Predicting morphological changes along a macrotidal coastline Using a Two-Stage Machine Learning Model

Pavitra Kumar[1*] and Nicoletta Leonardi[1]

[1]Department of Geography and Planning, School of Environmental Sciences, University of Liverpool, Chatham Street, Liverpool, L69 7ZT, UK

* Corresponding Author: pavitra.kumar@liverpool.ac.uk

Abstract: Within the context of climate change, understanding and predicting coastal change is of the foremost importance to protect coastal communities and coastal assets. This study analyzes field data from 125 locations along the Morecambe coastline, consisting of beach transects collected twice a year for more than a decade (2007 to 2022). To model the sediment volume changes observed along the Morecambe coastline, this study proposes a two-stage machine learning model that incorporates beach behavior classification and deep learning techniques to predict changes in sediment volumes along coastal environments. The first stage of the model, developed using a random forest classifier, classifies beach behavior into four categories: eroding, accreting, stable, or undergoing short-term fluctuations. The second stage of the model developed using LSTM and sequence-to-sequence models, uses the output of the first stage to predict the available sediment volume after erosion/accretion. LSTM model achieved a testing regression of 0.9961 for one-step-ahead (6 months) predictions of sediment volume time series, while sequence-to-sequence model achieved the testing regression of 0.9950 for three-time-ahead (1.5 years) predictions and 0.9916 for ten-time-step-ahead (5 years) prediction.

Plain Language Summary: This study investigates how coastlines change over time, especially as the climate changes. We focused on the Morecambe Bay in England and analyzed data collected over 16 years from 2007 to 2022. Artificial intelligence models were

developed that learn from beach data to predict if a beach will erode (wash away), grow bigger, or stay the same. These models work in two steps: first, it figures out if the beach is eroding (wearing away), growing, staying the same, or changing in small bursts. Then, it uses that information to predict how much sediment a particular beach location will be there in 6 months, 1.5 years, or even 5 years from now. These models are capable of accurately predicting beach behavior and sediments available, especially for short-term predictions. This information can help protect coastal towns and areas from the effects of climate change.

Keywords: Sediment volume; Morecambe Bay; Two-stage modeling; Random Forest; LSTM; Sequence-to-sequence

1. Introduction

Dynamic coastal processes continuously shape the coastline and understanding coastal dynamics is important to protect coastal communities and coastal infrastructures. Waves, tidal energy and sediment availability determine sediment transport and morphological variations but anthropogenic activities can also accelerate the rate of coastline change (Prasad & Kumar, 2014; van Rijn, 2011; Williams et al., 2018). Over the years, more and more infrastructures have been built along the coastline. Coastal erosion causes the coastline to retreat inland. The removal of sediments from infrastructure locations can expose their foundations, reducing their strength and stability, and making them unsafe. With sea level rise and changes in storms activity, there is increased uncertainty about the risk of erosion, flooding and on whether the project lifetime of these infrastructures will prove adequate to withstand the challenges posed by climate change.

Several soft nourishment and hard structures are designed to address coastal erosion problems. Soft nourishment includes, for instance, shoreface nourishment (beach fills) (Kumar & Leonardi, 2023b, 2024a) and submerged reefs (Harris, 2012), while hard structures include groins (Lima et al., 2020), detached breakwaters (Browder et al., 2015), seawalls

(Betzold & Mohamed, 2017), and revetments (Crawford et al., 2020). To be effective, these engineering solutions must be installed at identified vulnerable locations. Historic erosion and deposition data as well as predictive models can be used to identify such locations, specifically those that can be classified as having long-term chronic erosion or short-term fluctuating erosion trends. For instance, if an area of interest experiences substantial sediment loss over 5-10 years, it can be considered to have long-term chronic erosion and thus requires erosion protection measures (van Rijn, 2011).

Machine Learning and predictive models such as artificial neural networks (ANNs) can be useful for nonlinear forecasting of coastal change (Kumar and Leonardi, 2023 a, b). These can be especially helpful when long-term morphodynamical models are not available or prove to be too computationally expensive. Historic data, whether from remote sensing or direct field campaigns can also be used to feed into the ANN models and identify erosion prone areas to support coastal management.

ANN models are information processing systems modelled on the structure of the human brain (Anctil et al., 2009; Sharma et al., 2003) and effective in dealing with nonlinearities (Farzad & El-Shafie, 2017) and have been successfully applied to other coastal engineering problems. ANN models can learn the nonlinear relationships between the different variables that influence coastal erosion, making them well-suited for modeling this complex process. ANN models can even learn dependencies that process-based models fail to capture. Several researchers have developed models to predict coastal erosion, including Peponi et al. (2019), Corbella and Stretch (2012) and Adamo et al. (2014). Peponi et al. (2019) integrated geographic information systems (GIS) with ANN to predict erosion-prone areas at the coastal zones of Costa da Caparica in Lisbon, Portugal, in the near future. They mainly considered anthropogenic inputs from GIS, such as the number of residents, land cover, number of households, and vegetated and non-vegetated areas, to predict erosion-prone areas using ANN. Corbella and Stretch (2012) and Adamo et al. (2014) used process-based models to estimate coastal erosion. Corbella and Stretch (2012) used the SBEACH, XBEACH, and Time Convolution models to estimate coastal erosion trends at coastal areas of Durban, South Africa. Adamo et al. (2014) used directional wave spectrum and direction of wave propagation to estimate coastal erosion and used this it to estimate shoreline change.

This study proposes a combination of two prediction models to classify beach profiles based on their trends in morphological changes and to predict time series of morphological trends. Specifically, the objectives of this study are: 1) Utilizing high-quality field measurements from Morecambe Bay coastline, this study aims to harness real-time beach transect data for a comprehensive analysis. The primary goal is to construct a robust random forest classifier model that can accurately predict the long-term behavior of the coastline, categorizing it into erosion, accretion, stability, or short-term erosion fluctuation. 2) Focusing on the significant field measurements, this research seeks to advance predictive capabilities by developing a cutting-edge Long Short-Term Memory (LSTM) and sequence-to-sequence model. The central objective is to forecast the volume of sediment erosion or accretion at specific locations, further enhancing our ability to comprehend and anticipate coastal morphological changes.

