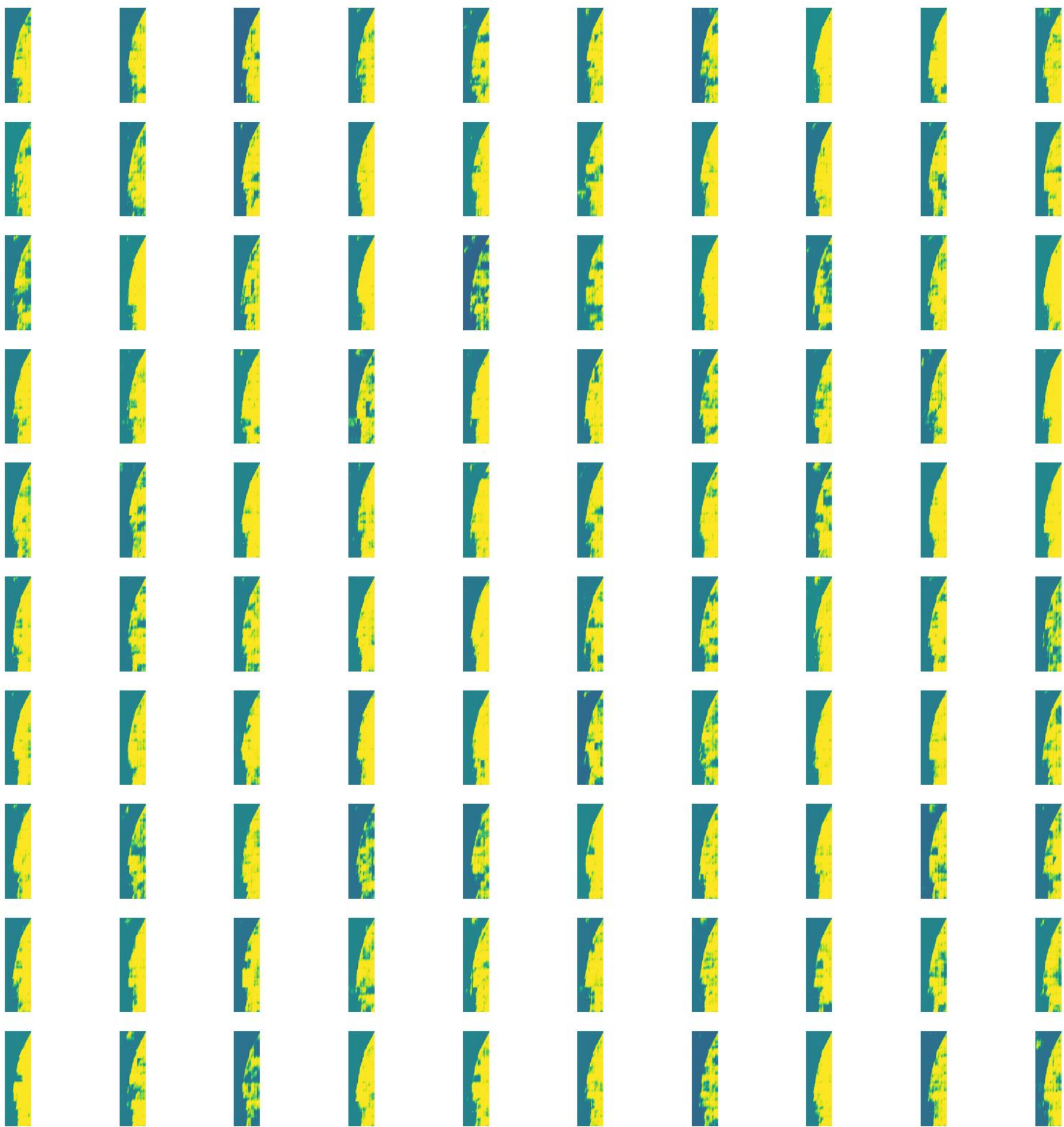


Figure 85: Output of 100 images produced by the trained GAN model.

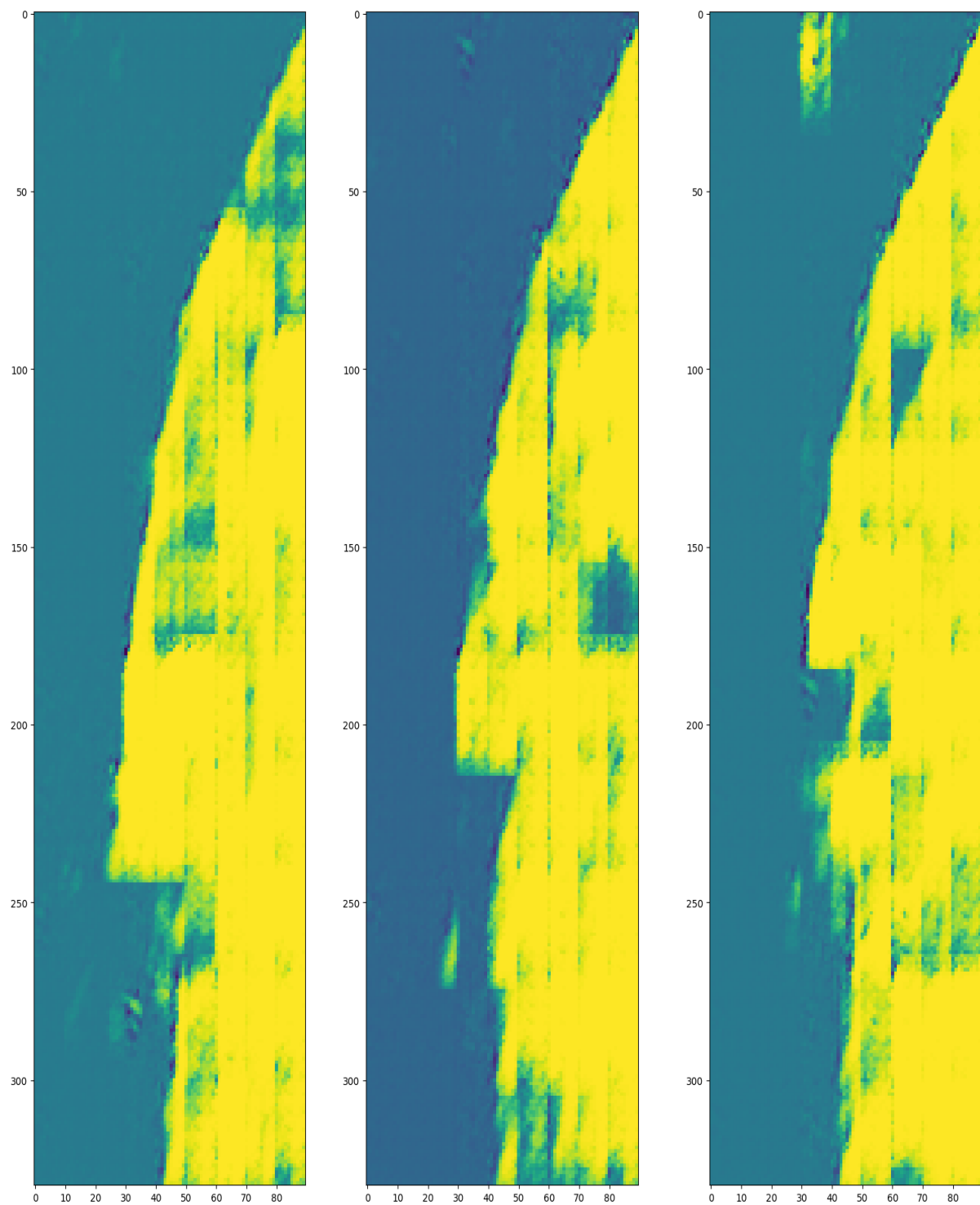


Figure 86: Three examples of the outputs generated from the GAN. They show the variation in the outputs for the different input images from 2016-2022. These figure also highlight the noise and blocky structure of the outputs.

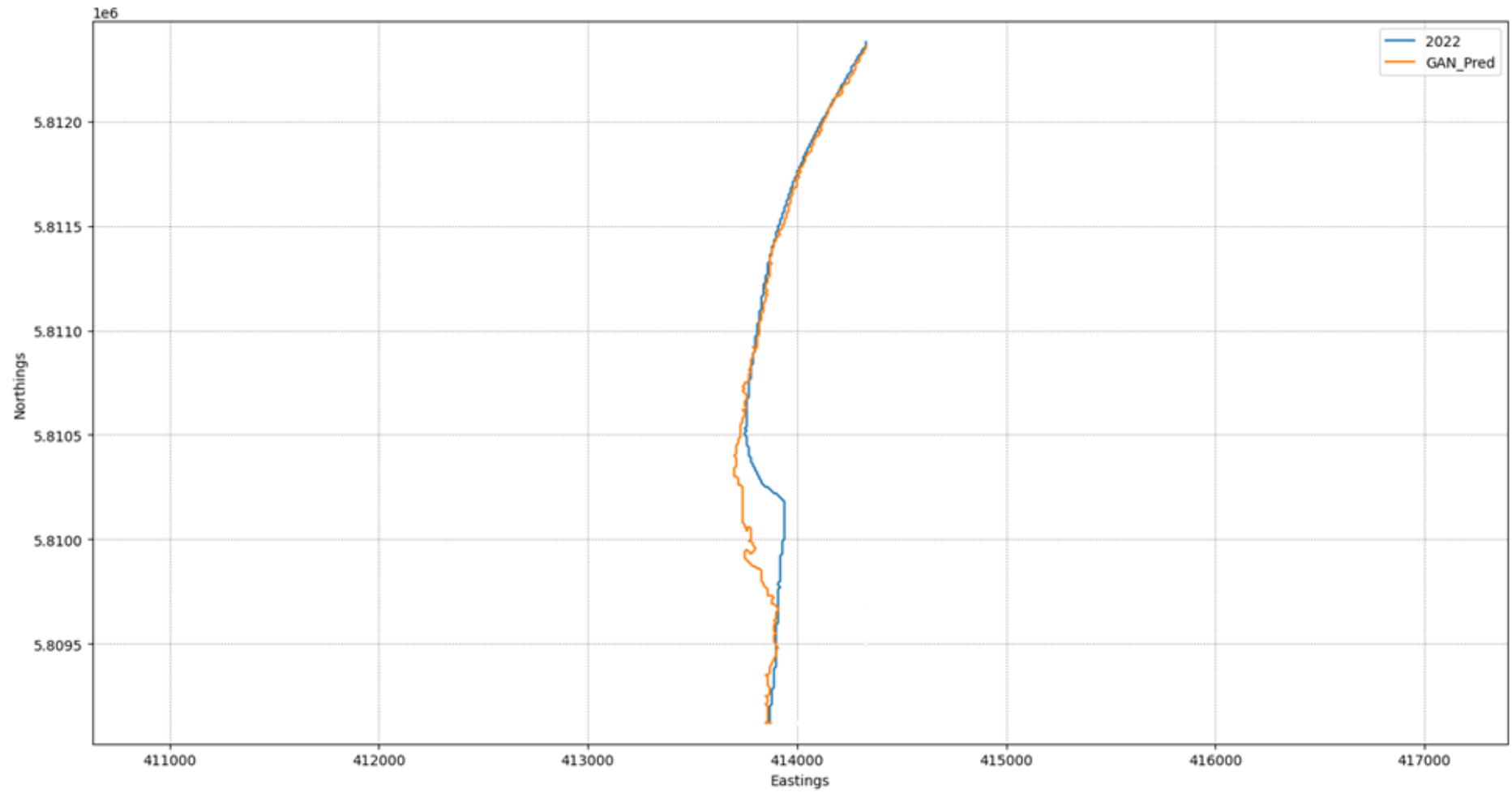


Figure 87: Comparison between the real 2022 shoreline line (blue line) and a GAN predicted shoreline (orange line).

### 6.4.2 CGAN

The CGAN model was trained to the fullest extent possible to generate outputs that closely resembled the input shorelines. Results for the CGAN are presented for the years 2016, 2022, and 2025. The purpose of including these specific years is to showcase the model's proficiency in handling both seen and unseen data, highlighting its ability to generalise effectively beyond the training dataset.

The results for the 2016 prediction are illustrated in Figure 88 and Figure 89. Figure 88 displays 100 model generated outputs for the label '2016'. While the results show some semblance of shoreline shape, none of them accurately represent the 2016 shoreline. Instead, they predominantly feature overextended shorelines (90%) or display noise, making the shoreline indiscernible (10%). In Figure 89, it is evident that the model fails to predict the correct position of the 2016 shoreline accurately, despite being provided with the corresponding label. The depicted minimum and maximum extents of the predicted '2016' shorelines further emphasize the model's tendency to overextend its predictions.

Several factors could contribute to this inadequate performance. First, the limitation in the available data, which might not be sufficiently diverse to enable the model to capture the details of shoreline variations effectively. Additionally, the model might be susceptible to overfitting, where it memorises specific examples from the training data rather than generalising well to unseen samples, leading to incorrect predictions (Eken (2021)). Mode collapse could have also occurred, when the generator failed to capture the full diversity of the training data distribution and instead produces limited variations of the same image (Xiang and Li (2017)).

The predicted results for 2022 are shown in Figure 90, Figure 91 and Figure 92. Figure 90 highlights the outputs of the GCAN model for 2022 shorelines. Here, the model's predictions exhibit a varied performance: 29% of outputs closely resemble the 2022 shoreline, 40% of

shorelines are overestimated, 15% underestimated, and 16% contain noise. The factors contributing to these outcomes, such as overfitting and insufficient data, might be influencing the performance of the model for 2022. Figure 91 provides a specific example of one of the predicted shorelines, which shows a similarity to the actual coastline. However, a notable limitation is observed in the form of blocky and unnatural-looking results, diverging from the features of a natural coastline. Figure 89 shows an example of the real 2022 shoreline compared with an example of a predicted 2022 shoreline, highlighting the minimum and maximum extents of the prediction. The minimum predictions closely resemble 2019 shorelines, while the maximum predictions resemble future forecasts, illustrating the model's wide variability in performance.

The observed similarities in the unseen predicted images for 2025 mirror what was noticed for 2016 and 2022. A collection of 100 images generated by the model for 2025 is shown in Figure 93, demonstrating resemblances to the final 2022 images. Among these images, 16% contained noise with no discernible shoreline, 27% featured underestimated shorelines (falling below the '2022 benchmark'), 43% closely resembled the 2022 shoreline, suggesting a plausible future prediction for the following years, and 14% were overestimated. This becomes more apparent in Figure 94, which also reveals variations in the predictions. Figure 95 provides a comparison between the final 2022 boundary and the predicted 2025 boundary, including the minimum and maximum extents of the model's outputs. Notably, there is an observed north/eastward movement of the predicted 2025 shoreline (orange line), aligning with a pattern similar to that of the natural shoreline. However, the minimum shoreline indicates the model's tendency to underestimate the shoreline position, while the maximum predicted shoreline exhibits an unnatural shape, overextending beyond expected boundaries.



