Exploring Mega-Nourishment Interventions Using Long Short-Term Memory (LSTM) Models and the Sand Engine Surface MATLAB Framework

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August 25, 2023

Abstract

Coastal protection is of paramount importance because erosion and flooding affect millions of people living along the coast and can largely influence countries' economy. The implementation of nature-based solutions for coastal protection, such as sand engines, has become more popular due to these interventions' adaptability to climate change. This study explores synergies between AI and hydro-morphodynamic models for the creation of efficient decision-making tools for the choice of optimal sand engines configurations. Specifically, we investigate the use of long-short-term memory (LSTM) models as predictive tools for the morphological evolution of sand engines. We developed different LSTM models to predict time series of bathymetric changes across the sand engine as well as the time-decline in the sand engine volume as a function of external forces and intervention size. Finally, a MATLAB framework was developed to return LSTM model results based on users' inputs about sand engine size and external forcings.

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Exploring Mega-Nourishment Interventions Using Long Short-Term Memory (LSTM) Models and the *Sand Engine Surface* MATLAB Framework

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Abstract: Coastal protection is of paramount importance because erosion and flooding affect millions of people living along the coast and can largely influence countries' economy. The implementation of nature-based solutions for coastal protection, such as sand engines, has become more popular due to these interventions' adaptability to climate change. This study explores synergies between AI and hydro-morphodynamic models for the creation of efficient decision-making tools for the choice of optimal sand engines configurations. Specifically, we investigate the use of long-short-term memory (LSTM) models as predictive tools for the morphological evolution of sand engines. We developed different LSTM models to predict time series of bathymetric changes across the sand engine as well as the time-decline in the sand engine volume as a function of external forces and intervention size. Finally, a MATLAB framework was developed to return LSTM model results based on users' inputs about sand engine size and external forcings.

Plain Language Summary:

Sand engines are a type of coastal protection where a large volume of sand is added to the coastline to protect low-lying areas from erosion and flooding. Sand engines, like other Nature-based solutions, are gaining popularity due to their potentially lower maintenance costs compared to other concrete-based coastal protection strategies and a number of co-benefits. However, there are currently no design guidelines or decision-making tools for sand engines. Here we address this gap in the state of knowledge and use Artificial Intelligence (AI) techniques to analyze the evolution of sand engines under different waves and external forcings. AI models are also used to predict the volume of sand being transferred by the waves from the location of deposition to the surrounding areas. To facilitate the use of AI models, this study proposes a computer software, *sand engine surface*, which includes all the

AI models developed in this study, predicting the evolution of sand engine and volume of sand being transported.

Key Points:

- This study explores the use of LSTM models to predict time series of sand engines' volumetric changes and morphological changes.
- All our Long Short Term Memory models' results are accessible through *Sand Engine Surface*
- *Sand Engine Surface* is MATLAB framework providing results about time-dependent morphological changes of sand engines based on users' inputs.

1. Introduction

Anthropization and climate change, including sea level rise and changes in storm activity, are expected to increasingly affect the world coastlines (Herman et al., 2021). Erosion and flooding pose a threat to human life and infrastructure along coastal areas. Protecting coastal regions is a top priority: millions of people live along the coast, and coastal systems and associated ecosystem services contribute billions of dollars to the economy each year (Deutz et al., 2018; UNCC, 2020). To mitigate these challenges and ensure effective coastal protection, conventional methods such as sea walls (Hosseinzadeh et al., 2022) and breakwaters (Zhao et al., 2019) have been traditionally employed with some success. However, these conventional approaches come with significant drawbacks, including high installation and maintenance costs, as well as their limited adaptability to sea level rise, which makes them economically unsustainable in the long term (van Rijn, 2011). As a result, alternative options for coastline protection through nature-based solutions, such as mega-nourishment interventions and wetland restoration, have been gaining attention. These Nature-based approaches offer a more economically viable alternative, while also supporting efforts towards achieving net-zero carbon emissions and numerous ecosystem benefits (Moritsch et al., 2021).

Mega-nourishments, often known as a sand engine, involve the deposition of large quantities of sand in the sea adjacent to a beach, either as an extension of the existing beach or as an artificial island. These sand engines act as localized beach nourishment measures, serving to prevent floods and erosion in low-lying areas (Stive et al., 2013) by effectively reducing wave energy and redistributing sediment along the coastline over several decades. The bathymetry of Sand engines evolves in time as natural forces such as waves and tides assist in the distribution of sediments, as seen in the case of zandmotor in the Netherlands (Huisman et al., 2016).