Continuous field campaigns were conducted from 2007 to 2022 to collect beach profiles using GS16 Leica antenna and a Leica CS20 handset at 125 locations along Morecambe Bay. Simulation data, including coastal parameters such as wave height, wave direction, wave velocity, and coastline composition are obtained from a hydrodynamic model built using Delft3D and were fed along with historical data into the ANN models. The manuscript is organized as follows: After presenting the study site, the methodology section details the field data collection methods, hydrodynamic modeling techniques, machine learning models employed, and performance criteria used to evaluate the models' effectiveness. The results section then presents the analysis of the gathered field data and model performance. Following this, the discussion section delves into the literature on coastline change in Morecambe Bay and explores the applicability of the developed models in this context. Finally, the conclusion section summarizes the study, highlighting key findings and implications.

2. Study Site

Morecambe Bay, a macrotidal embayment in northwest England, is the test case of this study. Its shoreline is mostly covered in fine sand, and the bay opens southwest into the Irish Sea (Mason et al., 2010). Intertidal zones, especially sandbanks and subtidal channels, are highly susceptible to change, and these changes can be observed even within a single season. The fetch length is constrained by landmasses such as Ireland and the Isle of Man. As a result, significant wave heights at the bay mouth reach up to 2 meters for only about 10% of the year, remaining around 0.5 meters for the rest of the year. Morecambe Bay has a large ordinary spring tidal range of approximately 8.2 meters and its subtidal channels experience maximum spring tide velocities of about 1.5 meters per second (Mason et al., 2010). During the 1991–2007 study period, Mason et al. (2010) found that the bay experienced significant sediment movement from below mean sea level to above mean sea level. This erosion and accretion caused the mudflat to retreat towards the landmass. Due to its dynamic behavior and significant sediment movement, this bay was selected for this study.

3. Methodology

3.1 Field Data

Sefton Council (Sefton MBC, UK) provided a dataset of beach transects at 139 locations along the Morecambe Bay coastline, collected mostly between 2007 and 2022.

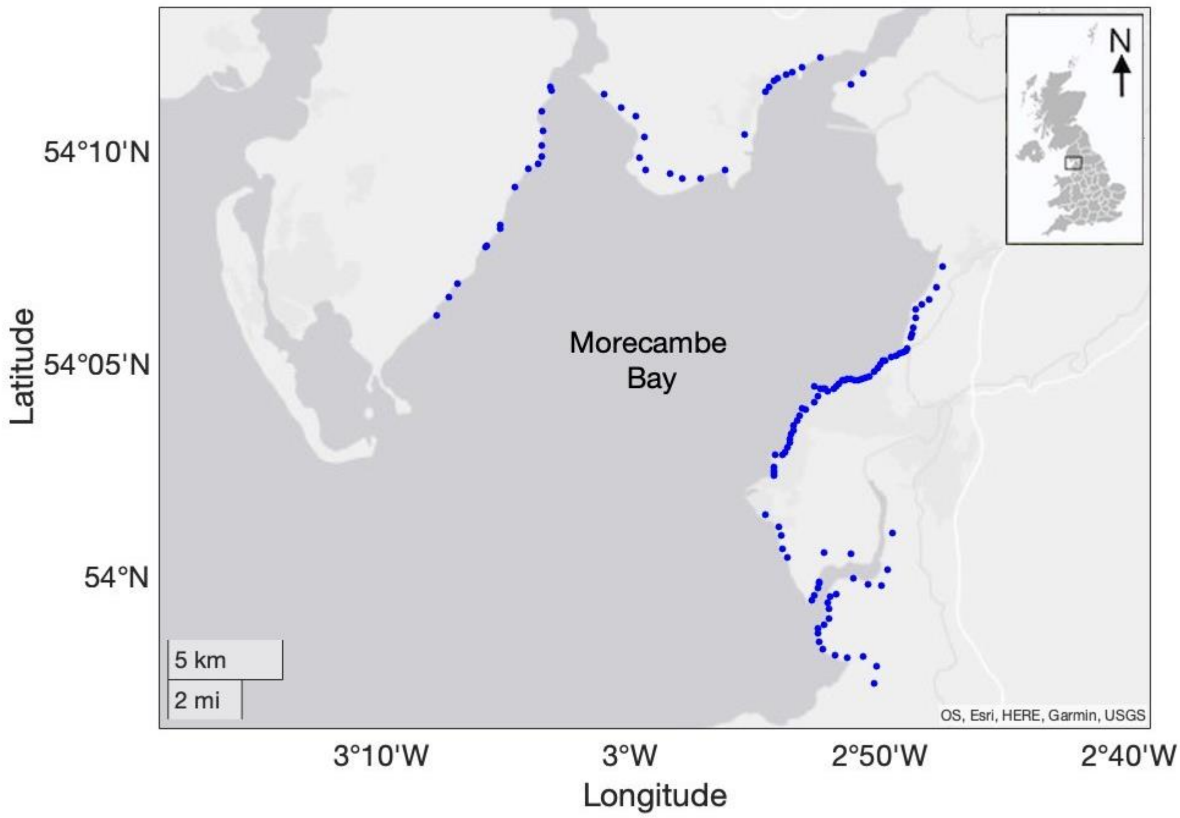

Fig 1. Location of data measurement sites (blue dots) along Morecambe coastline

The raw data from Sefton Council consisted of beach transects of varying lengths, measured twice a year (spring and autumn) from 2007 and 2022 using GS16 Leica antenna and Leica CS20 handset. The dataset was corrected in post processing using Lecia Infinity software with an accuracy of Hz 3 mm + 0.1 ppm/ V 3.5 mm + 0.4 ppm. Locations with two or fewer transects in time and those outside Morecambe Bay were discarded, leaving 125 locations with an average of 22 transects per location (Figure 1). Some of the transect had varying length from year to year. To address this, the data were pre-processed and missed datapoints were filled with the interpolated data from the three previous transects (e.g., if part of the Autumn 2019 transect was missed, the missed section was filled through the average of the 2019 (Summer) and 2018 (spring and autumn) values (see S1 for extended explanation and table for this)). The raw data for all locations is available through Kumar and Leonardi (2024b) and the raw data and interpolated transects are presented in supplementary file S1. This interpolation was needed for around 20% of the transects (591 out of 2883). At few locations, there were intervals in the transect data where measurements were taken with gaps in time. As presented in this file, these time gaps predominantly occurred in 2013 and 2015 at 54 locations. Moreover, for 22 locations where the initial profile was measured in 2007, there was a significant gap between 2008 and 2012. After calculating the volume of sand at each location using the area under the curve method, which provided volumes in cubic meters per meter of beach width, the sediment volumes during these missing time gaps were interpolated using spline curves. For locations with notable time gaps between 2008 and 2012, the transects from 2007 and 2008 were excluded, enabling the transect time series to commence from 2012. A total of 256 profiles were interpolated to effectively complete the time series from 2010 to 2022 with two transects per year.