#### **6.4.2.1 Summary of GAN and CGAN Results**

The results obtained from both the GAN and GCAN models revealed similar findings. The presence of noise in the predictions suggests the need for a more comprehensive dataset and regularisation techniques to ensure a better generalisation of the model to unseen data. Additionally, addressing the blocky nature of the generated coastlines requires further refinement of the model's architecture and optimization strategies to achieve more realistic and visually accurate predictions (Salimans *et al.* (2016)).

In the case of the CGAN model, difficulties were encountered in generating images that closely resembled the input images, and when labelled data was introduced, the models struggled to establish a meaningful connection between the labels and the generated images. Consequently, the final image in the dataset was frequently reproduced instead of producing diverse outputs corresponding to the given labels. The primary contributing factor to this limitation appears to be the insufficient training data. Despite numerous attempts at various iterations, these results represent the best outcomes achievable with the current data.

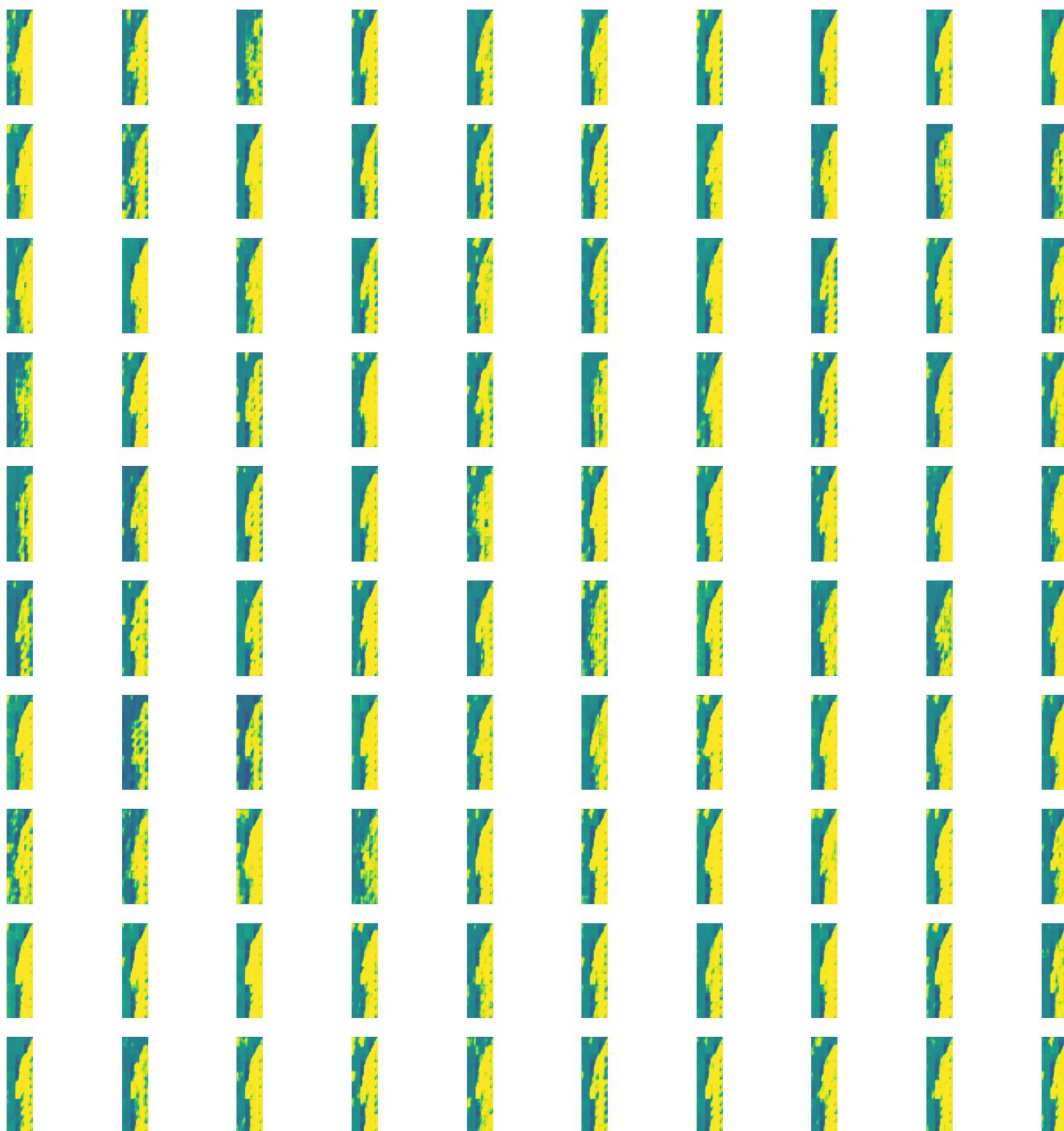


Figure 88: Output of 100 images produced by the trained CGAN model for images labelled 2016

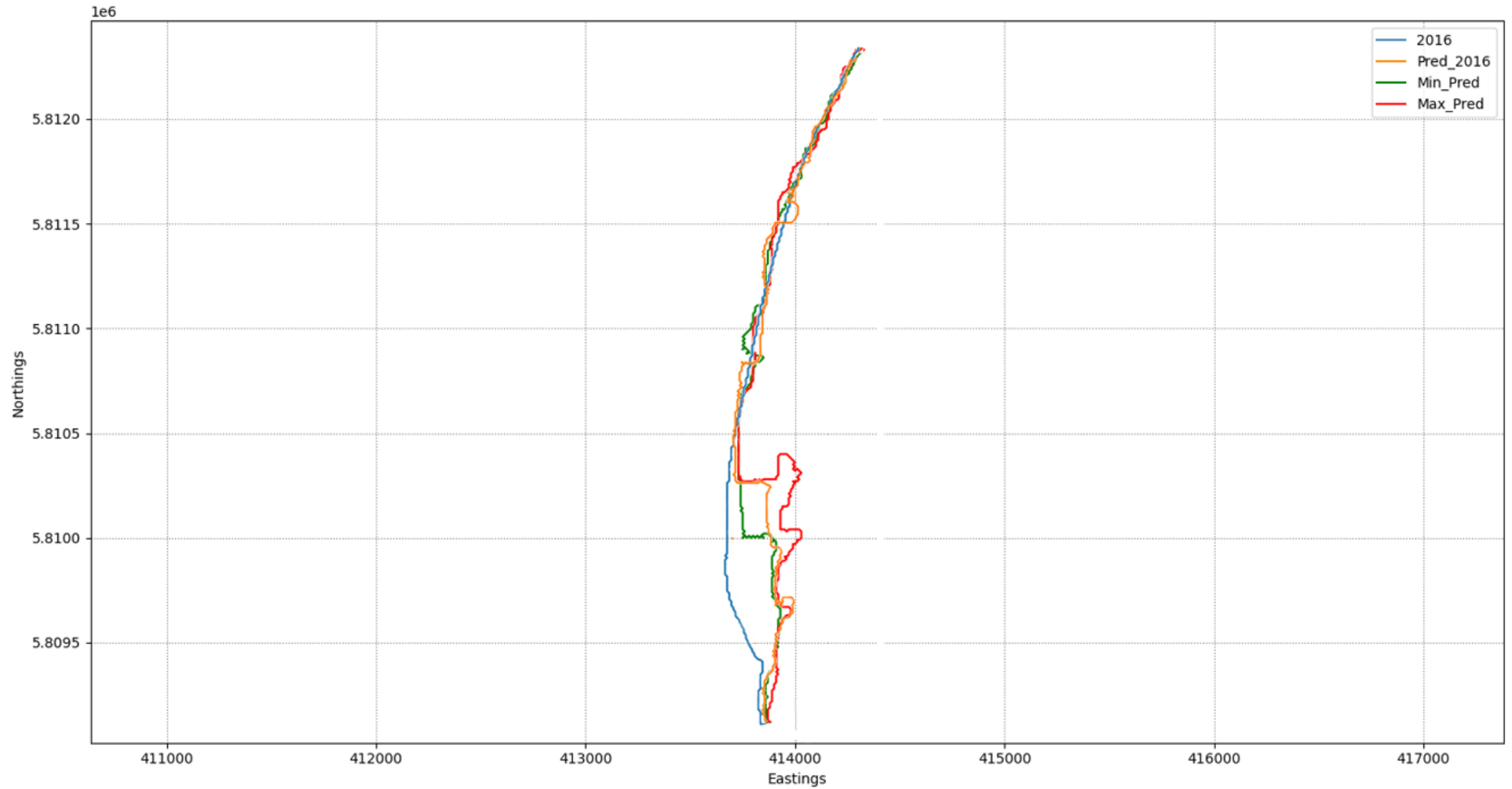


Figure 89: Comparison between real 2016 shoreline (blue), the example of a predicted 2016 shoreline (orange), and the minimum (green) and maximum (red) extent of the 2016 predicted shorelines produced by the CGAN model.

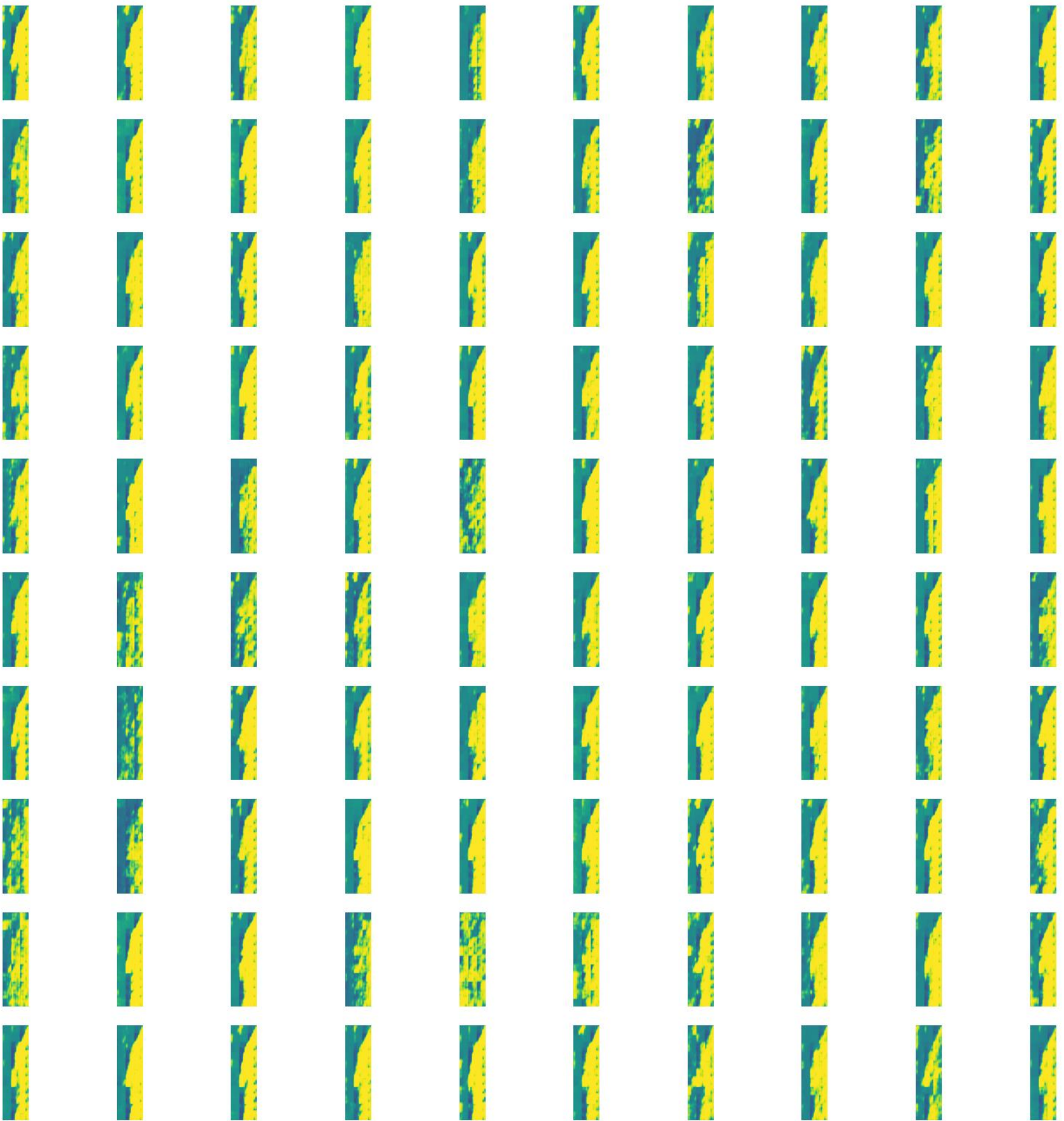


Figure 90: Output of 100 images produced by the trained CGAN model for images labelled 2022

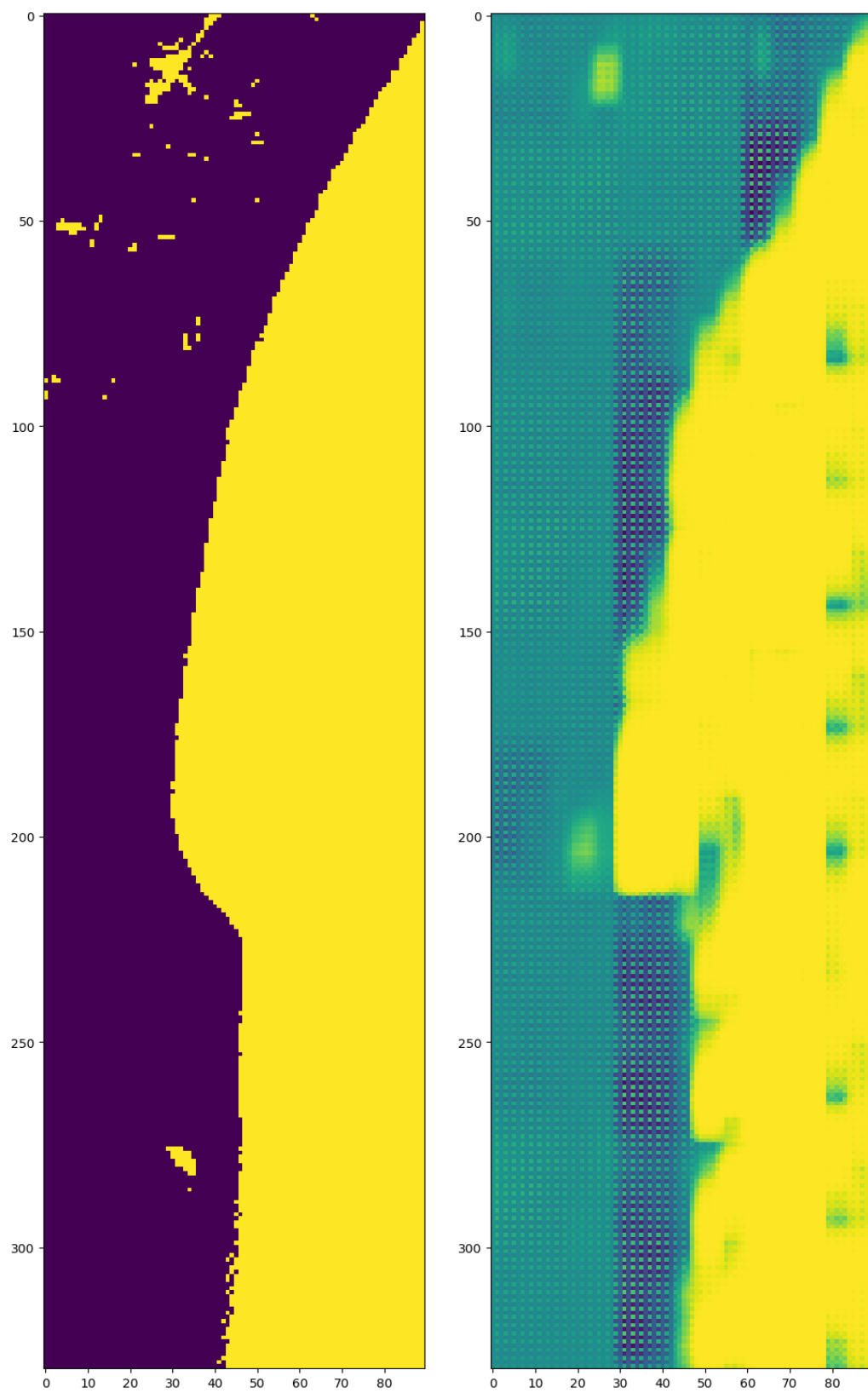


Figure 91: Comparison of real 2022 binary image with CGAN predicted image for 2022.