Understanding the behavior of sand engines, which is depended upon the configuration of the sand engine itself and its environmental settings is crucial for decision makers and coastal planning. However, there are significant uncertainties and challenges in relation to the morphological evolution of the coastline and evaluation of the effectiveness of different sand engines interventions. Artificial Intelligence (AI) can be an effective tool to address these challenges and offers promising solutions for comprehending and predicting complex coastlines dynamics (e.g., (Kumar & Leonardi, 2023a, 2023b)).

The objective of this research is to explore synergies between the use of hydro-morphodynamical models and AI techniques to create new tools providing stakeholders with baselines assessment about the suitability of different coastline interventions and aimed at optimizing both available and newly created datasets from numerical modelling. Specifically, this study focuses on the morphological changes of sand engines. Long Short-Term Memory (LSTM) models have been trained to predict time-dependent changes in bathymetry at various locations across a sand engine, as well as variations in sand engines' volume depending on its features and external forcings. The main advantage of this methodology is that, once trained, the LSTM models can be utilized independently, have a running time of the order of minutes rather than hours and models can be thus packed within simpler frameworks and graphical Users Interfaces. *Sand Engine Surface* is a MATLAB framework developed for this purpose and enabling users to obtain predictions about sand engines behavior based on their specific coastal parameters inputs.

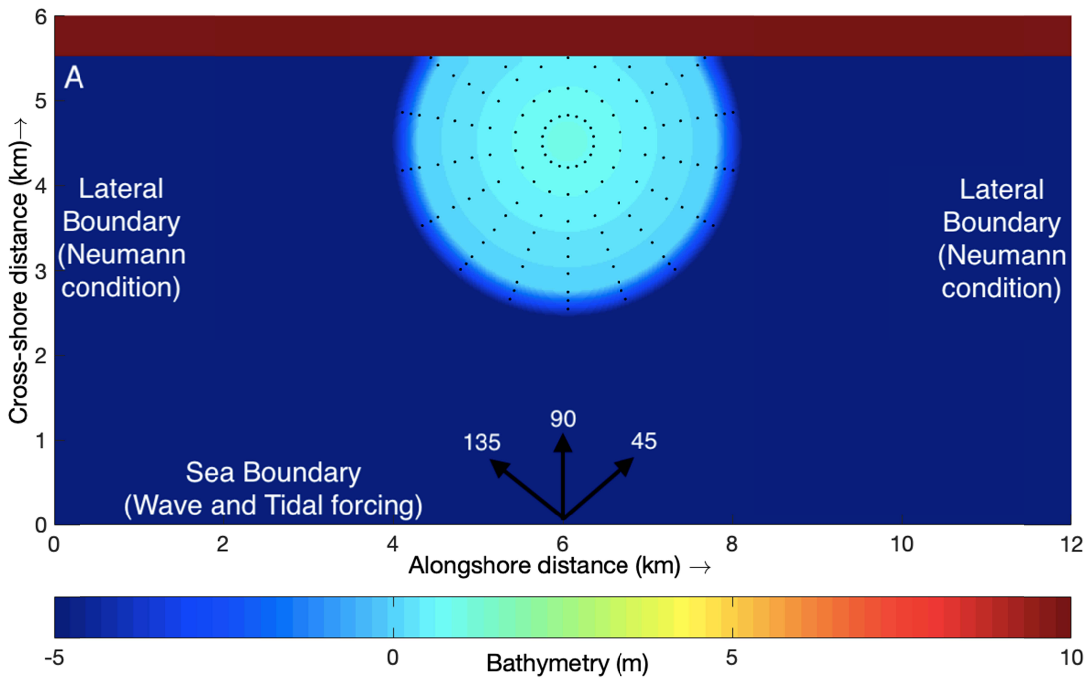
2. Methodology

2.1 Modellings setup and configuration

LSTM is one of the Recurrent Neural Networks (RNNs) which is commonly used for modeling time series data. LSTM was designed to overcome the problems associated with RNN, which had difficulty learning the long-term dependencies in the data due to gradient explosion and gradient disappearance (Kumar et al., 2023; Lindemann et al., 2021; Sun et al., 2022). RNN is different from Feed Forward Neural Network (FFNN) in the context of flow of data within the network. FFNN allows only one-way flow of data from input layer to output layer through hidden layers. However, RNN allows feedback of data back to the hidden layers to create time lag effect which helps in memorizing the previous time steps (Aslam et al., 2020). LSTMs are designed to memorize long term dependencies and has the capability of selectively storing the important data and deleting not important data through different gates (Text S1 in Supplementary Information).