3.2 Hydrodynamic modelling

To obtain localized wave data, we simulated the hydrodynamic in Morecambe Bay using Delft3D. From the hydrodynamic model, we extracted wave height, wave velocity, and wave direction at each transect location. Details about the model setup and model validation can be found in Kumar et al., 2023a, b.

The model was calibrated using wave buoys at Morecambe Bay at Cleveleys and Heysham. To model realistic waves, we downloaded real-time wave data for the Cleveleys buoy station for the year 2022 from open source catalogue of coastal monitoring https://www.coastalmonitoring.org/realtimedata/?chart=104&tab=download&disp_option=. We applied this wave data to the sea boundary of the simulation domain. The model grid had a variable resolution, from 120×130 m onshore to 1000×300 m offshore. The simulation domain extended 57 km along the coastline and 20 km across, with a maximum distance from the sea boundary of 50 km. Wave and tide forcings were applied at the sea boundary, and a Neumann condition was applied at the lateral boundaries to allow wave energy to propagate freely. Real-time wave forcings were obtained from the Cleveleys buoy station for 2022. The model was run for 5 days, with a time step of 1 minute, from January 1st to 5th. Morphology was not updated during the simulation, as the focus was on obtaining localized wave height, wave velocity, and wave direction. Modeling results were recorded every 10 minutes at observation points regularly spaced, at a distance of about 150 m, along the coastline and at a distance of about 500 m away from the starting point of beach transect measurement, which are usually on the landmass. This distance was chosen to ensure that the observation points are in the sea or in intertidal zone, allowing for a sufficient duration of water exposure for the collection of wave data. Most of the transects intersect with these observation points. The 125 observation points nearest to each location were then selected from these observation points.

The coastline angle at each location was obtained using QGIS software, and the coastline was visually assessed using Google Earth based on vegetation presence to classify it as sandy, marshy (when vegetation is present across the whole transect), or marshy with mudflat. For some marsh areas, the length of transects were within the marshy area, so they were classified as marshy. For other locations, the length of transects were measured beyond the marshy areas into the mudflat, so they were classified as marshy with mudflat.

3.3 Machine Learning modelling

The preprocessed and simulation data were combined to match the selected 125 locations and fed to the predictive models. Two predictive models were developed:

- Model A1 was developed to classify beach behavior as erosion, accretion, stable, or short-term fluctuation based on wave direction, wave velocity, coastline angle, and coastline composition.
- Model A2 to predict the available volume of sediment after erosion/accretion based on wave height, wave velocity, beach behavior (output of Model A1), and historical changes in sediment volume.

Model A1 is a random forest (RF) classifier. Model A2 is based on LSTM and sequence-to-sequence models. The methodology flowchart is presented in Figure 2.