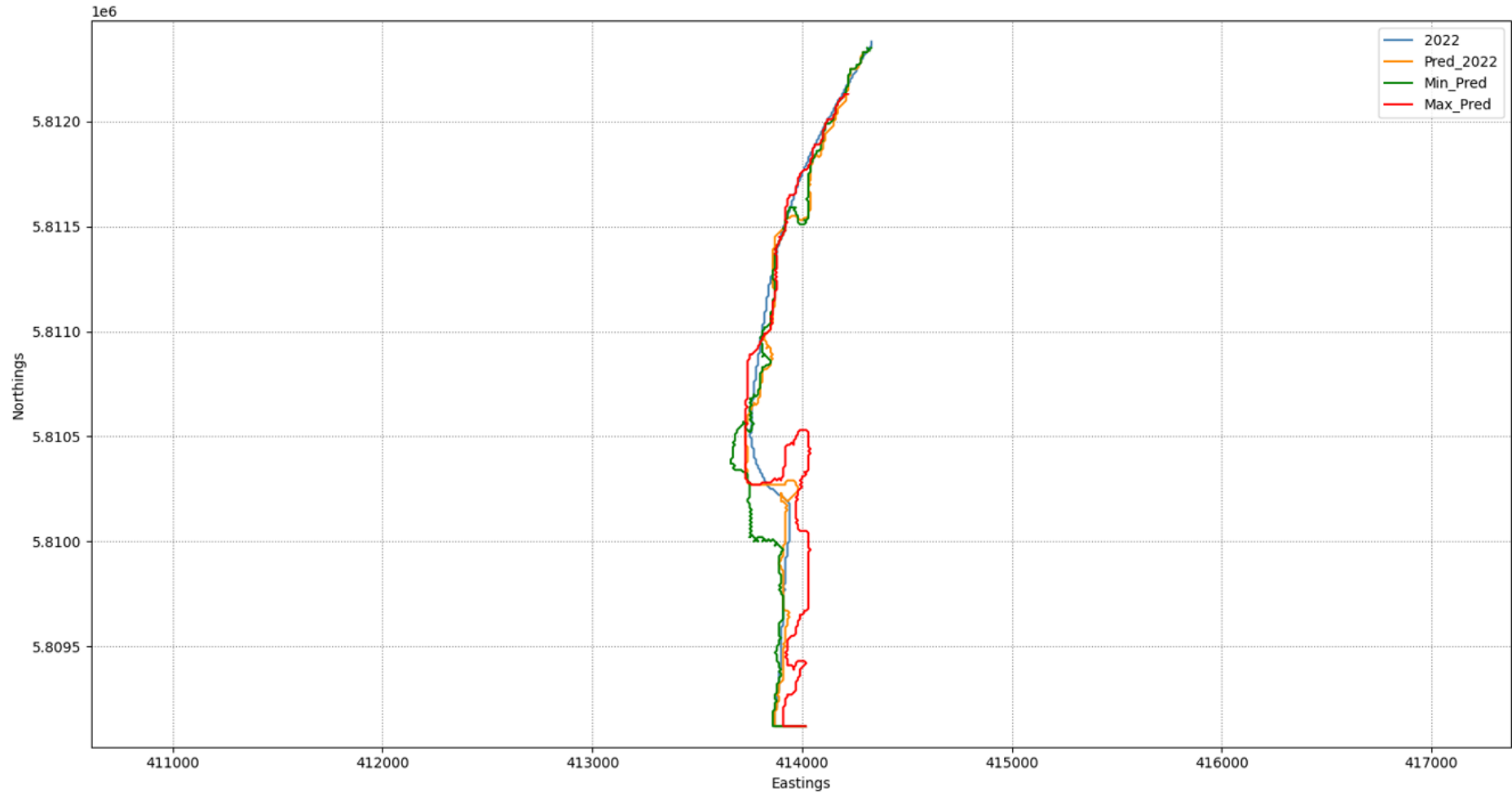


Figure 92: Comparison of real 2022 shoreline, the CGAN predicted shoreline for 2022, and the minimum (green) and maximum (red) extent of the 2022 predicted shorelines produced by the CGAN model.



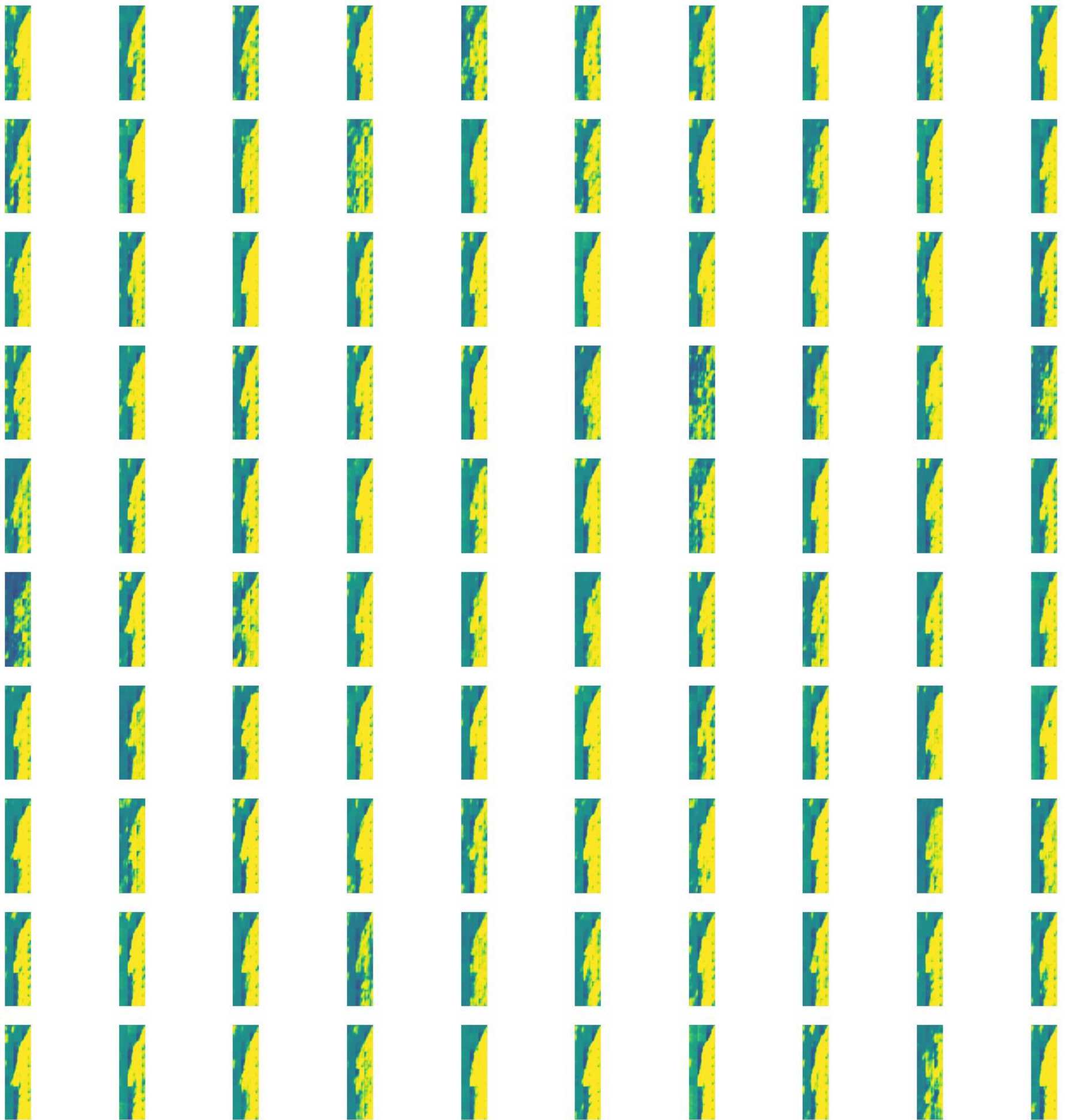


Figure 93: Output of 100 images produced by the trained CGAN model for images labelled 2025.

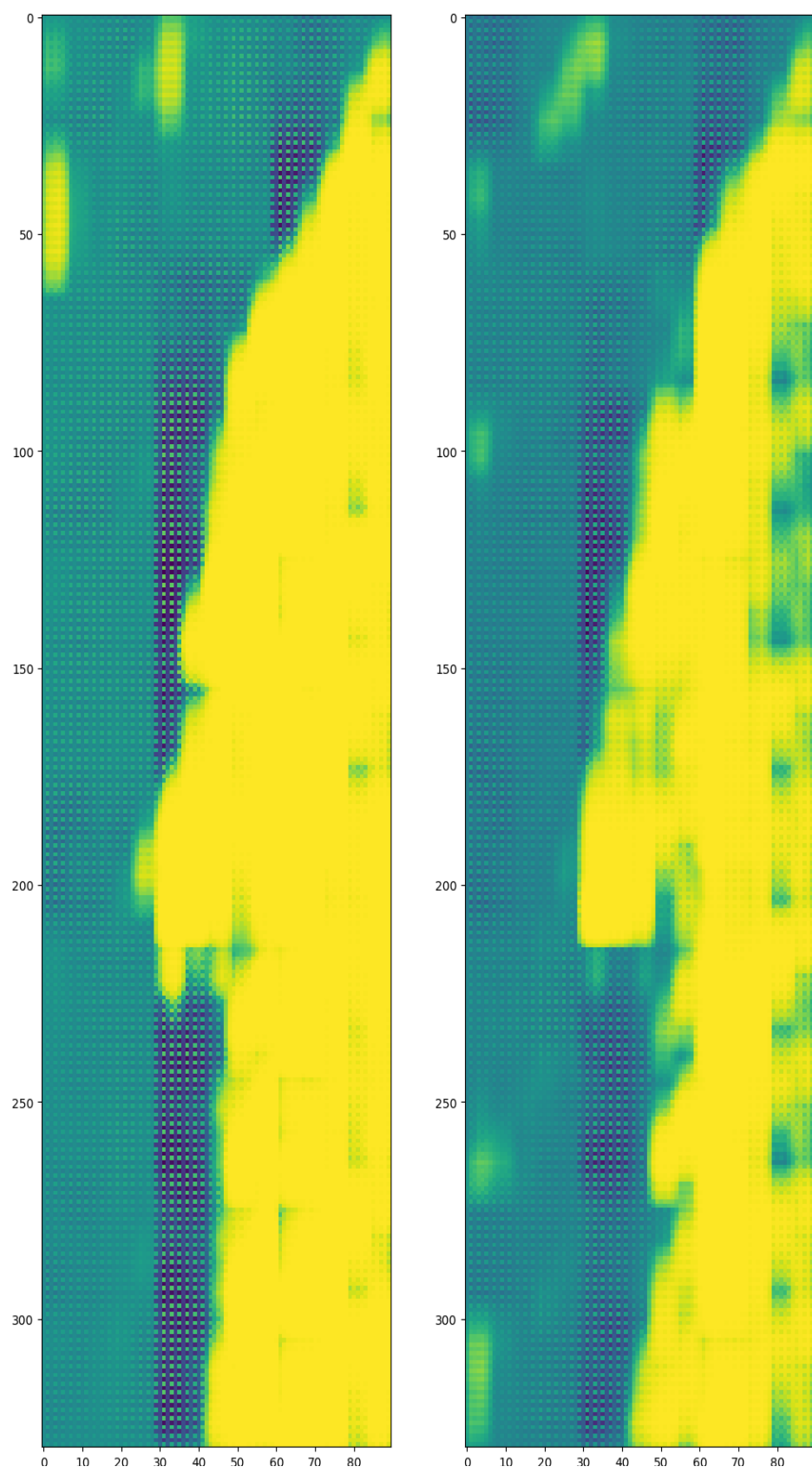


Figure 94: Example images of the 2025 shorelines produced by CGAN.