LSTM models were trained utilizing numerical modelling outputs from the hydrodynamic and morphodynamic model Delft3D. Delft3D is a process based numerical modelling platform capable of computing the hydrodynamics, waves, sediment transport, water quality, morphology of coastal regions (Lesser et al., 2004). Its base model, Delft3D-Flow (hydrodynamic module), solves the 3-D Navier-Stokes equations for incompressible free-surface flow under the shallow water approximation for unsteady, incompressible, and turbulent flow. For this study, the hydrodynamic and morphodynamic modules are fully coupled so that the flow field adjusts in real time as the bed topography changes. The module Delft3D-WAVE was used to simulate wave generation, propagation, and nonlinear wave-wave interactions (Booij et al., 1999).

For the idealized modelling setup, a circular sand engine with a 2 km radius was positioned within a flat seabed having -5 m depth relative to mean sea level (Table S1 in Supplementary Information). The grid size for the numerical model setup varied from 16×16 m at the location of the sand engine to around 100×300 m near the boundary. The domain extends 12 km along shore with the sand engine placed at the center and 6 km cross-shore, providing sufficient space for sediment movement. Within the time scale explored in our study there is no or negligible amount of sediments exiting the model domain. Tidal levels and waves forcing were imposed at the sea boundary. Neumann boundary conditions were used at the lateral boundaries. A non-cohesive sediment type with a specific density of 2650 kg/m^3 and dry bed density as 1600 kg/m^3 was used. The diameter of the sediment was 120μm. The hydrodynamic model was run for 15 days and a morphological scale factor of 30, to represent a time scale of the order of 15 months (following the method from Roelvink (2006) and Ranasinghe et al. (2011)). The sand engine center was located 1km from the coastline so that we could monitor differences in the morphological evolutions of points directly and indirectly exposed to wave forcings. Around 15% of the sand engine radius is located below MSL with a slope of around 1.5% as opposed to a vertical slope which was leading to hydrodynamic instability. The inner 85% of the radius of the sand engine is above MSL with a suitable slope depending on sand engine height. Different sand engines heights were considered (1m, 2m and 3m). Different tidal levels were tested (0.5m, 1m, and 2m) together with different uniform wave height conditions (0.5m, 1m and 2m) and waves directions (45°, 90° and 135° with respect to the boundary) (Figure 1A). Observation points were located within the sand engine to obtain time series of morphological changes at multiple locations (Figure 1A).