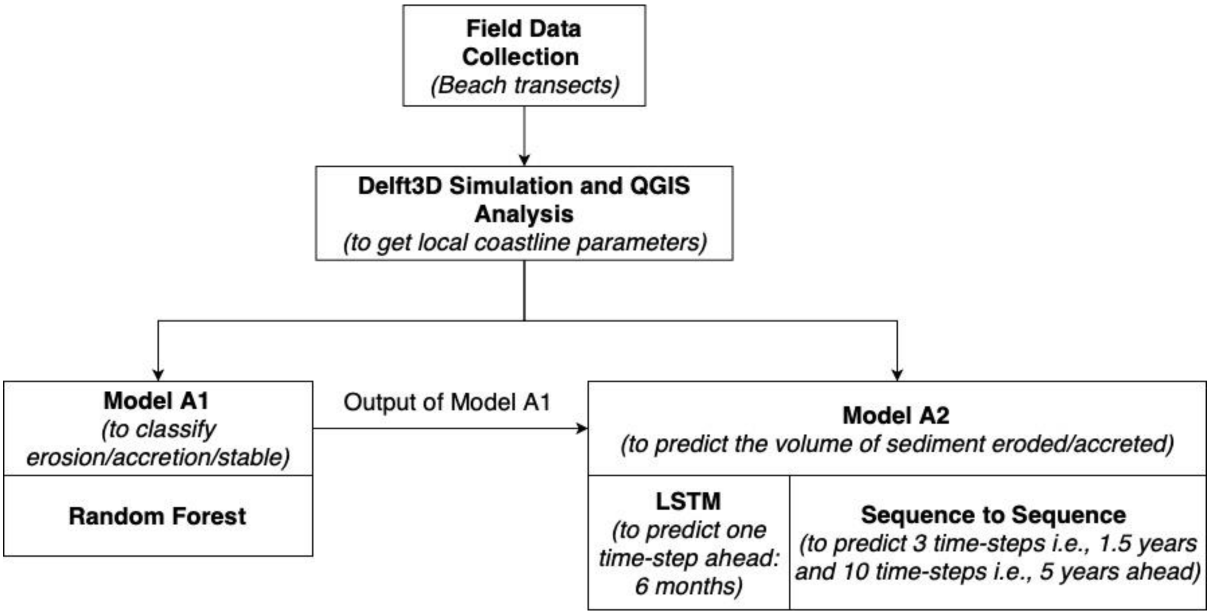

Fig 2. Flow chart of methodology

3.3.1 Model A1

As shown in the methodology flowchart (Figure 2), field data and modelling data are fed into Model A1, which classifies beach behavior as long-term erosion, accretion, stable or short-term erosion fluctuation based on wave direction, wave velocity, coastline angle, and coastline composition. A random forest (RF) classifier was used to classify beach behavior. RF is a machine learning algorithm that builds an ensemble of decision trees to make predictions. Decision trees are hierarchical classifiers that learn rules based on the values of input variables. RF improves the performance of decision trees by averaging the predictions of the trees, which reduces the variance of the model and makes it more robust to noise in the data. RF can be used to solve both classification and regression problems. In classification problems, the outcome is typically determined by the majority vote of the trees in the ensemble, while in regression problems, the average of the predictions of the trees in the ensemble is used. RF models are trained by resampling the training data using bootstrap sampling (Pham et al., 2022; Wei et al., 2022) or bagging (Rodriguez-Galiano et al., 2015). These methods create multiple training datasets by randomly sampling the original data with or without replacement. Training each tree on a unique subset of the training data helps to reduce the correlation between the trees (Rodriguez-Galiano et al., 2015). This is because some data points may be present in multiple subsets, while others may be excluded from all subsets. This reduced correlation makes the model more robust to variations in the input data and improves its predictive accuracy (Breiman, 2001).

The problem for this study was to train a RF model for multiclass classification on the MATLAB platform. Ensemble aggregation methods tried for this model were bagging, AdaBoostM2 (adaptive boosting for multiclass classification), LPBoost (linear programming boosting), RUSBoost (random undersampling boosting), and TotalBoost (totally collective boosting). Tree pruning was allowed based on the error. The number of trees tested was 50, 75, and 100.

The inputs consisted of coastline angle (radian), wave direction (radian), and coastline composition (sandy, marshy, and marshy with mudflat), which was fed as categorical input. The target was classification of coastline behavior (long-term erosion, accretion, stable, and short-term erosion fluctuation), which was also fed as a categorical parameter. The output of Model A1 was used as input to Model A2 to provide a prediction of the available volume of sediment.

3.3.2 Model A2

To develop Model A2, we tested two models: LSTM and sequence-to-sequence (S2S), both of which were built using LSTM cells. LSTM is a type of recurrent neural network (RNN) that is commonly used for modeling time series data. LSTMs are designed to learn long-term dependencies in time series data by selectively storing important information and discarding unimportant information through different gates. These models were developed to address the problems associated with RNNs, which have difficulty learning long-term dependencies due to gradient explosion and gradient vanishing (Kumar et al., 2023; Lindemann et al., 2021; Sun et al., 2022). Unlike feed-forward neural networks (FFNNs), RNNs allow for feedback of data back to the hidden layers, which creates a time lag effect that helps the model learn from previous time steps (Aslam et al., 2020). LSTM models can learn long-term dependencies in time series data using the gating mechanism in it. Kumar and Leonardi (2023a) provide a detailed discussion of the gating mechanism of LSTM models.

3.3.2.1 LSTM model

LSTM model was developed to predict sediment volume one time step ahead where each time step in the transect data corresponds to 6 months. The network consisted of a feature input layer, a sequence input layer, a sequence unfolding and folding layer, LSTM layers, and two fully connected layers followed by a regression layer. The feature input layer received feature inputs such as wave height, wave velocity, and coastline behavior (categorical). The sequence input layer received the previous three-time steps, equivalent to 1.5 years of sediment volume as its input. These feature and sequence inputs were combined at each time step using sequence unfolding and folding layer before feeding it to LSTM cells. The network was created and trained on a MATLAB platform. The number of LSTM layer tested were 3 and 4, each with 5, 10, 15, or 20 nodes. The cell weights were initialized using the He initializer. The cell state and hidden state of each layer were connected to the next layer in the sequence. This interconnection between cells allows LSTMs to capture and propagate information over time steps, which is crucial for modeling sequential data effectively.

3.3.2.2 Sequence-to-Sequence (S2S)

Sequence-to-Sequence (S2S) model S2S model was developed, in this study, to predict volume of sediment three-time step, i.e., 1.5 years, ahead based on the previous three-time step of volume of sediment time series and feature inputs. The S2S model consists of an encoder layer, which extracts information from the input data (Tang et al., 2016), and a decoder layer, which generates the output data based on the learned states (Kim et al., 2020). The encoder and decoder layers of the S2S model were implemented using LSTM layers (LSTM cell in figure 3), with 6 layers in the encoder and 3 layers in the decoder (Figure 3). All feature and sequence inputs, as discussed above for the LSTM model, were fed to the corresponding LSTM layers of S2S model. The cell state (C) and hidden state (H) of each layer were connected to the following layer in the network. The C, H, and output of the last LSTM layer in the encoder were connected to the LSTM layers in the decoder, as shown in figure 3. The output of each layer in the decoder was connected to regression layer, which provided the output of the next three-time steps of sediment volume. The sequence input and target were selected using the sliding window technique, as illustrated in Figure 3. Time steps t-3, t-2, and t-1 were used as input to predict time steps t, t+1, and t+2. For the model predicting 10-time step ahead, this network structure was extended by adding more LSTM cells, along with their fully connected layer, in decoder to accommodate ten time steps from t to t+9. The number of nodes of each LSTM layers tested, in this study, varied from 5 to 50. The model architecture was manually assembled, and its connections were managed manually. The model was trained using a custom training loop on the MATLAB platform.

