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Beach morphodynamic response to hurricane events using new metamodeling approach. Case study in Martinique

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Abstract:
The vulnerability of small islands in the Lesser Antilles to coastal erosion and submersion is particularly pronounced, due to their occasional exposure to tropical storms and hurricanes. These meteorological events unleash energetic waves and increase water levels, with substantial modifications of the coastline playing a crucial role in the long-term evolution of beaches. In the context of Martinique, the complex links between extreme weather events and coastal erosion remain poorly documented while shoreline retreat projections in this region critically rely on the development of a comprehensive quantitative understanding of the sediment budget. This includes an acute consideration of short-term sedimentary contribution associated with extreme events as well.
To better understand and anticipate the impacts of extreme events on the shoreline, we build a deep neural network model fed by 600 numerical simulations from an offline-coupling 2D morphodynamic model at one beach in Martinique. The use of this innovative approach marks a step towards improving our ability to predict and understand the ramifications of severe weather events on the fragile coastal landscapes of Martinique and Caribbean region in general.

Keywords:
Coastal erosion, Tropical storms, Hurricanes, Martinique, Caribbean, Xbeach, Deep neural network, Surrogates, Beach morphodynamics.

1. Introduction

The Caribbean area faces a variety of impacts due to climate extremes. In the context of Martinique, the complex links between extreme weather events and coastal erosion remain poorly documented. Shoreline retreats projections in this region critically depends on a precise consideration of short-term sedimentary contribution related to extreme events. Tropical cyclones (TC) and especially intense hurricanes pose a significant threat

to coastal regions, mainly due to the destructive hydrodynamic forces of storm surges and wind-generated waves. Within a short period, such forcing factors can cause severe coastal erosion and flooding. Numerical models are useful in order to understand the interactions between such drivers and coastal system dynamics. Currently, XBeach is considered one of the most detailed instruments for the prediction of the morphological response of sandy coasts to extreme storms (ROELVINK *et al.,* 2015).
However, morphodynamic process-based models are complex and come with high computational costs, which limits their applicability for use as forecasting tools or as a component in early-warning systems. To this end, data-driven methods based on statistical approaches can offer a good alternative to achieve faster estimations combining numerical models outputs with statistical/machine learning tools. Among these statistical approaches, Artificial Neural Networks (ANNs) have been used in coastal engineering due to their effectiveness for solving complex non-linear systems with great speed (e.g. LÓPEZ *et al.*, 2017, VAN GENT *et al.*, 2007, among others). Unfortunately, statistical modelling and machine learning techniques can be limited by the availability of long-term datasets encompassing a significant number of extreme storm events. Since beach erosion observations (with large spatial and temporal coverage) are scarce, a common approach is to generate synthetic data based on plausible storm conditions using process-based modelling (POELHEKKE *et al*., 2016; SANTOS *et al.*, 2019). Despite these advancements, few studies have focused on developing surrogate models specifically dedicated to coastal beach erosion forecast. Recently (SANTOS *et al.*, 2019) tested the use of ANNs, among other statistical models, to predict changes in dune geometry during storms at Dauphin Island in the USA, and ATHANASIOU *et al*., (2022) used ANNs for the prediction of dune erosion volume (DEV) on the Dutch coast, both using synthetic dataset created with XBeach models. GHARAGOZLOU *et al*., (2022) developed an emulator to predict the morphological response of the subaerial beach to storms.
The present study aims to address the limitations of computational cost and data scarcity by developing a surrogate model to better address the morphodynamic beach response to hurricane event. Firstly, a great subset of synthetic TC is selected from a synthetic database, considering time-dependent evolution of the oceanographic variables. Secondly, the XBeach model is used to compute the morphological responses to selected storms. Thirdly, we develop and test an ANN-based surrogate model to mimic XBeach at low computational cost.

2. Methods and Study area

2.1 Methods

As part of the INTERREG CARIBCOAST project (https://www.carib-coast.com/en/actualites/workshop-hydrodynamics-observation-and-modelling-in-the-caribbean/) BRGM has developed an approach that utilizes the STORM database

(BLOEMENDAAL *et al*., 2020), a powerful resource containing simulations of tropical cyclone tracks in the Caribbean basin. The STORM database is constructed from the historical data archive IBTrACS (KNAPP *et al.,* 2018). It offers a significant advantage over previous databases (e.g., MIT or CHAZ) by exhibiting a more accurate representation of cyclone frequency across various categories (tropical storm to category 5) compared to IBTrACS itself.