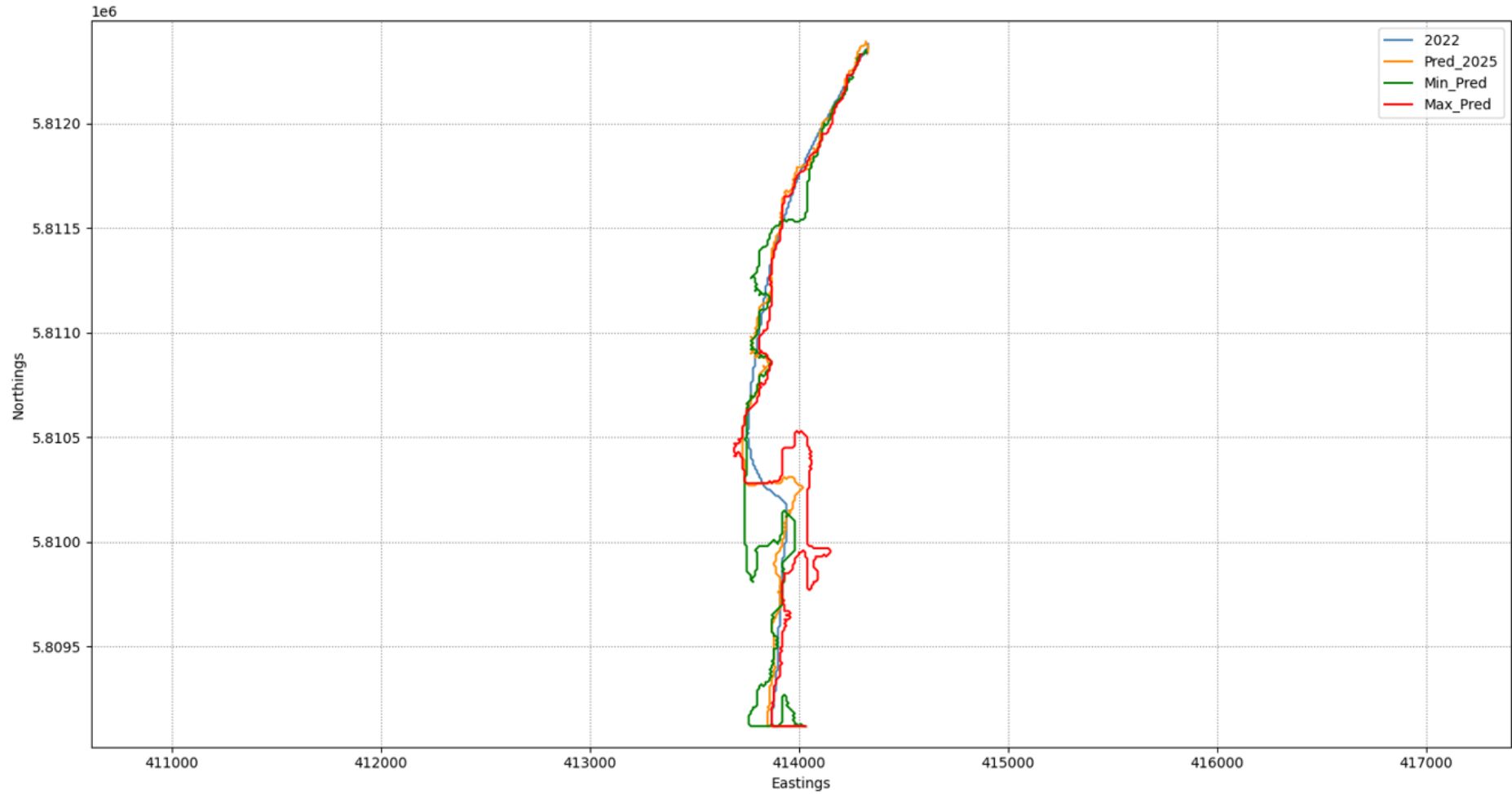


Figure 95: Comparison of real 2022 shoreline (blue), the predicted 2025 shoreline (orange), and the minimum (green) and maximum (red) extent of the 2025 predicted shorelines produced by the CGAN model.

### 6.4.3. LSTM

The LSTM model was expected to generate the subsequent image in the sequence. However, Figure 96 shows that the model was outputting similar results as the final image of the sequence. This pattern was consistently observed across all outputs produced by the model. A comparison between the original 2022 boundary and a predicted boundary in the sequence is illustrated in Figure 97. While a slight movement is observed, potentially indicating a natural shoreline shift, the overall movement remains quite restricted for all the LSTM model outputs.

The performance of the LSTM model might have been influenced by the length of the input sequences, which plays a critical role in its predictive capabilities. Short input sequences may limit the context available for generating meaningful predictions for the next image. To address this limitation, longer input sequences should be considered, as they allow the model to better capture the underlying progression and patterns present in the data. However, it is important to note that dealing with long sequences has been a recurring challenge in many studies (Sutskever *et al.* (2014)). In this specific case, the issue may not necessarily be related to the length of the input sequences but rather the availability of an adequate number of sequences for training the model, with recent research suggesting that models tend to perform better when trained with a higher number of input sequences (Urosevic and Dimitrijevic (2021)).

It is important to highlight model architecture's simplicity, consisting of a single LSTM layer, where this minimal architecture might have been insufficient to capture the complexities in the image data and the underlying temporal dynamics. To address this limitation, incorporating more layers could potentially enhance the model's capacity to learn and generate more accurate images, leading to improved performance overall.

The decision to employ the LSTM in this study was based on its widespread usage for prediction tasks. Although the singular LSTM model did not exhibit the capability to produce

time sequences independently, it served as a valuable foundation for exploring alternative approaches. Consequently, the focus shifted towards considering the ConvLSTM, a model commonly employed in the literature for its ability to effectively handle spatiotemporal data.

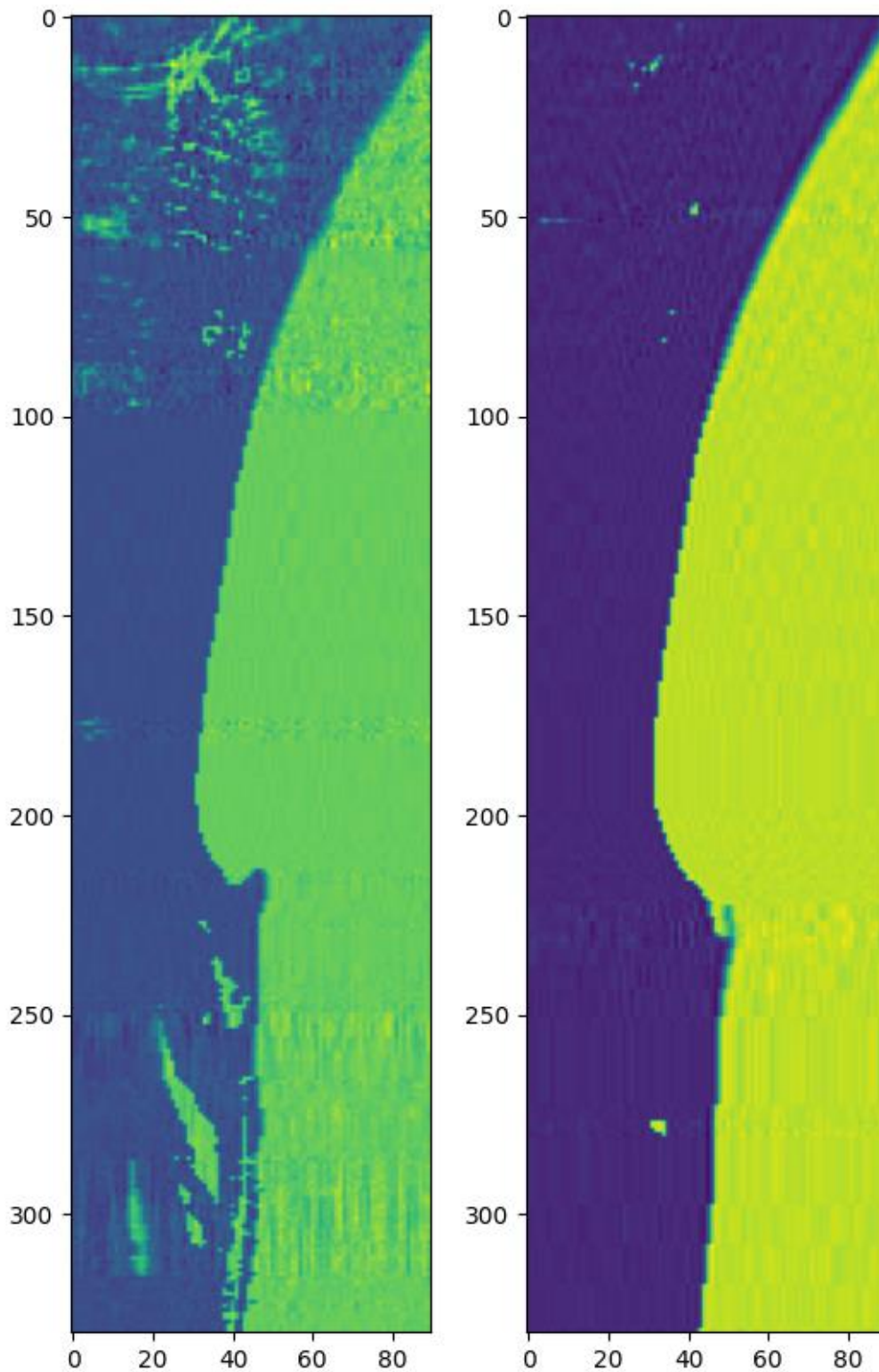


Figure 96: Example of the outputs produced from the LSTM model.

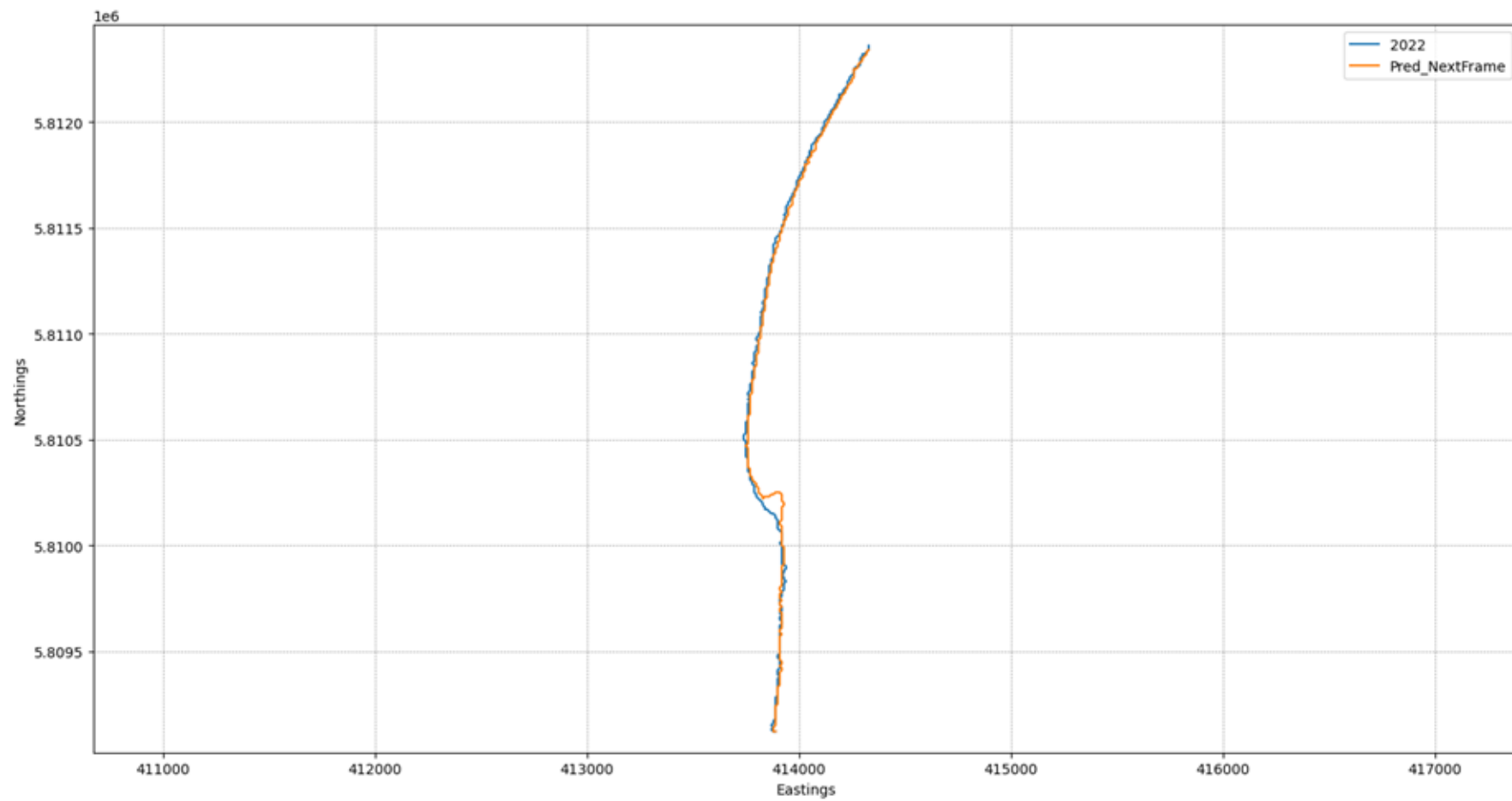


Figure 97: Comparison of the real 2022 shoreline (blue) with the next predicted frame shoreline (orange) from the LSTM model.

#### 6.4.4. ConvLSTM

The ConvLSTM model demonstrated the best performance compared to the other tested models. The combination of temporal information from the convolutional operation with the sequential data from the LSTM model allowed the model to effectively capture and predict future shoreline changes.

The ConvLSTM model had many interactions to determine the optimal batch size and number of epochs for achieving the best results. Through experimentation, it was found that the model yielded the best output when trained with a batch size of 2 and at 50 or 60 epochs. The obtained results are presented in Figure 98 - Figure 103.

Figure 98 showcases the outcomes obtained from the ConvLSTM model with a batch size of 2 and 50 epochs. The top row displays the input images, while the bottom row depicts the corresponding output images. Notably, the initial predicted images following the testing sequence exhibit evident movement, indicating the model's capability to capture temporal information and predict future shoreline changes. However, as the frames progress, the generated images begin to lose their structure and quality. Despite the possibility of mode collapse in later sequences, it is important to note that this ConvLSTM model initially produces clear and distinct results that signify boundary position changes in the images. In Figure 99, the noticeable reduction in the quality of the output in the later sequence is shown. This is evident from the 2023 predicted shoreline, which represents the furthest boundary position, followed by successive years showing a retreat of the boundary position. In comparison to the historical original shoreline position, the model's output displays no growth of the ness. Instead, it adheres to the shape of the original 2022 and 2021 shorelines, with the predicted 2026 shoreline resembling the 2016 shoreline.

The results in Figure 100 and Figure 101 were also obtained with an epoch of 50 and a batch size of 2, yielding significantly more distinct outcomes. In Figure 100, the subsequent predicted frames reveal a continuous growth of the shoreline, which is then compared with the boundary lines depicted in Figure 101. When comparing these predictions with the historical original shoreline position, it becomes evident that there is growth in the ness with the future predictions. However, it is notable that the predicted 2026 shorelines mark the first instance where growth extends beyond the real 2022 shoreline, while predicted shorelines for 2023, 2024, and 2025 all closely resemble the furthest extent of the real 2022 shoreline.