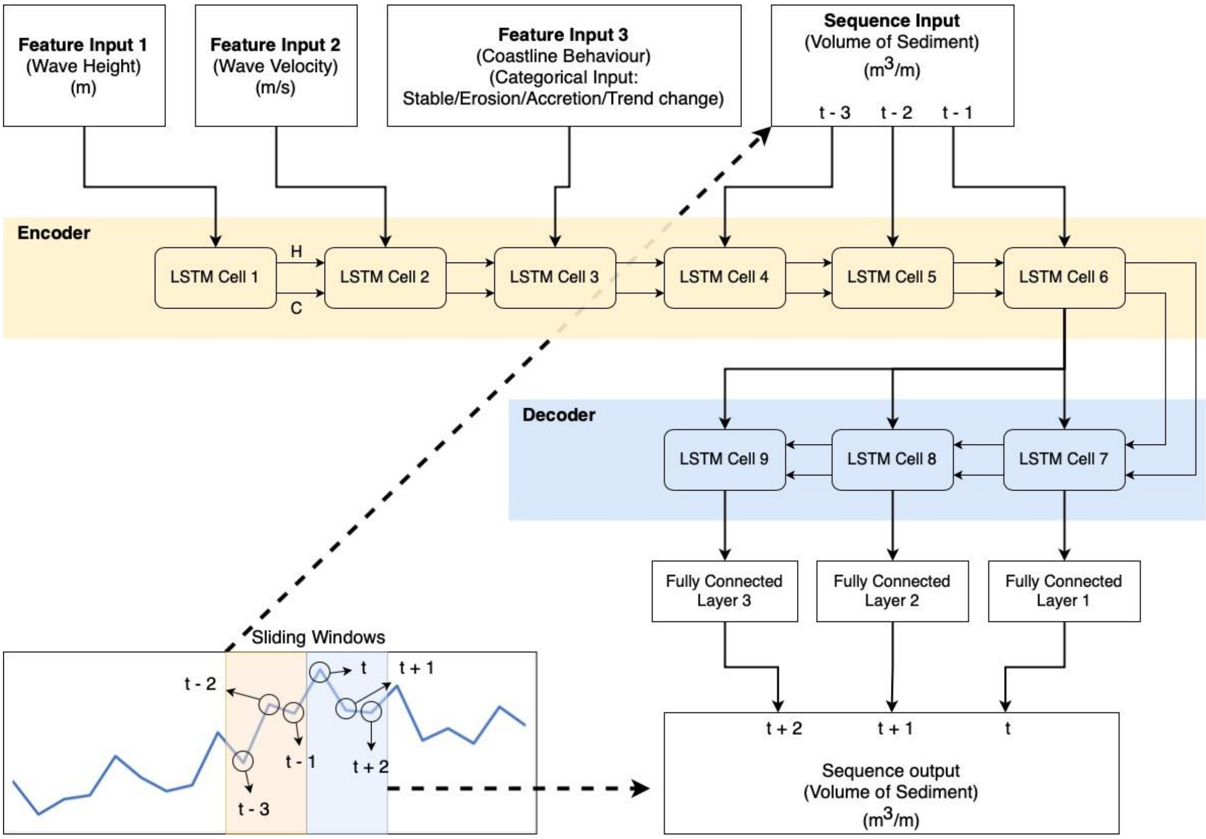

Fig 3. Model A2 structure

3.4. Performance criteria

This study utilizes both classification and regression models. The RF classifier performs multi-class classification between four categories, while the LSTM and S2S models perform regression prediction of time series. The prediction performance of both models is evaluated using different criteria. Accuracy, precision, recall, and F1 score were used to assess the performance of the RF classifier model, while regression mean absolute error (MAE) and Nash-Sutcliffe efficiency (NSE) were used to assess the performance of the LSTM and S2S models.

Accuracy measures the model's ability to correctly classify a given observation (equation 2). Precision measures the proportion of observations classified as positive by the model are actually positive (equation 3), indicating how reliable the model is for positive classifications. Recall measures the model's sensitivity by calculating the percentage of items actually present in the input that were correctly identified by the model (equation 4). F1 score measures the weighted harmonic mean of precision and recall scores (equation 5).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

$$F_\beta = \frac{(\beta^2 + 1) * Precision * Recall}{\beta^2 * Precision * Recall} \tag{5}$$

where: TP = true positive i.e., positive observation correctly classified as positive; TN = true negative i.e., negative observation correctly classified as negative; FP = false positive i.e., negative observation wrongly classified as positive; FN = false negative i.e., positive observation wrongly classified as negative; β is the weightage factor between precision and recall. For this study β = 1 which gives equal weightage to the precision and recall, hence F_1. Equations 2, 3, 4, and 5 are designed for binary classifications, but this study involves multiclass classification with four categories: erosion, accretion, stable, and short-term fluctuation. When the model correctly classifies an erosion beach as erosion, it is considered as a true positive. However, if the model classifies any other category as erosion, it is counted as a false positive. This process applies to all four categories. In multi-class classification, a weighted average approach is employed, where precision, recall, and F1 scores are calculated for each category and then averaged weighting according to the number of samples in each category present in the dataset.

The performance of regression models is evaluated using various metrics, including regression (equation 6), MAE (equation 7), and NSE (equation 8). Regression provides a statistical measure of how closely the predicted data aligns with the target data, indicating the model's generalizing ability. MAE quantifies the error in the predicted values, while NSE assesses the model's efficiency on a scale ranging from -∞ to 1, where 1 represents the most efficient model.

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}} \tag{6}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x - y| \tag{7}$$

$$NSE = 1 - \frac{\sum(y - x)^2}{\sum(x - \bar{x})^2} \tag{7}$$

n is the number of data points, x is target value, y is predicted value

4. Results

4.1 Coastline analysis

Analysis of the data obtained from Sefton Council revealed rapid sediment movement and instability along most part of the Morecambe Bay coastline. Marshy areas, mudflat edges (defined as mudflat crossing zero mean sea level), and clifftops have retreated significantly, indicating rapid coastal transformation. Sediment Volume changes indicate that only a minority of sites is stable.

Figure 4 shows a selection of representative transects along Morecambe Bay for the stable, accreting, eroding and fluctuating cases. Figure 4B shows Sunderland Point in Morecambe, where according to our analysis the clifftop retreated about 5 meters between 2010 and 2022. The first three profiles in Figure 4B (2010, 2012, and 2015) show significant retreat towards the landmass. As observed from Google Earth, rock armor was placed between 2013 and 2015, which reduced the retreat, as seen in its next profile in 2022. Figure 4C and 4F show the transects experiencing mudflat edge retreat. Figure 4C shows transects near Morecambe city, where mudflat edge retreated about 150 m between 2010 and 2022. Figure 4F shows transects near Bardsea, where massive erosion of about 5012.7 m^3/m sediment has caused the mudflat edge to retreat more than 2 kilometers between 2007 and 2022. Figure 4D, near Morecambe city, shows significant erosion of 308.06 m^3/m of sediment between 2012 and 2022. Figure 4E shows transects near Ravenstown, a mostly marshy area that has experienced significant marshland loss in recent years. The location shown in Figure 4E has seen the marshland retreat about 500 meters between 2007 and 2022. Figure 4G shows short-term fluctuations in erosion between 2007 and 2022. The beach eroded between 2007 and 2017, accreted until 2021, and then eroded again in 2022. Figure 4H shows transects between 2007 and 2022, which shows accretion of about 346.4 m^3/m of sediment resulting in the extension of mudflat edge towards the bay.