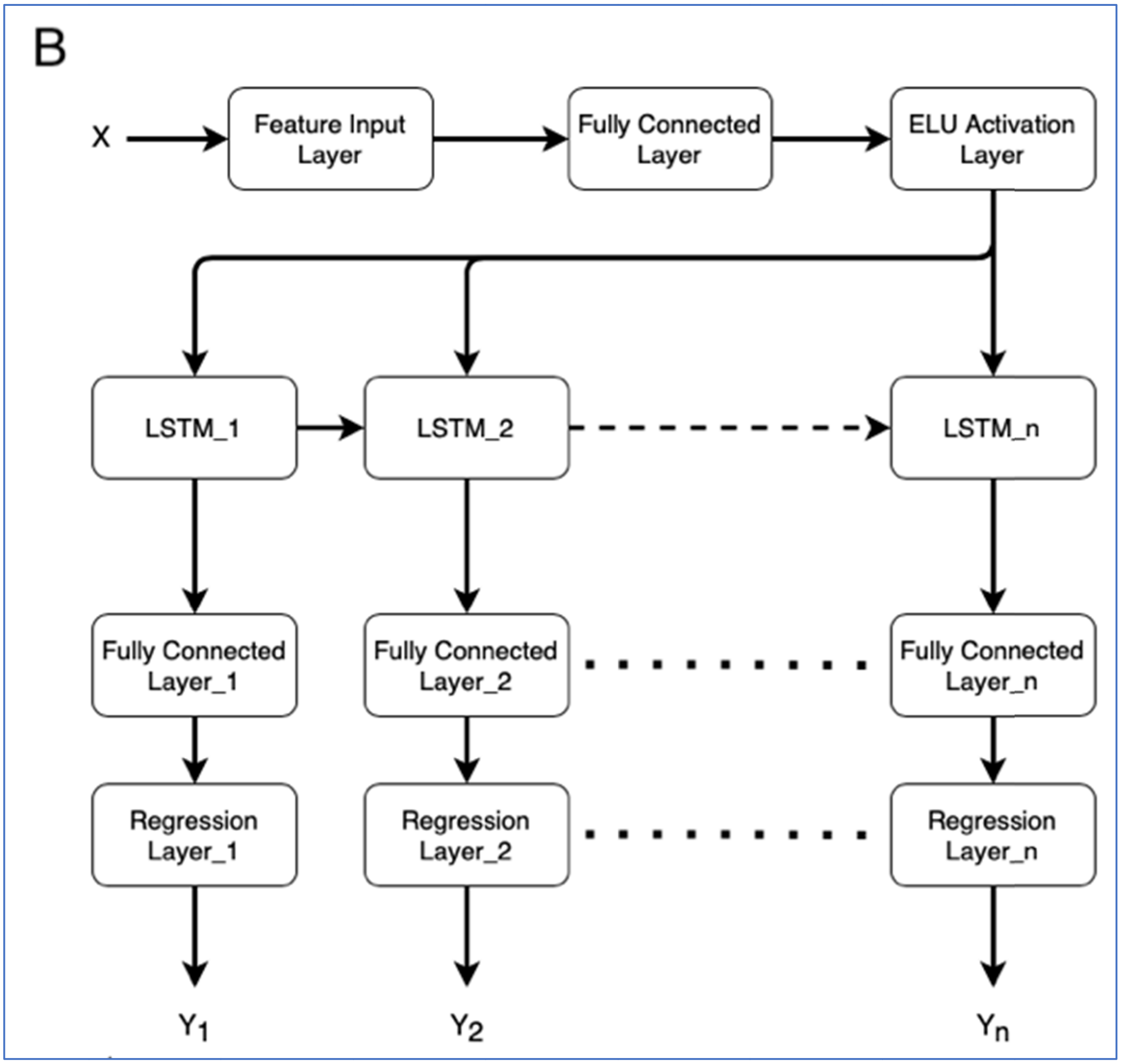


Fig. 1: A) *Sand engine simulation domain with indicated wave directions (45°, 90° and 135°) and boundary conditions. Black dots indicate locations where the time dependent morphological changes were tracked and used for training/predictions through LSTM models.* ***B)*** *Customized LSTM network with indicated input (X) and outputs ($Y_1 \ldots Y_n$). $Y_1 \ldots Y_n$ are the outputs at each time step, n is 172 for this case.*

The results obtained from each Delft3D simulation included time series of morphological changes at each observation point (Figure 1A). These time series consist of 172-time steps. Furthermore, we calculated changes in the total volume of sand remaining within the sand engine radius by multiplying the bathymetric elevation for each grid cell by the grid size. LSTM models were trained to reproduce bathymetric changes in time at each observation point and changes in the total volume of sand.

LSTM models are generally used to reproduce single time series, predicting one time step into the future. However, in this case we have multiple time series. Therefore, following Wang et al. (2019), the LSTM model was reconfigured and all the connections were managed manually. Specifically, inputs were received at feature input layer which was connected to fully connected layer with Exponential Linear Unit (ELU) activation layer. Output from the ELU activation layer was connected to 172 parallel LSTM cells (figure 1B). Given that each time series consisted of 172 time step, each LSTM cell is designed to produce output for each time step. Each LSTM cell received the input from ELU activation layer as well as output of previous 10 LSTM cell after concatenating them using a concatenation layer. Hence, each LSTM cell was providing prediction based on the feature input and output of previous 10 times steps. The hidden state and cell state of each LSTM cell were connected to following cell in the sequence. The output of each LSTM cell was connected to a fully connected layer followed by a regression layer. The output of each regression layer represents the value of each time step in the time series.

The entire network (figure 1B) was trained using a custom training loop in MATLAB where inputs were fed to the feature input layer and the output of the network was collected from each regression layer and arranged in a sequence to form a complete time series. To optimize the model's performance, the final time series output was used to calculate the loss value, which was measured by the mean squared error. This loss value was used to update the internal parameters, such as weights, biases, and state values, using the MATLAB function *adamupdate* (adaptive moment estimation). For the purpose of this study, we developed three models having a similar LSTM model structure: one for modeling the total volume of sand remaining (volume model) and a second and third model to track the bathymetric evolution above MSL and below MSL.