For this specific study, 685 tracks were strategically selected from the STORM database, focusing on their proximity to the islands of Guadeloupe and Martinique, representing 1000 years of cyclonic activity for both islands. Parameters of each tropical cyclone along track (maximum wind speed, pressure, radius to maximum winds) were then used to compute separately wind speed (CYCLO), the associated wave field (WW3, ABDOLALI *et al*., (2021)) and water levels (UHAINA, FILIPPINI *et al*., (2018)). The entire procedure was rigorously validated with historical hurricane events, including Irma, Maria, Hugo, the 1928 Okeechobee hurricane, and Dean. XBeach (2D surfbeat) models have been set up at five beaches. The main Xbeach calibration parameters, obtained with historic storms, include wave dissipation coefficient, breaker index, sw friction (already calibrated), and the facua (wave asymmetry related), magnitude of the sediment transport related to bed slope effects.

DNN (deep neural networks) are powerful models that have achieved excellent performance on difficult learning tasks (SUTSKEVER *et al.,* 2014). Here, inspired by the work of ADELI *et al.,* (2023) on storm surge predictions, the authors build a performance model for predicting beach morphodynamics by combining ConvLSTMs (Convolutional Long Short-Term Memory) and an Encoder-Decoder architecture used for dimension reduction.

ConvLSTM, a class of recurrent neural networks, is used for its ability to work on a spatial and temporal learning framework. Encoder-Decoder is a popular approach of organizing recurrent neural networks for sequence-to-sequence prediction applications. It is used for tasks that involve predicting an output sequence based on an input sequence.

The encoder acts, characterized by three convolutional layers, as the first part carefully reading and analyzing the input storm data sequence (e.g. size, intensity, past location). It then compresses this information into a more concise representation, where a ConvLSTM cell is employed. The second part, the decoder, is upsampling through pixel shuffle, takes this compressed representation and uses it to generate the predicted output sequence – the topo-bathymetric variability in this case. Additionally, a residual connection network is incorporated to enhance the model's performance. By breaking down the prediction process into these two distinct stages, the model can handle the final lack of variation in the data more effectively, like used in storm surge model of ADELI *et al*., (2023).

2.2 Study area

The methodology is applied at Le Carbet Beach located on the island of Martinique which has been triggered over the last ten years by severe storms. Martinique is a small volcanic island with a total coastline length exceeding 450 km and encompasses a rich variety of coastal environments. Notably, the island accounts for 120 beaches, which collectively span approximately 63 km, with a maximum width less than 20 meters. To monitor this dynamic coastline, a coastal monitoring network was implemented in 2017, which include smartphone-based cameras.

Le Carbet is a 2.4-kilometer-long beach located in the north-west side of Martinique (Figure 1). The beach is characterized by a slope of around 10 %, exposed to a low energy climate, with an average height of only 0.3 meters and period of 9.2 seconds and a microtidal range, with a maximum amplitude of 0.7 meters at a semidiurnal cycle. In its southern part, the beach exhibits a high level of morphodynamic seasonal variability (10 meters in shoreline variability throughout the year).