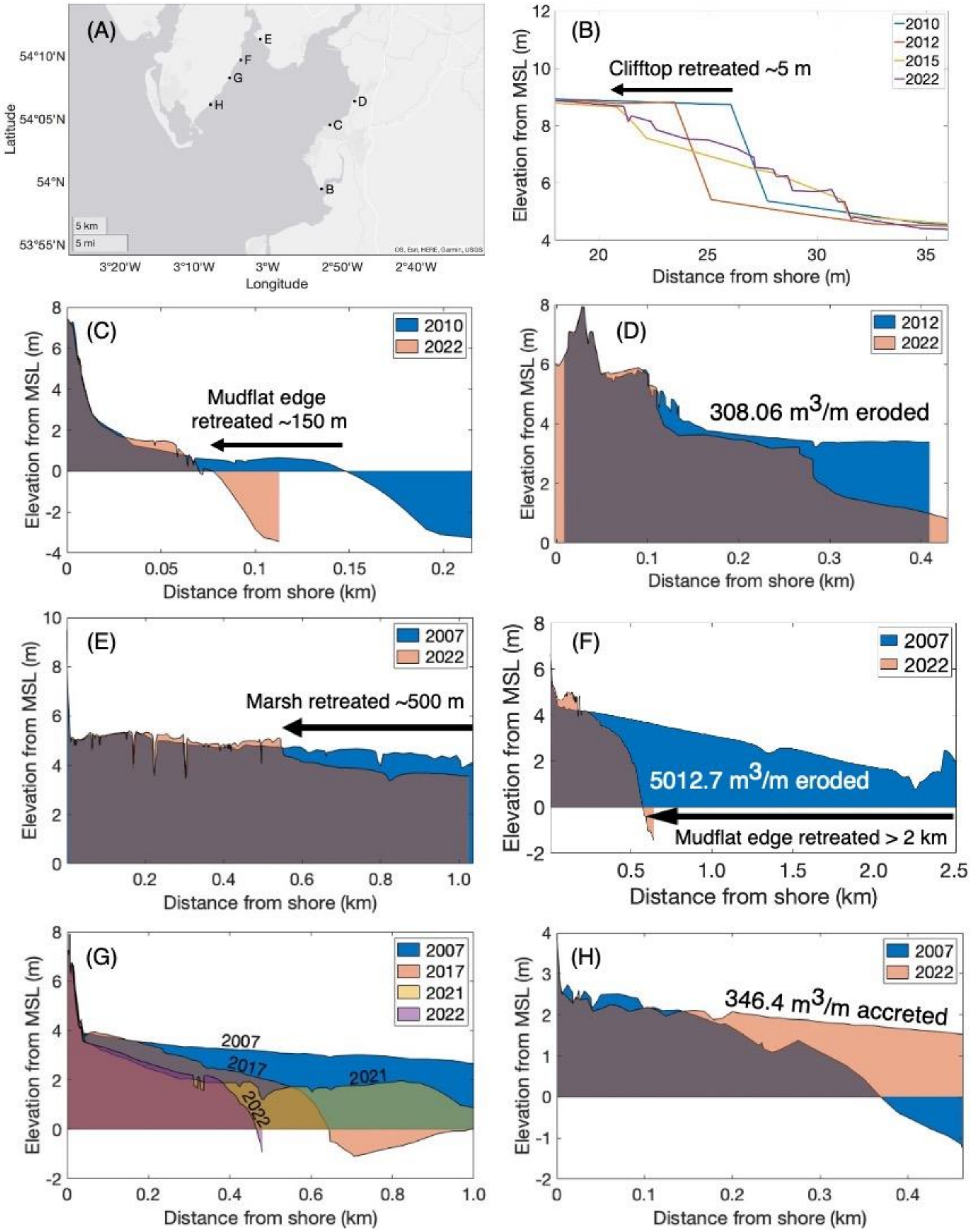

Fig 4. Beach profiles at different locations along Morecambe Bay coastline

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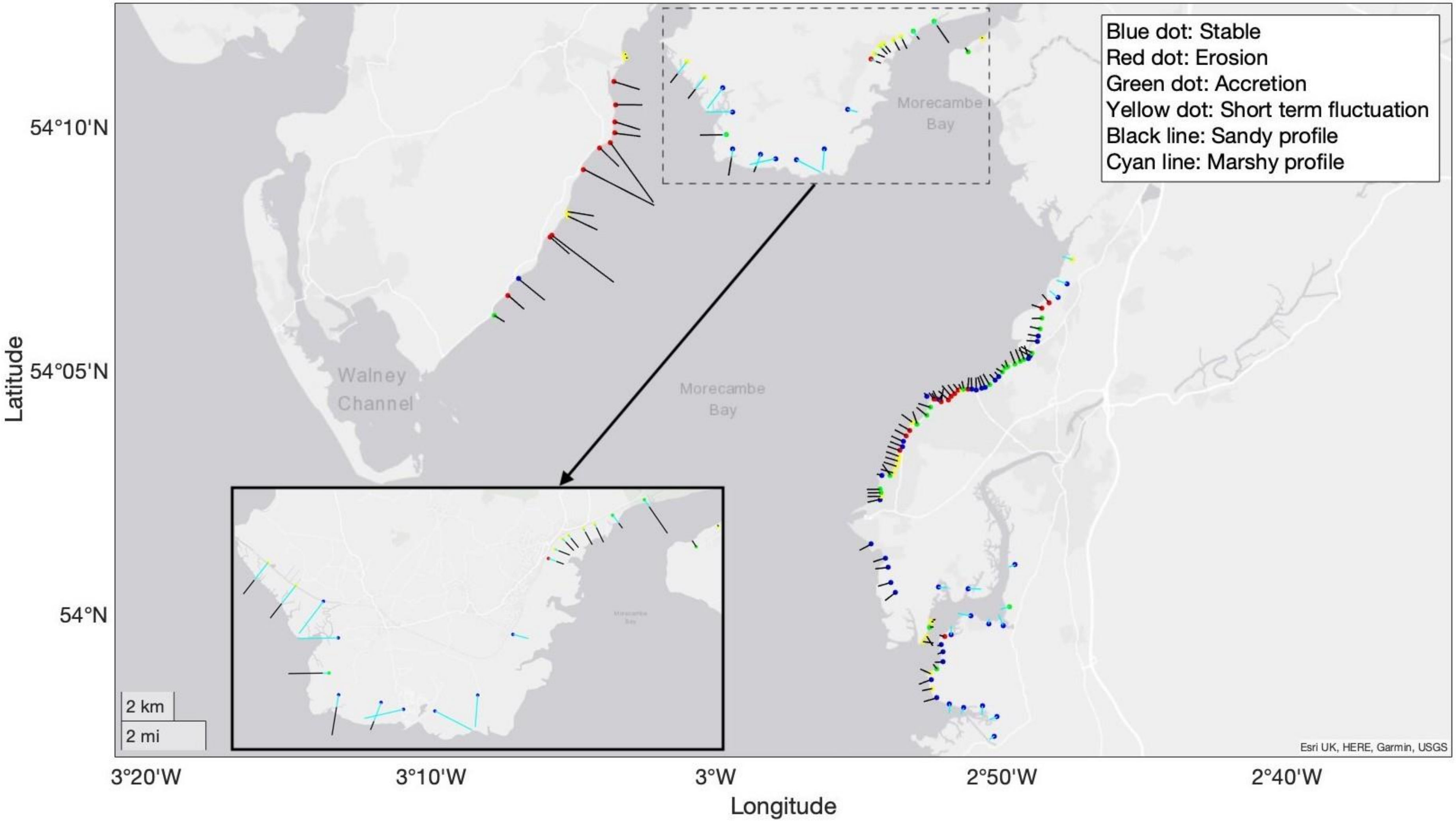