While these observations indicate the model's capability to grasp and represent meaningful spatial patterns, it is important to note that the predictions do not align with the expected behaviour. Specifically, there is an excessive seaward movement, whereas the sediment is more likely to predominantly move northward, following the coastline and the beach.

The results for batch size 2 and 60 epochs are displayed in Figure 102 and Figure 103. Figure 102 exhibits encouraging outcomes, with the shoreline movement aligning with the expected behaviour. It is worth noting that the images suffer from a reduction in quality, and a division in the binary image occurs, resulting in the exclusion of half of the beach from the boundary line extraction. Figure 103 displays the predictions up to 2025, showcasing the shoreline's positional changes in the first 3 output images. The image quality reduction limits the display to these specific images as the boundary lines cannot be distinctly identified beyond this point. Nonetheless, when compared to historical shorelines, the rate of growth depicted in these model outputs appears to resemble natural growth patterns.

It is important to address the reduction of quality in further iterations of the ConvLSTM model. Fine-tuning hyperparameters, exploring regularization techniques, and experimenting with different model architectures are potential approaches to mitigate this and enhance the model's overall performance in predicting future image sequences. By addressing this challenge, the ConvLSTM model can be optimized to produce high-quality and coherent output images across all temporal frames, contributing to more accurate and reliable predictions of shoreline changes.

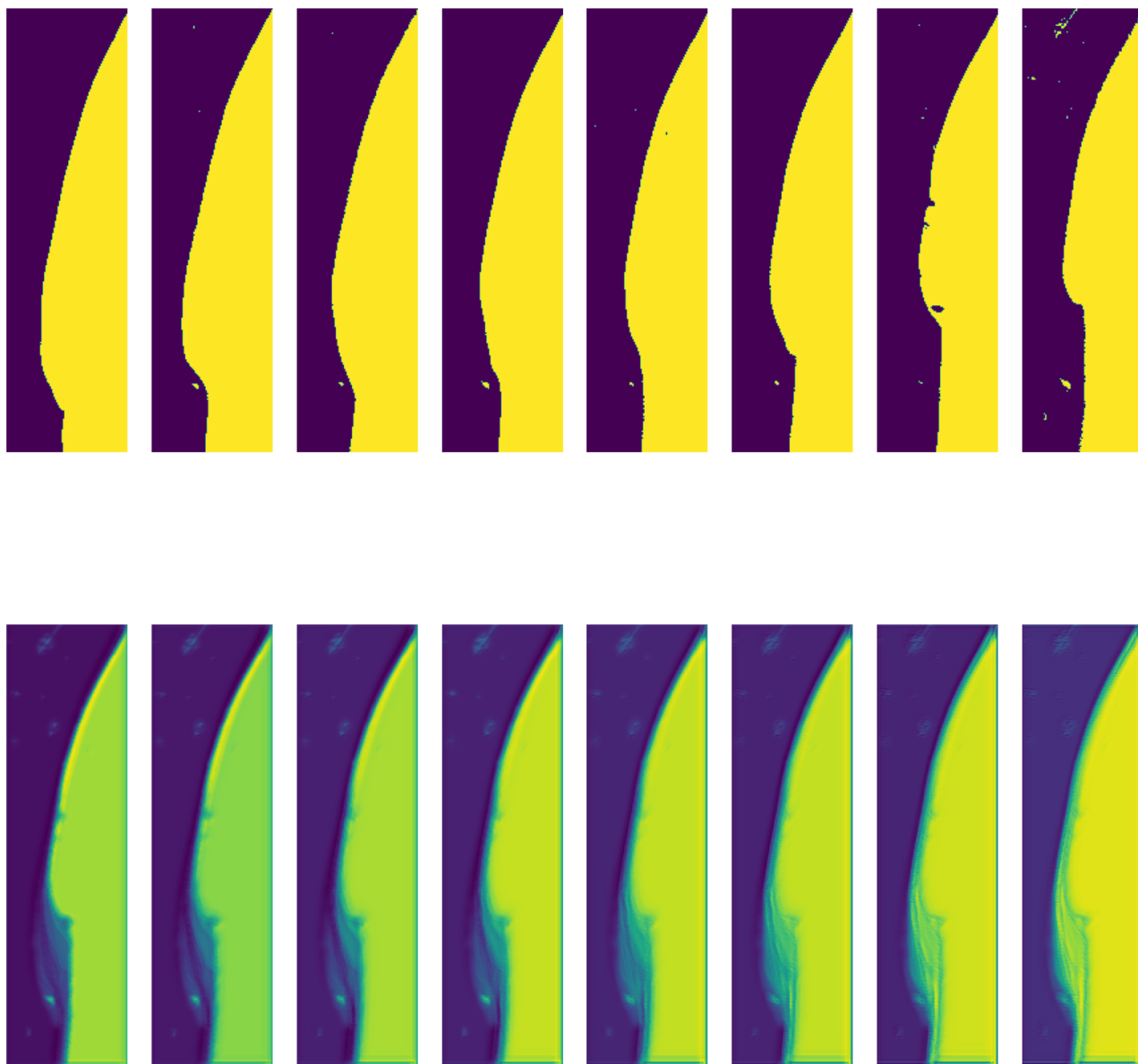


Figure 98: Top row made up of real input images. Bottom row shows the predicted output of the ConvLSTM model with a batch size of 2 and Epoch of 50



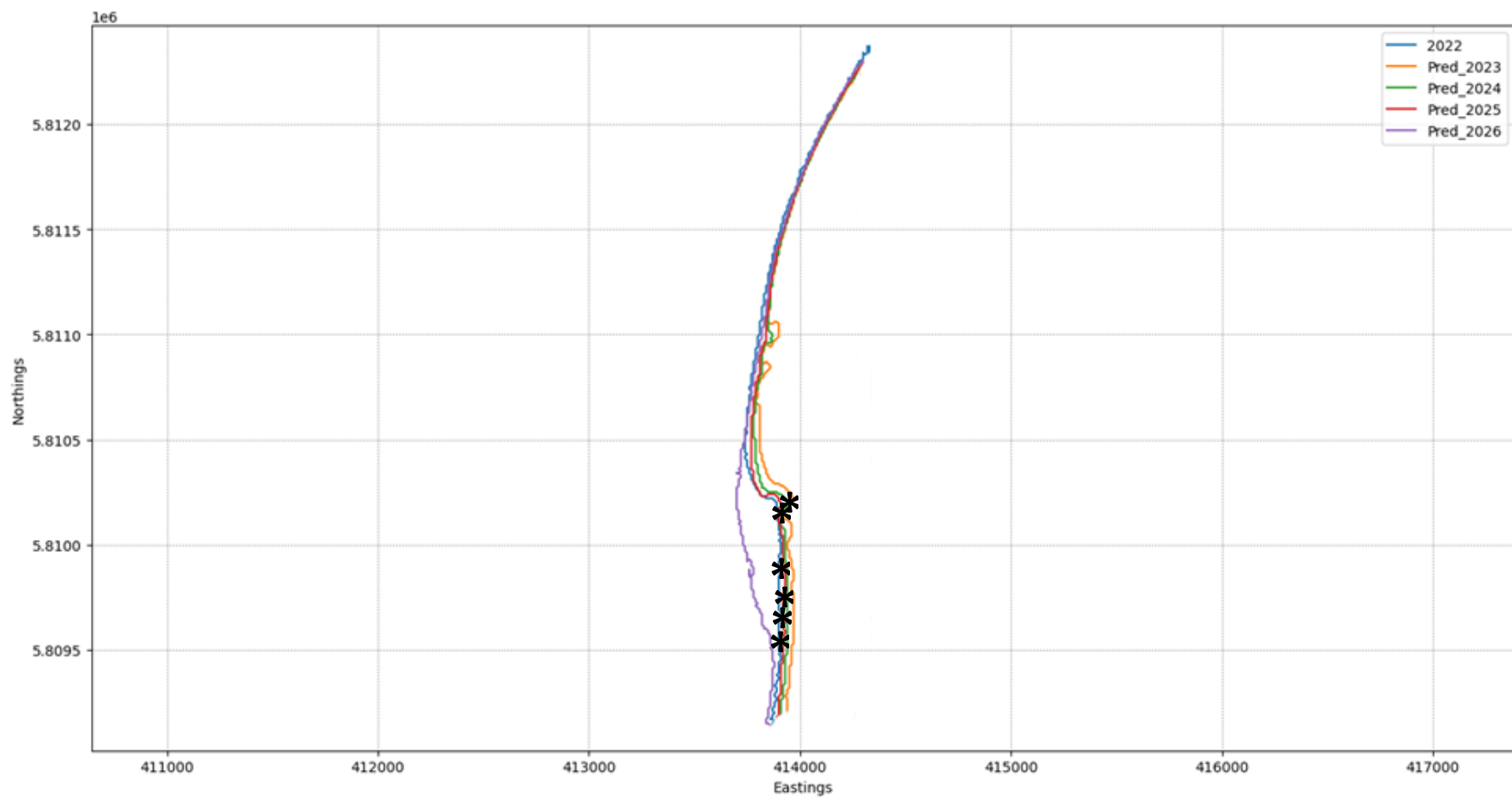


Figure 99: Comparison of real 2022 shoreline (blue) with output shorelines for 2023 - 2026 produced from the ConvLSTM. Asterisks (\*) denote the locations of peak of the ness in previous shorelines spanning 2016-2022. First example using batch size 2 and 50 epochs.

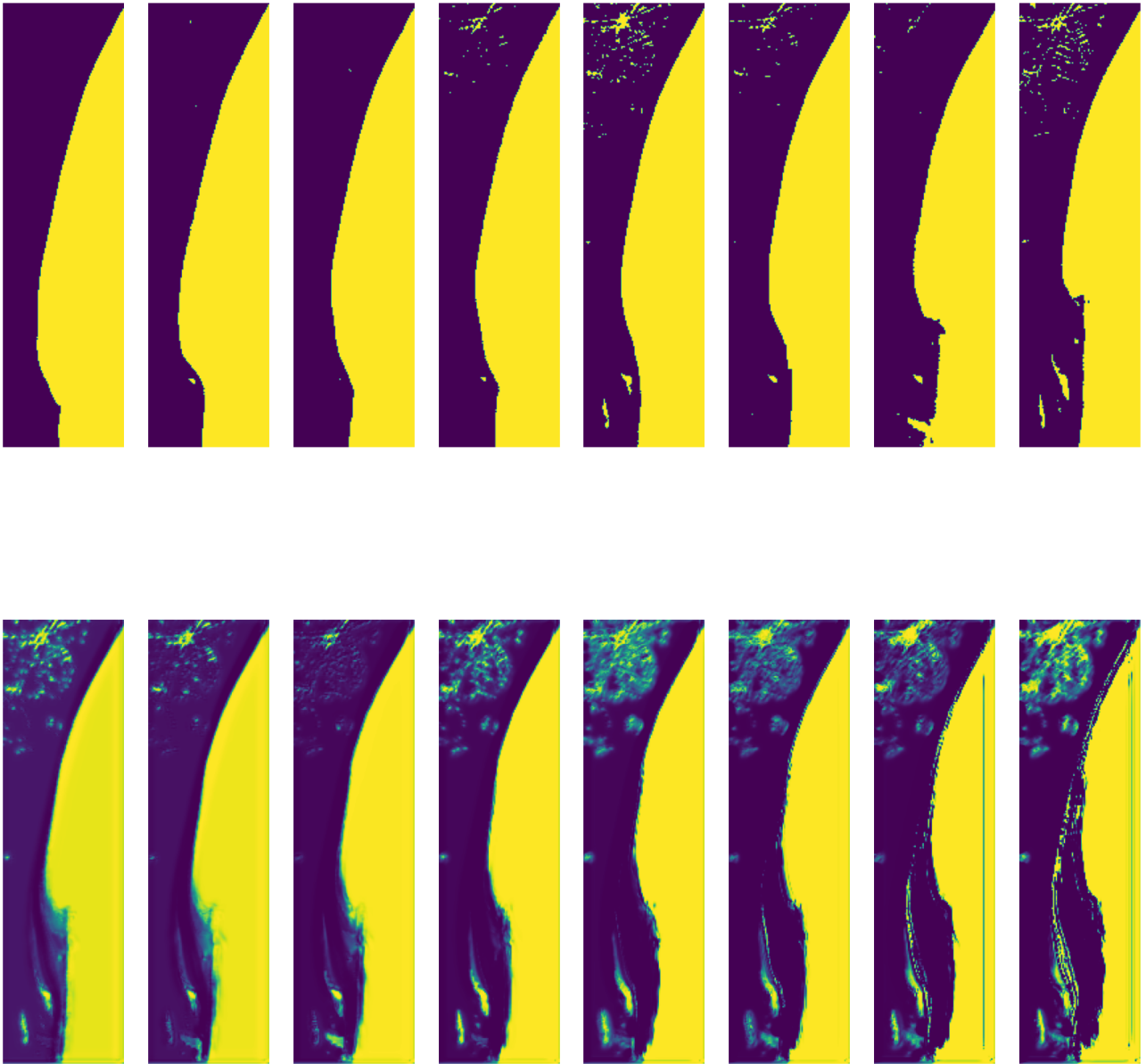


Figure 100: Top row made up of real input images. Bottom row shows a second example of the predicted output of the ConvLSTM model with a batch size of 2 and Epoch of 50