The Volume model takes in 5 inputs (wave height (m), tide (m), height of sand engine (m), angle of the wave (radian) and the initial volume of sand at the sand engine) and predicts a time series representing the volume of sand left within the radius of the sand engine (Table S2 in Supplementary Information). The efficiency of the nourishment over time is also calculated using the following equation (Roest et al., 2021):

$$\eta = 1 - \frac{\Delta V_{net}}{V_{nourishment}} \tag{1}$$

where, η is nourishment efficiency, ΔV_{net} is change in volume of sand and $V_{nourishment}$ is the total volume of sand placed. Results about the morphological evolution of the Sand Engine Efficacy are presented as part of the *Sand Engine Surface* MATLAB Framework.

The LSTM models predicting the bathymetric evolution at each observation point (whether above or below MSL) require 6 inputs (wave height (m), tide (m), height of sand engine (m), angle of the wave (radian), the radial distance (km) and angle (radian) from the center) and predicts multiple time series representing the bathymetric evolution at each observation point. The performance of the LSTM models is measured based on regression (eq. 2) and mean absolute error (MAE) (eq. 3).

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

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x - y| \tag{3}$$

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

3. Results

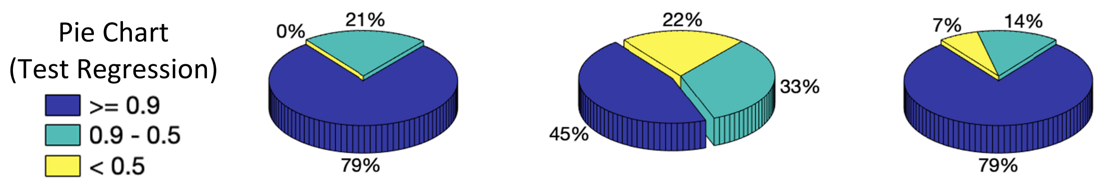
Table 1a represents the performance of all three LSTM models based on regression and MAE. The Volume model and the below MSL model perform well in training and testing with regression values around 0.9. However, for points above MSL the model has a testing regression of 0.69. Points near the center of the sand engine remain dry throughout the simulation and no bathymetric changes are observed there, leading to flat time-series, forming a straight line in the training dataset. These constant lines in the training dataset affect the overall learning capability of the model. The pie charts in Table 1 represent the summary testing regression for different time series in the testing dataset. Volume and below MSL models predicted 79% of their time series in the testing dataset with regression greater than or equal to 0.9. The above MSL model has 45% of the testing time series predicted with regression greater than or equal to 0.9.

Table 1. *Performance of LSTM models. A) regression and MAE values B) regression pie chart*

(A)

Model		Volume	Above MSL	Below MSL
Regression	Train	0.9	0.92	0.92
	Test	0.9	0.69	0.89
MAE	Train	0.89	0.03	0.04
	Test	1.02	0.19	0.16

(B)



The morphological evolution of a Sand Engine depends on its configuration as well as waves and tidal forcing. Figure 2 provides an example of the final morphological configuration of the intervention for a sand engine having a 3m height and exposed to constant 2 m waves, 1 m tidal amplitude and waves approaching at a 90° angle. Throughout the simulation, sediment is observed moving toward the coastline on both sides of the sand engine. Additionally, the combination of waves and tidal forcing create channels within the sand engine. The central portion of the sand engine remains instead mostly unaffected because it remains dry for the simulation period.