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337 **Fig 5.** Beach transects at different locations along Morecambe Bay coastline

Figure 5 shows the results of a transect analysis of all locations along the Morecambe Bay coastline. The length of each line represents the length of the transect measured at each location. Locations are classified as stable, eroding, accreting, or experiencing short-term fluctuations based on sediment volume changes at each location. Volume changes are calculated by subtracting the calculated sediment volume of each profile from the sediment volume of first profile measured in time.

This classification is indicated by different colored dots in Figure 5. Locations with less than 10% change in sediment volume are classified as stable. As shown in Figure 5, most marshy are classified as stable (blue). This is because transect length data is only available within marshy areas, where very little change is observed. Higher volume changes are noticeable for those transects extending to the mudflat and which are classified accordingly. For the remaining marshlands, transects extend beyond the marshland into the mudflat, recording sediment erosion from the mudflat and the retreat of the marshland. These classifications were fed to the prediction models (A1 and A2) to predict the volume of sediment available after erosion/accretion.

4.2 A1 model

Model A1 was trained to classify beach behavior as eroding, accreting, stable, or undergoing short-term fluctuations based on four input parameters: coastline angle (radians), wave direction (radians), wave velocity (m/s), and transect type (categorical, e.g., marshy). The RF classifier model was tested using various ensemble aggregation methods (bagging, AdaBoostM2, LPBoost, RUSBoost, and TotalBoost) and different numbers of trees (50, 75, and 100). 15% of the data was reserved for testing, another 15% of the data was reserved for validation and the remaining 70% was used for training. These configurations yielded good prediction performance in terms of accuracy, precision, recall, and F1 score (table 1) with 75 trees and RUSBoost method. This model effectively classifies beach behavior with training accuracy of 0.95 and testing accuracy of 0.79, providing valuable input for Model A2's prediction of sediment volume.

Table 1. Performance of A1 model

Criteria	Training	Testing
Accuracy	0.95	0.79
Precision	0.96	0.81
Recall	0.95	0.79
F1 Score	0.95	0.77

4.3 A2 model

Model A2 was developed to predict the available volume of sediment based on four input parameters: wave height (m), wave velocity (m/s), coastline behavior (categorical output from Model A1), and the previous 18 months (three-time steps) of sediment volume (m^3/m). Three models, one LSTM and two S2S, were evaluated for predicting 0.5 year (one time step) ahead, 1.5 years (three time steps) and 5 years (ten time step) ahead, respectively. For the LSTM model, three and four LSTM layers were tested. The number of nodes in the LSTM layer was varied from 5 to 50. Ten percent of the data was reserved for testing, another 10% was used for validation, and the remaining 80% was used for training. Both models demonstrated remarkable accuracy in predicting available sediment volume (table 2). The LSTM model achieved excellent accuracy when tested with four LSTM layers and 20 nodes in each layer, while the two S2S models achieved excellent accuracy with 50 and 40 nodes in its LSTM layers for predicting 1.5 and 5 years ahead, respectively.

Table 2. Performance of A2 model

Model	Phase	Regression	MAE (m^3/m)	NSE
LSTM	Training	0.9966	0.0504	0.9929
	Testing	0.9961	0.0567	0.9915
S2S	Training	0.9967	0.0491	0.9933

(1.5 years)	Testing	0.9950	0.0552	0.9900
S2S	Training	0.9951	0.0645	0.9900
(5 years)	Testing	0.9916	0.0656	0.9828

The S2S models predict multiple time-step values simultaneously, with Table 2 presenting the average accuracy across individual time steps. A detailed breakdown of accuracy reveals testing MAE values for t, t+1, and t+2 at 0.0434, 0.0567, and 0.0656, respectively, for a 1.5-year prediction. For a 5-year prediction, testing MAE values are listed as 0.0481, 0.0597, 0.0625, 0.0607, 0.0647, 0.0615, 0.0692, 0.0712, 0.0736, and 0.0851 m^3/m. Notably, the accuracy for the first-time step is lower than that of the LSTM model, which is tailored for single-step prediction. The S2S models exhibit a decreasing accuracy trend, indicating an increasing error as the number of predicted time steps increases. While the LSTM model excels at one-step prediction, the S2S model is recommended for longer predictions. However, it's essential to consider the escalating error in later time steps when utilizing the S2S approach.