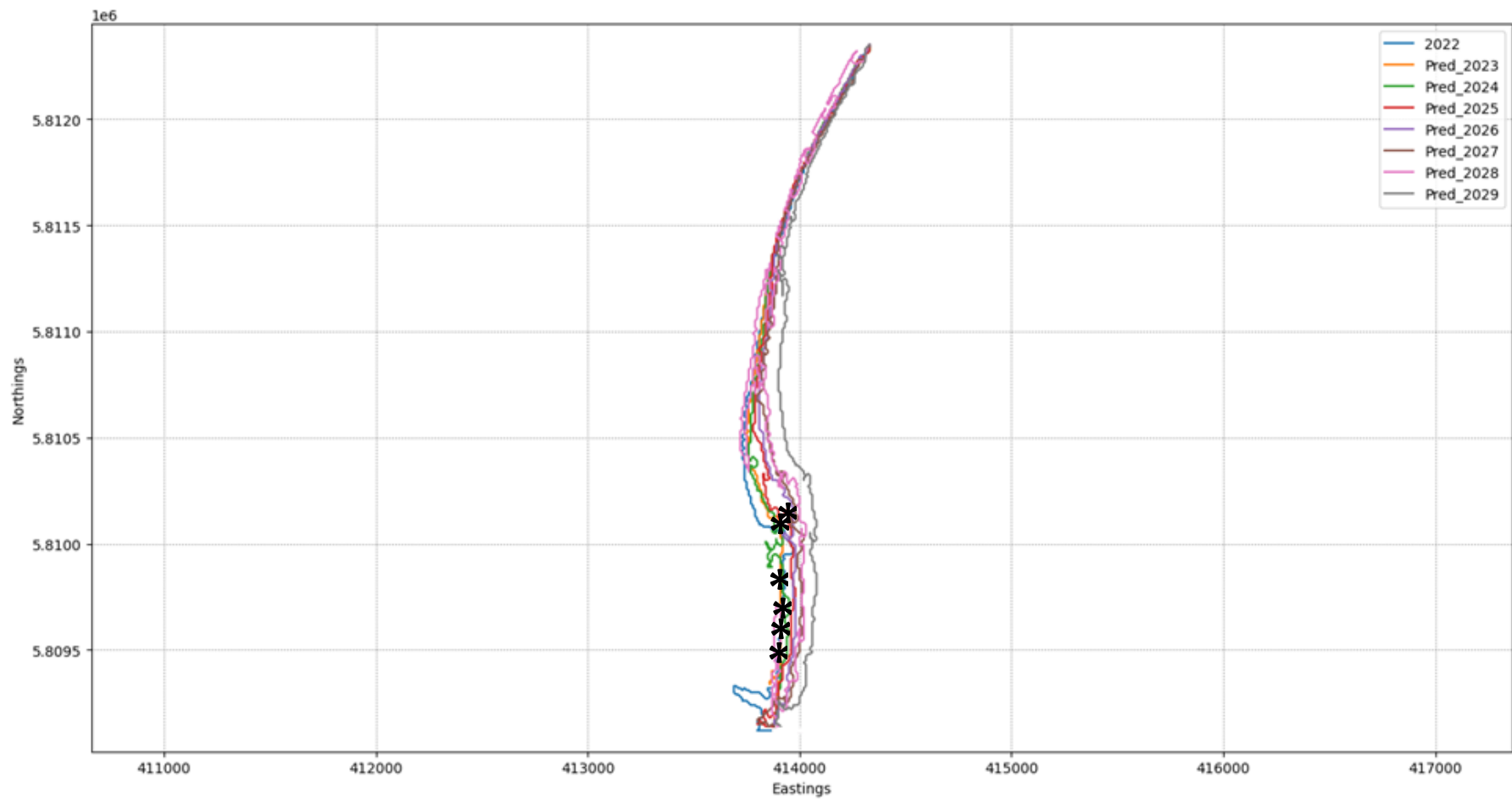


Figure 101: comparison between real 2022 shoreline (blue) and predicted ConvLSTM shorelines from 2023 – 2029. Asterisks (\*) denote the locations of peak of the neck in previous shorelines spanning 2016-2022. Second example using batch size 2 and 50 epochs.

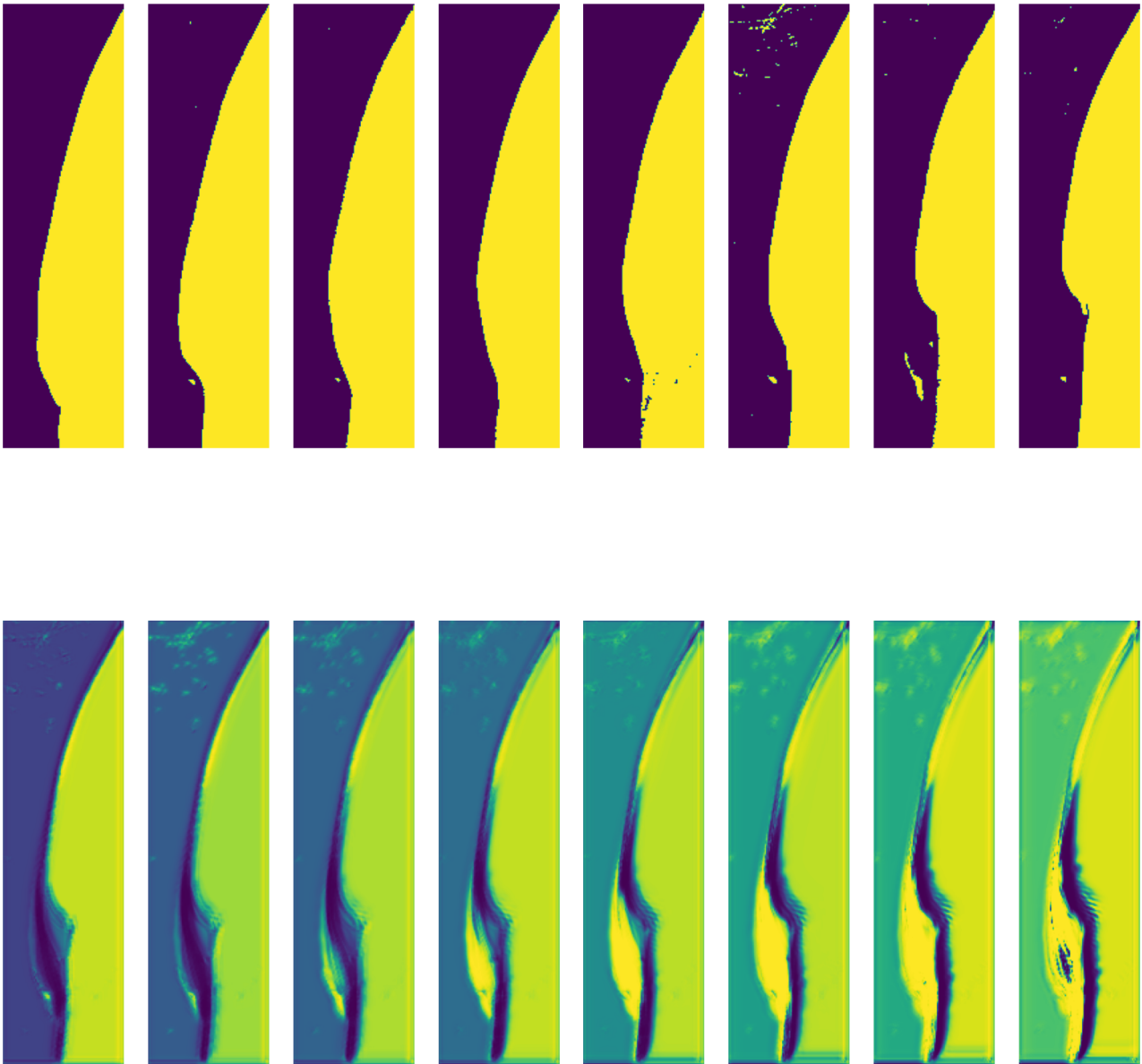


Figure 102:Top row made up of real input images. Bottom row shows the predicted output of the ConvLSTM model with a batch size of 2 and Epoch of 60.

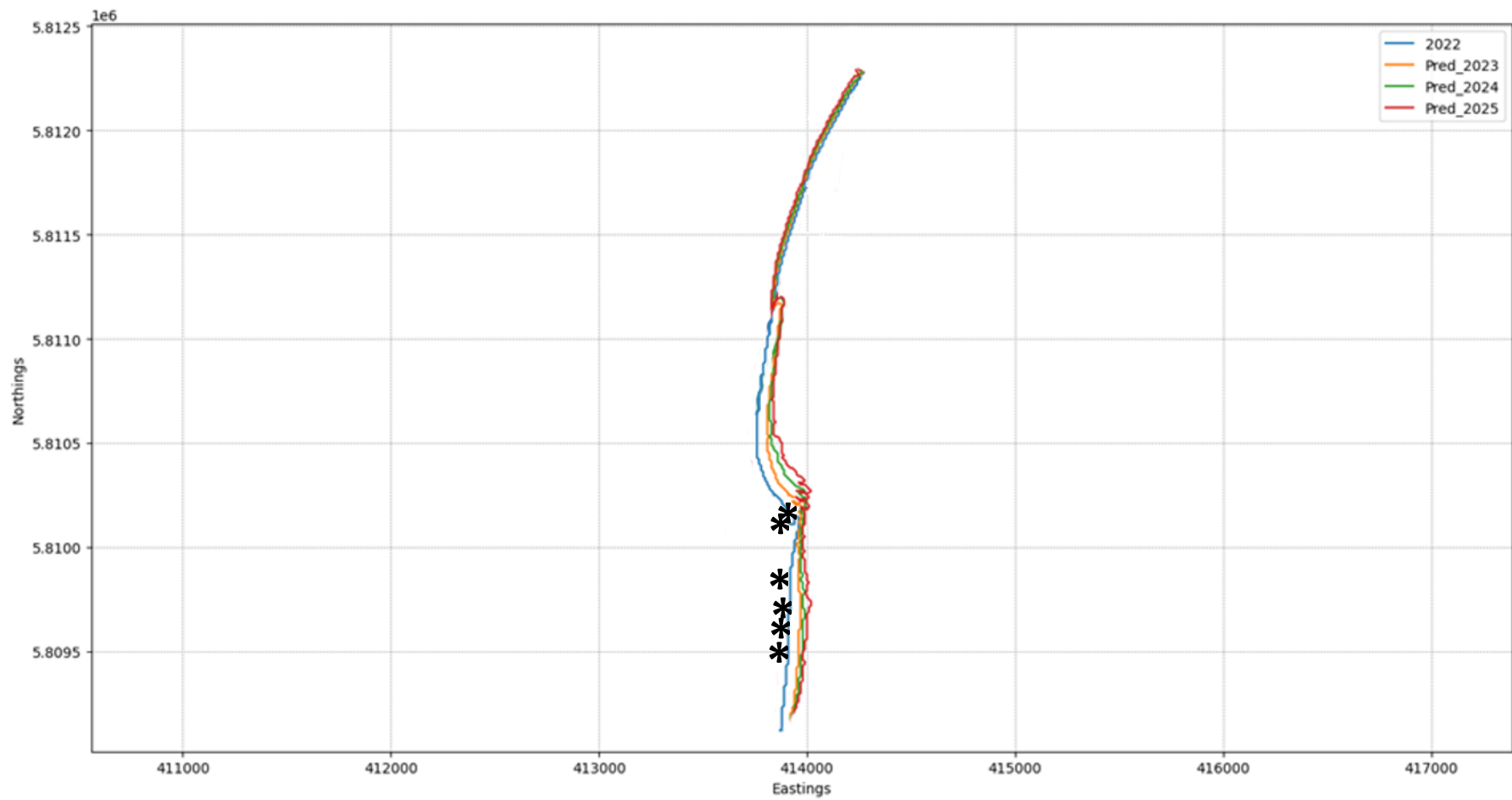


Figure 103: comparison between real 2022 shoreline (blue) and predicted ConvLSTM shorelines from 2023 – 2025. Asterisks (\*) denote the locations of peak of the ness in previous shorelines spanning 2016-2022 Example generated using batch size 2 and 60 epochs.

## **6.5 Future Directions and Areas for Improvement:**

### **6.5.1 Proposed Enhancements to Overcome Existing Limitations**

Throughout this chapter, a significant constraint has been the lack of training data, showing a notable impact on all models which were tested. It is widely acknowledged within predictive modelling and neural networks that a substantial volume of training data is needed to produce successful outcomes. This chapter effectively highlights the validity of this principle in the context of the models used.

Multiple methods exist for generating data to train models. In the context of satellite imagery, the use of Landsat satellite imagery is an option to increase training data size. However, it is necessary to think about how using data with lower resolution might impact the training process. Could significant changes still be detectable in larger pixel sizes? The likelihood is high, and the inclusion of diverse data inputs might aid in training the model to generalise effectively without encountering issues of overfitting.

The enhancement of training dataset diversity can also be achieved using image augmentation techniques. In the study conducted by Xu *et al.* (2023), a collection of image augmentation methods is provided, addressing specific challenges to the models used here. The continuation of consistent image dimensions is beneficial, and methodologies demonstrated by AlexNet (Rasheed *et al.* (2022)) and DenseNet (Bian *et al.* (2019)) are viable options. Alternatively, integration of augmentation can be applied within frameworks such as Keras (Ahmed *et al.* (2019)) or TensorFlow (Taqi *et al.* (2018)), to produce more training datasets.

While this study involved testing limited data, it is evident that this constraint contributes to the model overfitting (Eken (2021)). Another aspect to consider is the model's

architecture and hyperparameters, which may offer opportunities for enhancement. (Durrani *et al.* (2023)). However, it is important to recognize that exhaustively exploring every conceivable combination of structure and hyperparameters may not be practically feasible. A possible way to find the best hyperparameters involves the use of Bayesian networks for optimizing GAN parameters. This approach allows for a larger range of hyperparameters to be explored, while considering the interactions between these settings, allowing for decisions to be given with increased levels of certainty (Vrskova *et al.* (2021)). Bayesian methods have the added advantage of offering uncertainty estimates alongside predictions. The incorporation of Bayesian neural networks or probabilistic models, as noted by Luo *et al.* (2022), can assist in evaluating the confidence of predictions, thereby facilitating more informed decision-making.

### **6.5.2 Integration of Additional Data Sources for more Accurate Predictions**

Having examined improvements in training data and hyperparameters, another aspect to consider for shoreline prediction involves the inclusion of supplementary data sources. Among the models utilised, the CGAN is the best model for incorporating additional data sources. The incorporation of image labels for the specific year is important for temporal analysis; however, the addition of variables such as beach slope, wave height, sea level, and SLR, as featured in models like Bayesian approaches, could yield valuable insights into the dynamics of shoreline evolution. This expanded dataset has the potential to provide an understanding of the factors governing shoreline change.

### **6.5.3 Large Scale Predictions**

Another aspect to take into account when predicting shorelines involves the adaptability of the model across different scales. Models that solely rely on input images and time stamps or labels, such as a CGAN, can be effectively applied to larger scales since they

can accommodate shifts in patterns easily. However, when aiming for precise shoreline predictions that encompass factors such as sea level and beach slope, a localised application needs to be applied. These factors exhibit spatial variability and depend on local conditions. Attempting to apply such models on a broader scale without considering these spatial factors could prove to be challenging. This particular consideration could serve as a direction for future research in the realms of coastal and remote sensing studies.

#### **6.5.4 Potential for Incorporating other Machine Learning Techniques**

Incorporating additional ML techniques into GANs, cGANs, LSTMs, and ConvLSTMs can enhance their performance and capabilities.

One technique which might be beneficial for these models include the use of autoencoders. Autoencoders (AE) can be used for feature extraction and dimensionality reduction. An AE can be pre-trained on the image data to capture relevant features, which can then be used as input to the ConvLSTM model. This can help improve the representation learning and potentially enhance the performance of a model.

Effective training algorithms for addressing mode collapse and gradient vanishing in GANs were introduced by Tran *et al.* (2018). In their work, a generator is constrained through an AE to mitigate these issues. Where reconstructed samples from the AE are deemed as "real" samples for the discriminator. This connects the convergence of the AE with that of the discriminator, slowing down rapid discriminator convergence and mitigating gradient vanishing.