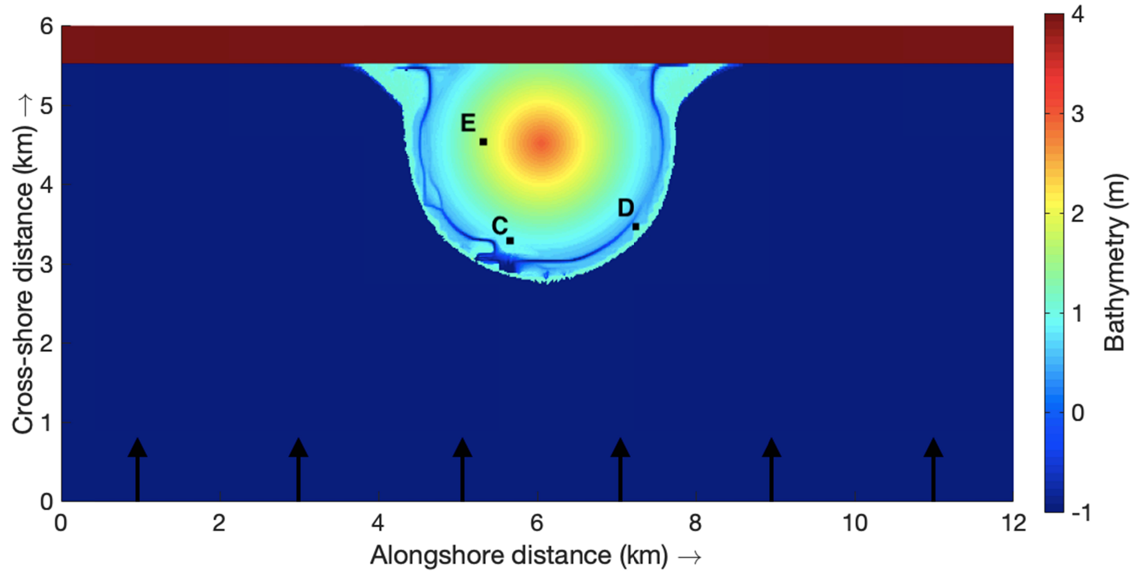


Fig. 2 *Sand engine bathymetry at the end of the simulation period (15 months). Simulation configurations: sand engine height, 3 m; wave direction 90° angle; wave height, 2 m; tidal amplitude 1m. Points C, D and E represent the locations where time-varying bathymetry is plotted in figure 3c, d, and e, respectively.*

Figure 3 presents results from the Delft3D and LSTM model for the sand engine of Figure 2. Results are presented in terms of total Volume remaining and time series of morphological changes. The blue line represents results from the Delft3D model, while the orange line represents results from LTSM model. The LSTM model is able to clearly reproduce Delft3D modelling outputs.

As a reference, we have also included data from the Netherlands sand-motor (august 2011 to august 2012). These were obtained from Luijendijk et al. (2017). While our simulations were not meant to replicate that specific sand engine, it is worth having a comparison with a real case scenario. The steeper decline in volume change for the Netherlands sand motor (encircled in the fig 3a) over the winter period is due to the increased wave activity during winter (Huisman et al., 2016; Luijendijk et al., 2017). However, in this study, constant wave height is applied at the sea boundary throughout the simulation period, and we thus register a more constant decline in Volume.

Figure 3c, d, and e represent the simulated and predicted bathymetry evolution at points c, d, and e, respectively (location in figure 3). Point d is predicted using the below MSL LSTM model and other two points are predicted by above MSL model. Figure 3e is for the points near to the center which shows no bathymetry change because it remains dry throughout the simulation period. As the point moves towards the center of the sand engine and towards dry areas, the model struggles to predict the bathymetric evolution accurately. Results for all observation points and all simulations are presented as part of the *Sand Engine Surface* MATLAB framework as outlined in the next section.