Discussion

Coastline changes in Morecambe Bay have been observed and studied since 1990s by several researchers including Pringle (1995), Mason et al. (1999) and Mason et al. (2010). These studies have documented significant changes in the bathymetry near the coastline. Pringle (1995) noticed the erosion of salt marshes, which began in mid-1970s and continued into the 1990s at a relatively slow rate. In addition to the erosion of salt marshes, the Kent channel of Morecambe also shifted eastward along with its minor channels during the late 1970s, leading to rapid saltmarsh erosion. Mason et al. (1999), observed the movement of the Leven estuary of Morecambe towards the north-east by about 2 km during the period of 1992-1997. Mason et al. (2010) also observed the migration of the Ulverston channel of

Morecambe north-east by about 5 km between 1991 to 2004. Similarly, this study, conducted with the data between 2007 and 2022, also observed significant erosion of mudflat platforms and marshy regions in most parts of Morecambe. This erosion has resulted in the mudflat edges, i.e., zero mean sea level crossing of mudflats, retreating up to 2 kilometers (crossing of mean sea level) and marshes up to 500 meters towards the landmass (figure 4). These dynamic changes in bathymetry near the coastline pose significant challenges for the infrastructure sector and coastal communities.

The models developed in this study can effectively identify erosion hotspots and predict sediment volume changes based on simplified modelling and QGIS inputs. Model A1 is designed to classify the coastline behavior as eroding, accreting, sable or undergoing short term fluctuations based on inputs of coastline angle, wave velocity, wave direction and coastline composition. Model A2 is specifically designed to estimate the volume of sediment eroded or accreted along the coastline based on inputs of wave height, wave velocity, coastline behavior (output from Model A1), and the previous 18 months of sediment volume and at a time scale of 1.5 years and 5 years.

These models have the advantage of providing highly accurate predictions for Morecambe Bay, as they are trained on a comprehensive field dataset from Morecambe Bay. While their accuracy may decrease when applied to other embayments, they can still be effectively utilized in areas with similar coastal dynamics and wave conditions to Morecambe Bay. The advantage of this methodology lies in its development of two predictive models. One of these models (model A1) is dedicated to identifying erosion hotspots, critical information for effective coastline management. According to a report by Masselink et al. (2020), 17.3% of the UK coastline, equivalent to 3008 km, is currently experiencing erosion. The report further notes that only 45.6% of England's coastline is protected by coastal defense structures such as groynes, seawalls, or artificial beaches. Model A1 can be utilized to pinpoint erosive locations along the coastlines, facilitating targeted deployment of coastal defense measures to protect vulnerable areas. Additionally, this model feeds its output into the second model (model A2), enabling the latter to learn beach classification—whether eroding, accreting, fluctuating, or stable—and subsequently predict sediment volumes in the future. Accurately estimating sediment losses from various beaches, including cliff beaches (as discussed by Brooks and Spencer (2010)), holds regional significance as these sediments play crucial roles in beach maintenance, nearshore bank systems, and nearshore sediment transport pathways. Model A2 can thus be applied to forecast sediment erosion volumes along beaches, thereby assisting in better understanding and managing coastal erosion processes and their impacts on coastal ecosystems and communities.

Another advantage of using ANN models are that these are computationally inexpensive (Hashemi et al., 2010), as compared to the simulation models which typically require hours for simulation. Thus, the sediment volume change can be predicted instantly in the scale of 5 years. A drawback of ANN, as suggested by Hashemi et al. (2010), is that its prediction accuracy is depended on quality of data. However, this study has the advantage of training models on high quality field data.

Additionally, these models are trained to forecast data points three and ten steps ahead in the time series, equivalent to 1.5 and 5 years into the future respectively, using only 18 months of historical sediment volume data. The prediction performance was evaluated across two different time scales to assess the model's ability to forecast over longer durations. For a 5-year forecast, the model demonstrates high accuracy with a testing regression of 0.9916. However, upon analyzing the ten individual time steps, an increasing error trend becomes apparent. The MAE rises from 0.0481 m^3/m for the first-time step to 0.0851 m^3/m for the tenth time step, nearly doubling from the initial prediction. Nevertheless, the prediction error for the tenth time step remains within acceptable bounds, supported by a testing regression of 0.9878.

Future developments of these models will involve incorporating additional historical data, enabling the models to scale up and provide forecasts for even longer time horizons. Moreover, enhancing the input list with additional features is certain to enhance prediction capabilities by enabling models to grasp the relationship between coastal erosion and various variables. As demonstrated by Peponi et al. (2019), factors such as urbanization and population influence coastal dynamics systems by modifying hydrological patterns, sedimentation regimes, land use and land cover. Additionally, coastal erosion is influenced by rising sea levels (Masselink et al., 2020). Thus, incorporating these factors into the model's input list will facilitate learning the relationship between sediment erosion along the coastline and these variables, ultimately enhancing the model's predictive robustness.

Conclusion

This study analyzes field data comprising beach transects at 125 locations along the Morecambe Bay coastline. The analysis reveals areas of rapid coastal change. Following the data analysis, this study investigates the potential of a two-stage machine learning model for predicting sediment volume change in a coastal environment. The model utilized a combination of beach behavior classification and deep learning techniques to achieve accurate predictions. The results demonstrated that the model effectively captured the complex relationship between beach behavior, wave conditions, and sediment erosion and accretion.

Model A1 successfully classified beach behavior into four categories: eroding, accreting, stable, and undergoing short-term fluctuations using Random Forests and based on input of coastline angle, wave velocity, wave direction and coastline composition. This classification provided valuable input for Model A2, which utilized LSTM and sequence-to-sequence models to predict available sediment volume for one-step-ahead and multi-step-ahead predictions, respectively. The LSTM model achieved a testing regression of 0.9961 for one-step-ahead (6 months) predictions of available sediment volume time series, while the sequence-to-sequence models achieved a testing regression of 0.9950 for three-time-step-ahead (1.5 years) predictions and 0.9916 for ten-time-steps (5 years) prediction. Proposed models offer several advantages over traditional time series models. Firstly, it explicitly classifies beach behavior based on input of coastline angle, wave velocity, wave direction, and coastline composition. Secondly, the model is highly generalizable and can be applied to different coastal environments with minimal adjustments.

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Open Research:

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