In a study by Fang *et al.* (2020), an AE was employed in conjunction with both DCGAN and LSTM architectures. In the case of DCGAN, the encoding module was used for the extraction of features from the radar image, while the decoding module was responsible



for the reconstruction of said radar image features. For the LSTM, images were input into the encoding module to extract spatial features. These extracted features were fed into the LSTM framework to facilitate prediction learning. Ultimately, the decoding module contributed to the generation of the predicted image.

### **6.5.5 Hybrid Model**

The models discussed in this chapter each have their own strengths, and there is potential to combine them for improved results. One idea is to use a GAN or CGAN to create new images and labels using training data. These newly generated imagery and labels could then be added along with the real training data as extra inputs for the ConvLSTM model. By incorporating additional data, the model's predictive capability is enhanced for predicting subsequent images in a sequence.

This combination offers several possibilities. The generated data could bring in new perspectives and variations to the training dataset, helping the model become better at recognising different patterns. The flexibility of CGANs to create samples based on specific conditions could enhance the ConvLSTM's response to different situations. Plus, using GANs or CGANs to generate new data might help when there is not enough real data available, making the ConvLSTM model more adaptable and better at making predictions. Overall, combining these different models could lead to improvements in various applications where predictive capabilities are important.

An AE could also be integrated into the framework to further enhance the model's performance. This could involve using the AE as an intermediary step in data preprocessing. The AE could be employed to capture intricate features and reduce the dimensionality of the training data. This preprocessed data, which retains the essential

characteristics while reducing noise, could then be fed into the GAN or CGAN for generating additional images and labels.

The AE could also be used to extract important features from both the original and generated data. These extracted features could then be combined with the ConvLSTM's input. Meaning the predictive accuracy of the ConvLSTM could be increased, as it benefits from the information from different sources. Incorporating an AE into this framework adds a layer of data preprocessing, and feature extraction, which could contribute to an overall enhancement of the model's capabilities. This integration not only increases the predictive power of the ConvLSTM but also aids in generating more realistic and contextually relevant data, thereby driving improved performance.

By integrating a Bayesian network into the process of hyperparameter optimization, a principled and efficient approach can be introduced. The network guides the search in a data-driven manner, leveraging probabilistic reasoning to explore the hyperparameter space more intelligently. This method not only enhances the ConvLSTM model's predictive capabilities but also streamlines the process of finding the optimal hyperparameter configuration.

## **6.6 Conclusion and Future Work**

This chapter marked the initial steps in understanding the integration of changing shoreline satellite imagery into predictive models, aimed at forecasting future shoreline changes. The models showed potential, even in the presence of constrained training data. While not all models achieved precise future shoreline predictions, their individual capacities stood out, highlighted in Section 6.5.5, which involved the generation of training data through real data-based image synthesis.

Regarding future work, a number of considerations and steps need to be undertaken:

1. **Augmentation of Training Data:** The acquisition of more training data is imperative. This can be accomplished using additional satellite imagery, employing data augmentation techniques, or resorting to image generation strategies.
2. **Hyperparameter and Model Structure Refinement:** An understanding of the influence of hyperparameters, and model structure is essential. This ensures the creation of an optimal model. Employing a Bayesian network, as outlined in the relevant section, can aid in this development.
3. **Inclusion of Supplementary Datasets:** The integration of supplementary datasets needs to be considered, including their feasibility within the existing models.
4. **Hybrid Model Incorporation:** The formulation of a hybrid model combining GAN image generation and the ConvLSTM model to predict future images is a promising avenue. This hybrid model could encompass autoencoders to further enhance its performance.
5. **Exploration of Alternative Models:** Exploring alternative and emerging models, such as LSTM-GAN or LSTM-CGAN, designed to incorporate labelled inputs, holds potential for augmenting the predictive capabilities further.

This chapter serves as a foundational step towards using changing shoreline satellite imagery for predictive modelling. Moving forward, addressing these outlined considerations, and pursuing potential advancements can significantly contribute to refining the accuracy and efficacy of the predictive models in question.



## Chapter. 7 Conclusion

The primary aim of this thesis was to investigate the ability to utilise ML and MSI analysis for extracting shorelines across various shoreline types. To this end, a novel methodology was introduced, employing a two-step classification approach utilising ML techniques (i.e. CART and ANN). The CART and ANN were applied to the two-step methodology, to automatically identify the wet/dry boundary from Sentinel-2 MSI (described in Chapter 3). The ANN approach was evaluated by comparing its performance against the results of the relatively simple CART algorithm, and the accuracy of both methods were validated against LiDAR derived shorelines and drone-based topographic shorelines. The ANN emerged as the best algorithm, consistently demonstrating superior performance in delineating the boundary between wet and dry sand across diverse shoreline types (as detailed in Chapter 4) highlighting the potential applicability of the methodology to beaches characterised by different compositions. This achievement allowed for further application of the ANN methodology to various sites, enabling the comparison of seasonal and multi-year shoreline changes. By delving into these variations, a deeper

understanding of the changing geomorphology of the beaches was obtained as it aligned with the behaviours observed from in situ and LiDAR/drone topographic data (discussed in Chapter 5). The thesis also explored future shoreline changes by testing predictive models trained on satellite-derived shorelines (detailed in Chapter 6). The results have been discussed in each chapter and the main findings of this thesis are summarised below:

### **7.1.1 Review of state-of-the-art methodologies**

- Chapter 2's primary objective was to review the methodologies used in past EO studies to map SIs using MSI data.
- The review also assessed processing technologies, such as ML and Artificial Intelligence, as potential tools for extracting diverse shoreline features across various scales from local to global.
- The review highlighted the role of SIs in coastal studies, providing a comprehensive understanding of shoreline changes. These indicators offer insights not only into land-water boundary shifts but also into broader impacts such as SLR effects on cliff erosion and dune degradation.
- No single method is universally used for extracting SIs for the entirety of global coastlines. Therefore, the review emphasised the need to explore multiple methods to identify distinct coastal indicators suited for diverse shoreline settings and scales. Local scales were found to be the most prevalent (53% of reviewed papers).
- Existing research primarily centres on extracting the instantaneous waterline SI from MSI data, which emphasizes the need for exploring additional indicators derived from MSI data.

- To broaden the ability to monitor changes across various temporal and spatial scales, it is crucial to leverage already developed SI techniques in conjunction with evolving ML technologies. Using the insights gained from available techniques and easily accessible satellite imagery, it becomes evident that there is a need to establish an automated and frequently updated global-scale shoreline change monitoring approach. This proactive method holds promise for deciphering change patterns, understanding relationships, and predicting future coastlines.
- Findings pave the way for a comprehensive understanding of shoreline change monitoring and highlight the potential of integrating advanced methodologies for more robust predictions and insights into the evolving coastal landscape.

### **7.1.2 Shoreline Extraction Methodology**

- Chapter 3 focuses on developing a methodology to automatically extract the shoreline from satellite imagery.
- Start Bay, Aldbrough, and Sizewell in the UK were chosen as study sites for their representation of diverse shoreline types, with different tidal ranges, wave exposure and sediment types. This allowed for the algorithms to be tested on different beach types so they could be applied on a larger scale in the future.
- The wet/dry boundary, representing the extent of the previous high tide, was chosen as the SI for determining shoreline positions as it is visible on MSI and its independence from tidal corrections. This allowed for examining if the wet/dry boundary was as stable as a SI regardless of tidal variations.

- Sentinel-2 satellite data was used due to its frequent revisit periods (5 days), high resolution (10 m) across 13 bands and public accessibility. The large amount of band information enabled the identification of the wet/dry boundary, even when not visible to the human eye.
- GEE provided a platform with a vast satellite imagery catalog, including Sentinel-2, allowing rapid and precise analyses without extensive data downloads.
- A two-step classification approach was employed to identify the wet/dry boundary using two ML techniques, CART and ANN. The classification initially divides the satellite image into five land cover classes (Artificial Surfaces, Agriculture, Forest, Sand, and Water) and later refines the 'Sand' class into wet and dry sand categories. This approach enables a more refined classification, free from the influence of external pixel values from other land classes.
- Validation shorelines were derived from LiDAR data for Start Bay and Aldbrough and drone-based shorelines for Sizewell. Although the validation data does not correspond to the same acquisition date as the satellite images, satellite images captured within 6 months of LiDAR and drone surveys were used for validation.
- Uncertainty analysis was conducted using statistical metrics such as RMSE, MAE, and SD to evaluate the accuracy and uncertainties associated with the extracted shorelines compared to validation data.
- The DSAS tool was employed to compare shoreline changes over time and quantify erosion or accretion rates using EPR and NSM. This allowed for an appropriate and accurate analysis of the output shorelines.



### 7.1.3 Shoreline Extraction

- Chapter 4 focused on assessing two supervised machine learning algorithms, CART and ANN, to accurately identify the wet/dry shoreline boundary using Sentinel-2 satellite imagery. Performance evaluation involved comparing the CART and ANN algorithm shorelines against validation waterlines derived from LiDAR and drone-based topographic shorelines.
- Results consistently show that the ANN algorithm outperformed the CART algorithm across all study sites. The challenge lies in precisely detecting the wet/dry boundary without encountering issues of model overfitting or underfitting.
- The CART algorithm faced difficulties due to sensitivity to depth level variations, leading to overfitting or underfitting. In contrast, the ANN algorithm exhibited stable performance with no visible overfitting issues.
- The ANN algorithm effectively extracted the wet/dry boundary from Sentinel-2 data, with a high accuracy at Start Bay ( $\pm 2.15\text{m}$ ), Aldbrough ( $\pm 10.67\text{m}$ ), and Sizewell ( $\pm 3.56\text{m}$ ).
- The results in Chapter 4 highlight that the wet/dry boundary can be successfully extracted from Sentinel-2 data and that the two-step classification process proves crucial for the identification of the wet/dry boundary and for improved accuracy in results.
- The extraction of the wet/dry boundary was successful on three different beach types, creating possibility of applying the methodology further on different shoreline types with different compositions.

#### **7.1.4 Shoreline Analysis on Diverse Shoreline Types**

- Chapter 5 examined shoreline changes at three distinct coastal locations: Start Bay, Aldbrough, and Sizewell, using Sentinel-2 MSI and wave data. The main objective was to determine if the wet/dry boundary line could reliably indicate short- and long-term shoreline changes.
- Start Bay analysis over 5 years indicated sediment movement landwards at Slapton Sands, Beesands, and Hallsands, while Blackpool Sands experienced sediment buildup due to south-southeast wave direction.
- The seasonal analysis aligned with Wiggins et al. (2019) findings in showcasing wave direction's influence on shoreline changes and sediment transport at specific time frames.
- Aldbrough displayed a recurring pattern of sediment moving southeast, leading to cycles of erosion and accretion likely influenced by natural cliff erosion and sediment transport.
- Deeper insights into Aldbrough's shoreline geomorphology could be gained by comparing cliff erosion with beach sediment input. To investigate the presence of a relationship between these two factors.
- Sizewell results showed a dynamic shifting shoreline position (patches of erosion and accretion) in different locations at different times, which is in line with current literature, and with an average seaward movement of 11.42 m over the study period. The changes at Sizewell were attributed to sediment movement rather than net erosion/accretion trends.
- Chapter 5 demonstrated the potential of the wet/dry boundary line as a SI for tracking shoreline changes. Overall, the chapter enhances the understanding of

coastal dynamics at the studied sites and suggests promising avenues for coastal research and management.

### **7.1.5 Future Shoreline Prediction**

- Chapter 6 marked the initial step in comprehending the integration of shorelines derived from satellite imagery into predictive models, aimed at predicting future shoreline changes from satellite MSI.
- Four models were tested for future image prediction, including GAN, CGAN, LSTM, and ConvLSTM. Their selection was based on their capacity to provide diverse perspectives on their performance when presented with satellite imagery as input.
- These models displayed promise, even when provided with limited training data. The ConvLSTM model, in particular, delivered the best results and successfully generated the following sequence of images.
- While not all models achieved the best predictions of future shorelines, their individual capabilities were shown. This chapter serves as the foundational cornerstone for incorporating evolving shoreline satellite imagery into predictive modelling.

## **7.2 Limitations and recommendations for future work**

### **7.2.1 Model Training**

It is important to note that training the ANN and CART models to achieve optimal classification performance encountered certain challenges. One obstacle was the difficulty in determining the precise moment when the model reached its peak accuracy. This uncertainty surrounding the model's optimal state impacted the training process. To

address this, an iterative strategy was employed to navigate the complexities of parameter settings and fine-tuning iterations. However, this approach itself introduces a limitation, as it does not offer a definitive guideline for pinpointing the ideal configuration. This limitation highlights the intricacies involved in model parameter tuning and the potential for subjectivity in the decision-making process. Further refinement is needed to ensure optimal results are achieved, minimising the risks of overfitting or underfitting the data. An additional factor demanding attention is the size of the input data, as this could influence the accuracy outcomes.

### **7.2.2 Misclassification**

In Chapter 4, a notable constraint has emerged due to the influence of whitewater caused by breaking waves, which has resulted in a distortion of the extracted shoreline, shifting it seaward and introducing an element of uncertainty into the obtained results. To mitigate this challenge, a potential solution could involve introducing an additional classification category, such as 'white water,' into the classification processes outlined in Chapter 3. This adjustment has the potential to further refine the accuracy of shoreline identification by accommodating this distinct feature.

### **7.2.3 Validation Data**

The limitations surrounding to the validation data used in Chapter 4 stem from the temporal misalignment between the LiDAR and drone data used for generating validation data and the dates of shoreline extraction. This temporal disparity introduces uncertainties, given the potential for rapid changes in beach morphology over short intervals. Consequently, there is a risk that the validation data may not accurately reflect the actual beach conditions at the time of shoreline extraction. Nevertheless, it is important to acknowledge that these sources of data were the only ones accessible, and it

is worth noting that these sources offered a substantial volume of data, which enhanced the overall comprehensiveness of the analysis.

#### **7.2.4 Wet/Dry Boundary Line**

The discussion in both Chapter 4 and Chapter 5 underscores the presence of errors and uncertainties associated with the extraction of the wet/dry boundary line. This boundary, which marks the farthest reach of the tide, is dependent upon the specific timing of the image capture. If the image is taken shortly after high tide, the wet/dry boundary becomes distinct. However, as time elapses after the last high tide, there is a potential for the boundary line to shift seaward, although this needs further investigation to validate its extent. It is worth noting that within the studied sites, this issue only presents a concern at Aldbrough. Both Start Bay and Sizewell have tidal extents that are closely aligned with a single pixel of the Sentinel-2 image, minimizing the impact of this particular uncertainty. Incorporating tidal data and automated high/low tide identification would enhance the wet/dry boundary applicability in this sense and for broader-scale use.