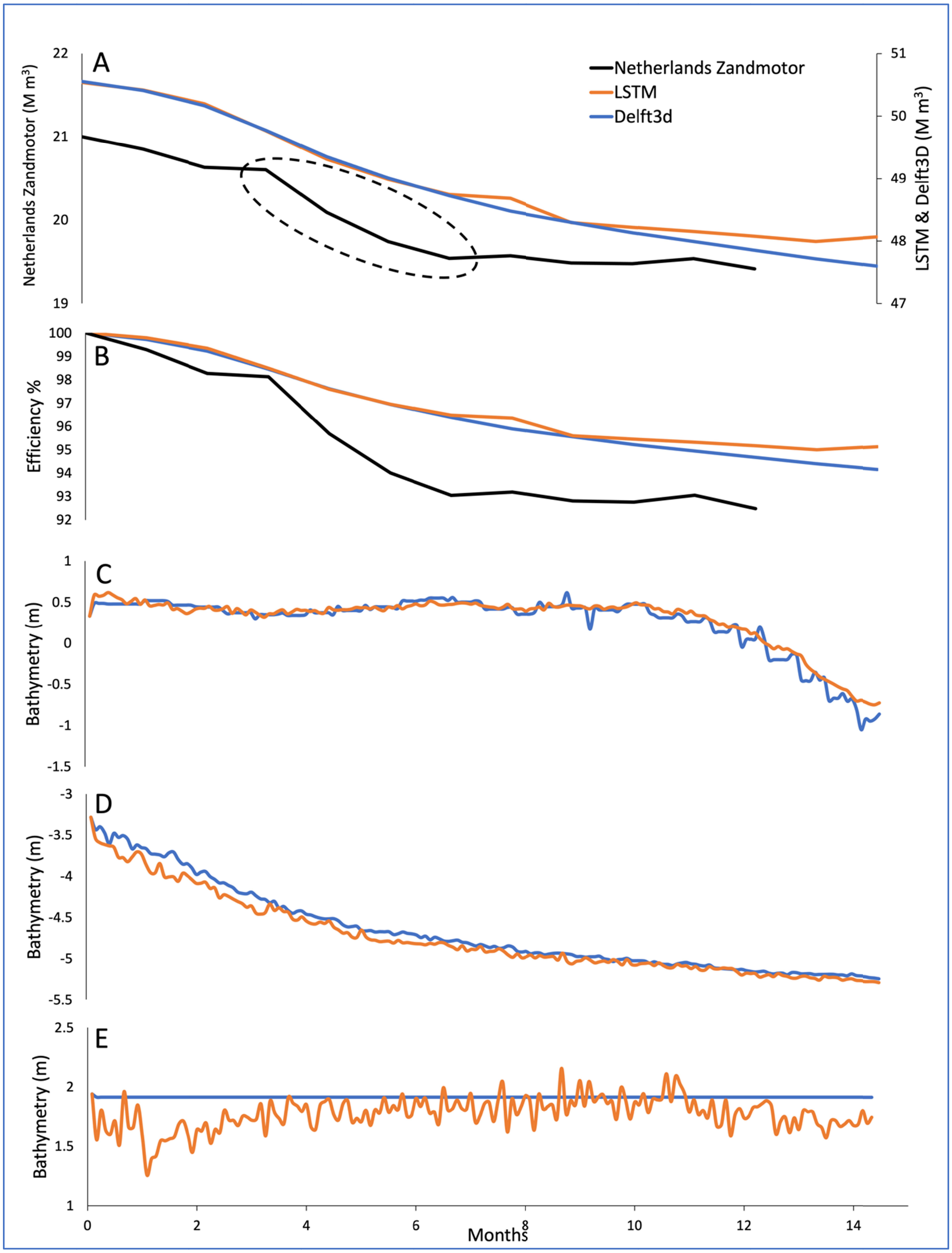


Fig. 3 A, B) *Sand engine volume and efficiency plots for simulated (Delft3D), predicted (LSTM) and Zandmotor in Netherlands (obtained from Luijendijk et al. (2017)). Encircled region is discussed in the text.* ***C, D, E)*** *simulated and predicted bathymetry plots for the points C, D and E (figure 2), respectively.*

3.1 Sand Engine Surface App

All the three developed LSTM models (Volume, Above MSL and Below MSL) along with the simulation results are packed into a MALTAB framework. The framework helps to better visualize the LSTM predicted results along with all simulation results. It accepts inputs (height of sand engine, wave height, tide, and angle of wave) in the configuration panel and provides the prediction results and simulation results (figure 4). To display the bathymetry evolution at different location on the sand engine, the framework displays all observation points on the sand engine (*Prediction Points panel,* left panel) for the user to click and view their bathymetric evolution in the *Bathymetry Variation* panel (right panel). The framework displays results from both LSTM models and Delft3D simulations (as a reference). While LSTM have been trained to predict and display configurations which haven't been modelled in Delft3D but can be chosen by the user as part of the Configuration panel; the displayed Delft3D simulation results are those matching the best the provided input configuration. These generated results can be exported through the framework in different formats, image, screenshot, excel and MATLAB file. The Framework is available for download in the following link together with a video ("Installation" and "Usage" video in Supplementary Information) demonstrating its usage and README file: https://github.com/pavitra979/Sand_Engine_Surface.

All the simulation results, displaying the simulated sand engine evolution, can be viewed as part of the readme section of the framework, where results can be viewed in the 3D plot or in video format. The 3d plot of sand engine evolution can be exported in an image format at any time step, however for all time steps it can be exported in video, gif, or MATLAB file format (Text S2 in Supplementary Information).

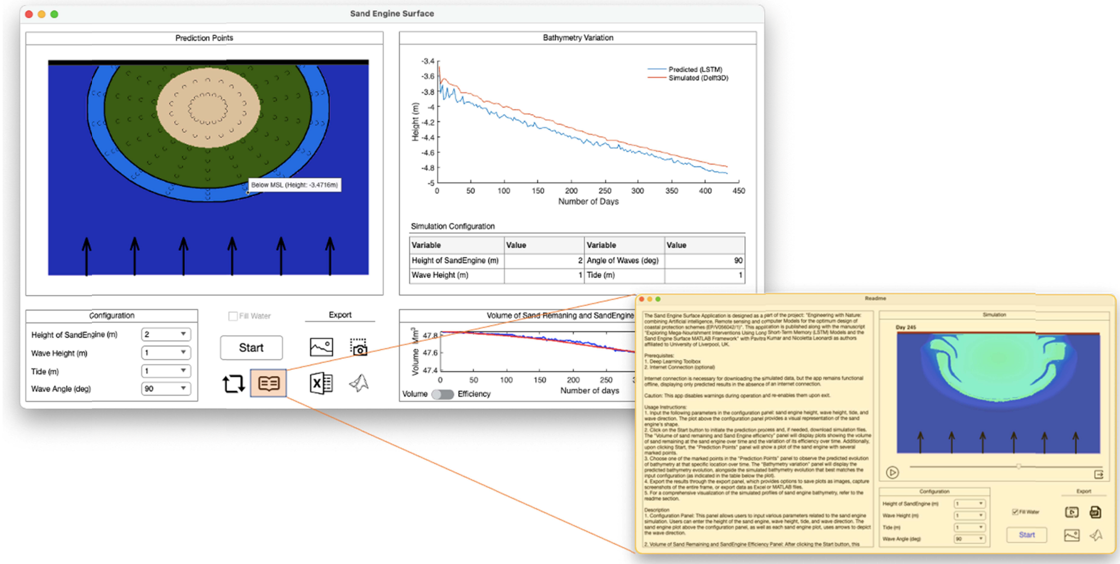


Fig. 4 Sand Engine Surface framework

4. Summary and discussion

Sand engines are a type of coastal protection where a large volume of sand is added to the coastline. Sand Engines are extremely dynamic as the sand is redistributed along the coast by the action of waves and tides. There are large uncertainties in sand engines behavior and currently no design criteria for their implementation. In this study, we investigate the synergies between the use of AI and numerical modelling for the creation of decision support tools aimed at facilitating the prediction of sand motor behavior. The advantage of AI over standalone numerical modelling is that AI algorithms, once trained, can deliver predictive results as standalone tools without the need for numerical modelling and more efficiently. (Kumar & Leonardi, 2023a, 2023b).

LSTM models were developed and trained based on Delft3D numerical simulations of idealized sand engines with different heights and subject to different tidal and wave forcings. An idealized modelling setup was chosen because it can hold applicability beyond its specific context, potentially benefiting any coastline, by considering the parameters used in the idealized simulation and correlating them with those relevant to realistic scenarios. Idealized modelling also allows neglecting site-specific processes and complexities and focusing on universal systems' behaviors. However, the idealized simulation has the limitation of not representing the real time conditions and hence they are essentially used for gaining generic insight in a specific physical mechanism (Roos, 2019), conceptual understanding and hypothesis testing (Hunt et al., 2015).

LSTM models are customized, for this use case, to predict the complete time series of volume of sand remaining and bathymetry evolution at different locations above and below

MSL (black dots in figure 1A) on the sand engine based on feature inputs (sand engine configuration and coastal conditions). The timeline of volume of sand remaining can be used to get the efficiency of the sand engine. And the bathymetry evolution can be used to study pattern of sand engine evolution when subjected to different wave forcings. Simulation results and LSTM models are packed into a MATLAB framework (*Sand Engine Surface* app) for better usability of the LSTM models and visualization of results. The app provides the prediction based on user inputs of the sand engine configuration and wave forcings. For better comparison, app displays the simulated results that best matches with the input configuration. All the simulation and LSTM model results are provided in the app and can be exported in video, image, or MATLAB file format.

Acknowledgments

We acknowledge the following funding source for this study: Engineering with Nature: combining Artificial intelligence, Remote sensing and computer Models for the optimum design of coastal protection schemes EP/V056042/1.

The Data driven models have been developed using the MATLAB libraries from the Deep Learning toolbox.

Data Access Statement:

The Sand Engine Surface App along with all simulation data is available to download as part of the Supplementary material. This requires MATLAB and the MATLAB Deep Learning toolbox to run. A video in support of the installation is also provided in the Supplementary material. The App is available here: https://github.com/pavitra979/Sand_Engine_Surface.

Code availability

Name of the Software: *Sand Engine Surface App*. Developer: Pavitra Kumar and Nicoletta Leonardi. Contact Information: pavitra.kumar@liverpool.ac.uk. Year First Available: 2023. Platform: MATLAB. Required Library: Deep Learning Toolbox. Cost: Free. Software Availability: https://github.com/pavitra979/Sand_Engine_Surface. Program Size: 60 MB

Reference:

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