#### **7.2.5 Applications to Larger Scales and different Shoreline Types**

In this study, three distinct trained models were needed to understand changes at the three sites, instead of employing a single model for all sites. While considering its application to large-scale studies, a potential challenge arises due to the absence of a universally applicable model for all shoreline types. However, a likely solution could involve an additional step or model that identifies beach or shoreline types, as demonstrated by Payo *et al.* (2020). This model could then guide the application of tailored models for different beach types. Notably, the models trained for individual sites in this thesis effectively identified shorelines, showcasing their ability despite being separate entities. This

highlights the potential for a more adaptable and systematic approach to shoreline analysis on a larger scale.

### **7.2.6 Prediction**

In Chapter 6, the focus is using a predictive ML model for shorelines using MSI. Although the tested models did not yield significant success, they did offer some promising insights. During the testing of these models, a few limitations became evident. First, the acquisition of more training data is crucial. This can be achieved through additional satellite imagery, employing data augmentation techniques, or adopting image generation strategies. Second, an understanding of how hyperparameters and model structure impact results is vital to develop optimal models. Leveraging a Bayesian network can assist in this improvement with the integration of supplementary datasets. Thirdly, developing a hybrid model by combining GAN image generation and the ConvLSTM model for predicting future images, with the incorporation of autoencoders could further improve performance. And finally, exploring other models like LSTM-GAN or LSTM-CGAN, engineered to incorporate labelled inputs, could augment the predictive ability further.

## **7.3 Final Remarks**

The methodology employed in this thesis represents a significant step towards understanding historical and future shoreline changes. Through this approach, it becomes evident that quantifying waterlines across diverse coastal types presents a considerable challenge. The idea of a universally applicable model is challenged as it becomes evident that a one-size-fits-all approach is not feasible without taking into consideration the characteristics of each shoreline setting. This emphasises the complex nature of shoreline analysis and highlights the importance of tailoring methodologies to the unique attributes of each coastal setting.

For coastal scientists, an important aspect revolves around the ability to compare shorelines, thereby enhancing the understanding of the shoreline position and dynamics. Although datum-based shorelines have traditionally served this purpose, there has been a surge in the utilisation of satellite-derived shorelines and shoreline proxies, with the availability of MSI, which identifies observable shoreline characteristics. This aligns with the expanding availability of satellite imagery that holds increasing potential for future research studies.

Another advancement for coastal studies is the ability to employ ML models and Deep Learning models, such as CNNs, without incurring substantial computational expenses. These models possess the capability to integrate diverse data sources, facilitating training and comprehension of coastal dynamics. This has allowed for a more universal approach to leveraging various data types and enabling a better understanding of coastlines and their behaviour.

Another advancement also involves the expansion of datasets. The act of labelling data conventionally involves a labour-intensive, and manual procedure. With supervised ML relying on access to labelled training data, Goldstein *et al.* (2021) created an online platform that presented a collection of images along with a set of questions to human-curated labellers. This approach allowed for the labelling of 1,600 images, with participation from two to seven coastal scientists. This streamlined process of image labelling could potentially be the way forward for generating mass amounts of data for training ML models in the future.

In summary, there has been great advancements through the combination of remote sensing and image classification techniques, offering a pathway to generate satellite-

derived shorelines for future predictive endeavours. As shown in Chapter 6, an array of models have been considered to forecast shoreline changes. With the wealth of satellite imagery, a continuously expanding collection of training data becomes available, strengthening the development of these predictive models. However, these models should extend beyond imagery alone. The integration of data, such as tidal information, wave data, and beach characteristics, is vital to understanding future shoreline changes. The accessibility of such data sources online is advantageous and increases the predictive capacity of these models. The creation of a predictive tool tailored to predicting future shoreline changes can highlight critical areas vulnerable to risk, thereby promoting informed decision-making for protection measures.

The development of such a methodology is significant within the coastal community. By harnessing the potential of remote sensing and advanced ML techniques this approach is an invaluable resource to address challenges concerning coastal dynamics, ultimately paving the way for more effective coastal management and preservation efforts.



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**Appendix A: Visualizing Temporal Change Across Scales and Associated ML Techniques. Diagrams created for McAllister et al. (2022).**

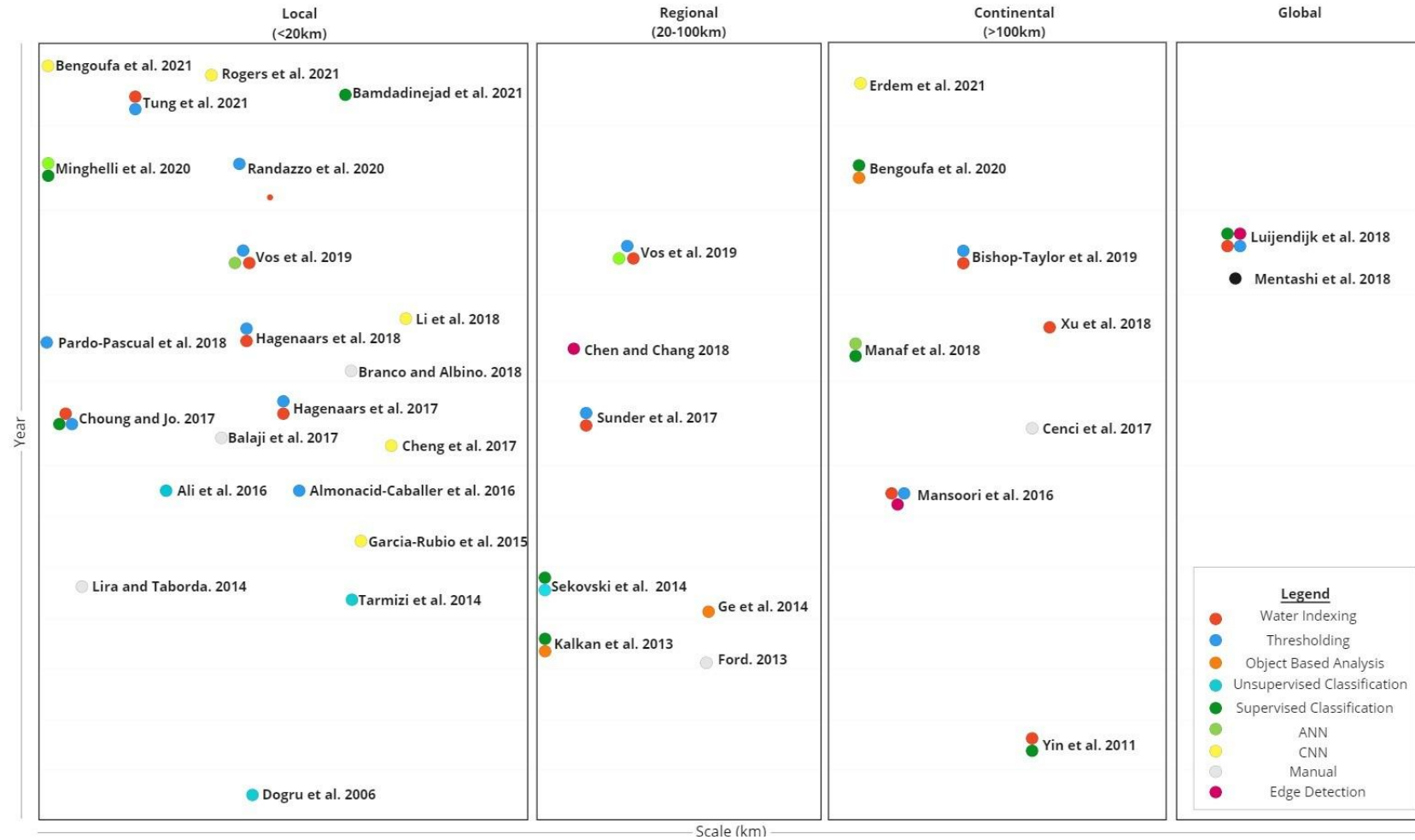


Figure 1: Temporal scale of studies produced for shoreline extraction using MSI between 2006 – 2021.

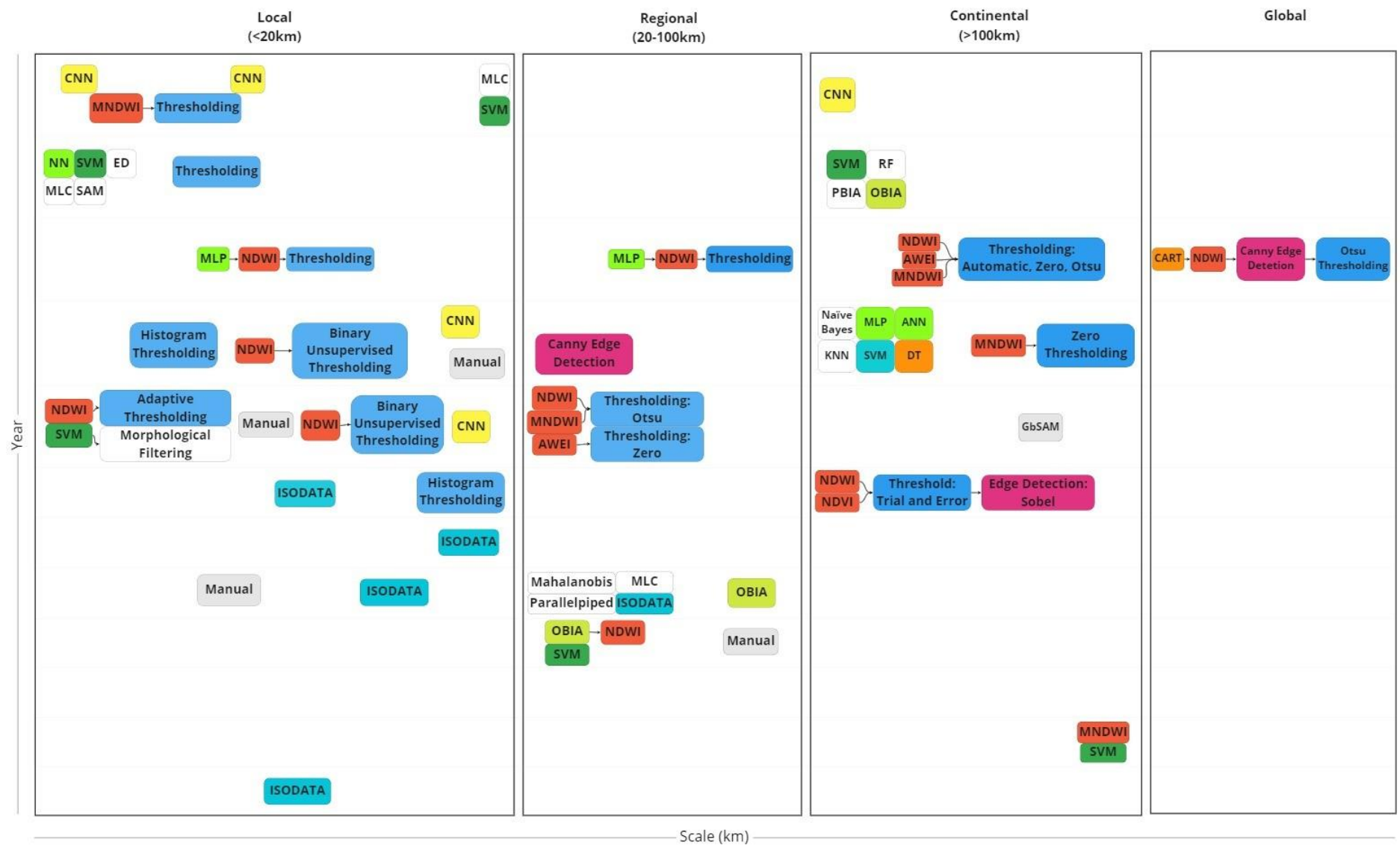


Figure 2: The techniques applied for shoreline extraction over scale (km) and time (years).

## Appendix B: Validation and Extracted Shorelines

Table 1: Table showing the dates of LiDAR and Drone shoreline acquisition, aligned with nearest extracted shoreline dates.

| LiDAR and Drone Capture Date |            | Extracted Shoreline                                                   |                                                         |
|------------------------------|------------|-----------------------------------------------------------------------|---------------------------------------------------------|
|                              |            | ANN                                                                   | CART                                                    |
| CCO                          | Start Bay  |                                                                       |                                                         |
|                              | 27/04/2017 | 25/01/2017,<br>25/05/2017                                             | 25/01/2017                                              |
|                              | 12/09/2018 | 05/05/2018                                                            | 05/05/2018                                              |
|                              | 14/09/2018 | 27/09/2018<br>22/10/2018                                              | 27/09/2018                                              |
|                              | 21/04/2019 | 24/02/2019<br>07/04/2019                                              | 24/02/2019                                              |
|                              | 20/09/2020 | 04/04/2020,<br>23/06/2020,<br>13/06/2021,<br>6/09/2021,<br>25/11/2021 | 25/03/2020,<br>29/05/2020,<br>23/06/2020,<br>21/10/2021 |
| BGS                          | Aldbrough  |                                                                       |                                                         |
|                              | May-2018   | 05/05/2018<br>07/05/2018<br>27/05/2018                                | 05/05/2018<br>07/05/2018                                |
|                              | Sep-2018   | 24/10/2018                                                            | 24/10/2018                                              |
|                              | Sep-2019   | 25/08/2019<br>17/10/2019<br>27/10/2019<br>10/01/2020                  | 17/10/2019<br>27/10/2019                                |
|                              | Jun-2020   | 21/04/2020<br>29/05/2020<br>25/06/2020                                | 29/05/2020                                              |
| CEFAS                        | Sizewell   |                                                                       |                                                         |

|  |            |                                                                    |                                        |
|--|------------|--------------------------------------------------------------------|----------------------------------------|
|  | 08/06/2018 | 07/01/2018<br>09/01/2018<br>07/05/2018<br>17/05/2018<br>22/05/2018 | 07/01/2018<br>07/05/2018<br>17/05/2018 |
|  | 24/07/2018 | 31/07/2018<br>12/08/2018                                           |                                        |
|  | 17/04/2019 | 17/01/2019<br>11/02/2019<br>05/03/2019<br>04/04/2019               | 05/03/2019<br>04/04/2019               |
|  | 28/10/2019 | 13/11/2019                                                         |                                        |
|  | 07/05/2020 | 19/01/2020<br>06/02/2020<br>28/05/2020<br>31/05/2020               | 19/01/2020<br>28/05/2020               |
|  | 20/08/2020 | 30/07/2020<br>18/09/2020                                           |                                        |
|  | 16/04/2021 | 22/03/2021<br>21/04/2021<br>16/04/2021                             |                                        |
|  | 14/05/2021 | 31/05/2021                                                         | 31/05/2021                             |
|  | 24/06/2021 | 17/07/2021                                                         |                                        |