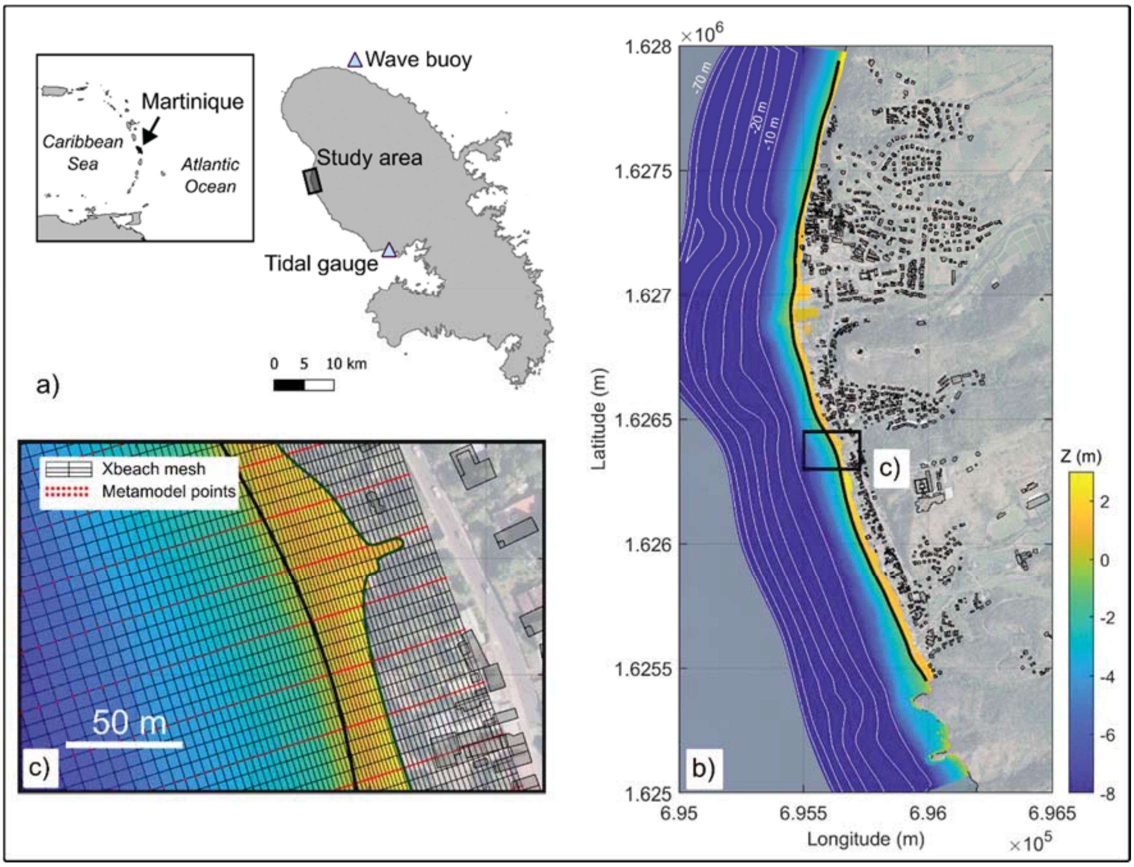

Figure 1. (a) Location of the study area with a directional wave buoy and tidal gauge illustrated. (b) High-resolution bathymetry (Z) at le Carbet beach with (c) a zoom on a random area to highlight the associated curvilinear grid used by the morphodynamic model XBeach (in black) and the location of computational points used by the metamodel (in red).

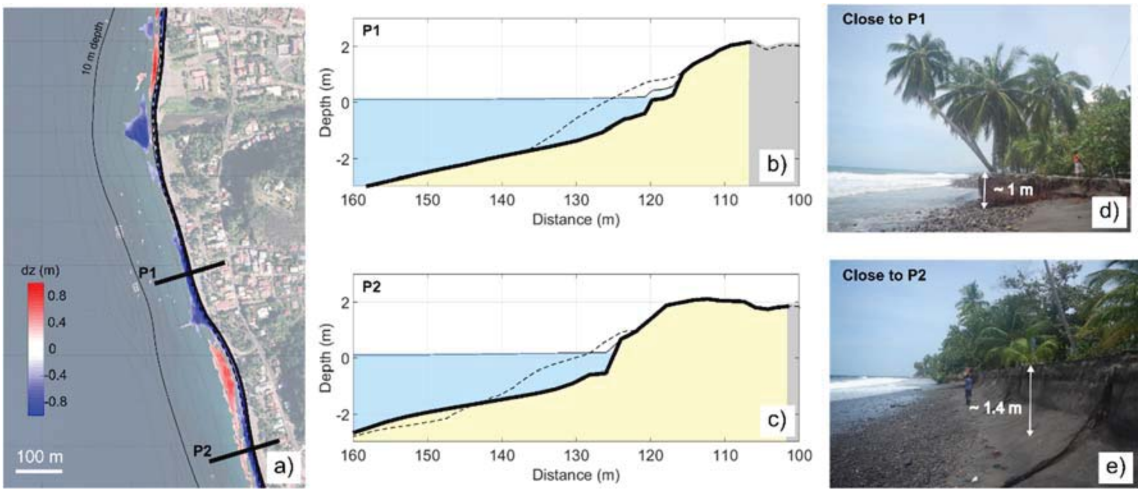

Figure 2. Beach response to hurricane Maria on September 2017 at le Carbet beach. (a) 2D erosion-deposition pattern simulated by the calibrated Xbeach model with the location of P1 and P2 profiles. (b, d) Cross-shore evolution along P1 and P2 with the dashed line indicating the initial beach morphology. (c, e) Beach response matches the observations and more particularly the distribution of maximum beach scarps along the coastal area.

3. Results and discussions

The 685 XBeach 2D simulations of synthetic tropical cyclones and hurricanes with associated morphological response were performed on the computing cluster at BRGM (*Leto* cluster). Each simulation used 60 cores and each day (24 h) of XBeach simulation required about ~1/2hr of wall-clock time. The simulations total duration time steps are between 12 and 82 hours. The XBeach simulations give process-based estimations of the beach response at more than 110 locations in the cross-shore with higher resolutions concentrated around the subaerial section of the beach. The successful application of this approach is demonstrated through the hindcasting of hurricanes Maria where the resulting storm-driven morphological evolutions were found to be satisfactory compared with historical observations (Figure 2). A total of 96 locations in the cross-shore and 48 in the alongshore are used for training the DNN model, 1 over 4 Xbeach transects is chosen in order to reduce model complexity (Figure 1c). A total of 640 randomly selected storms are used for calibration of the neural network emulator, and an additional 45 storms are used as a test sample for its validation. The inputs are the classic parametric meteo-marine variables with significant wave heights (Hs), pic period (Tp), pic direction (Dp) and sea level (SeaLev). The time evolution for all these four parameters is used as input to the neural network (Figure 3). For both the input and the output of the emulator, 82 time steps (1hr each) are used. This range is chosen to encompass the maximum duration TC manifests across the entire geographic domain of interest.

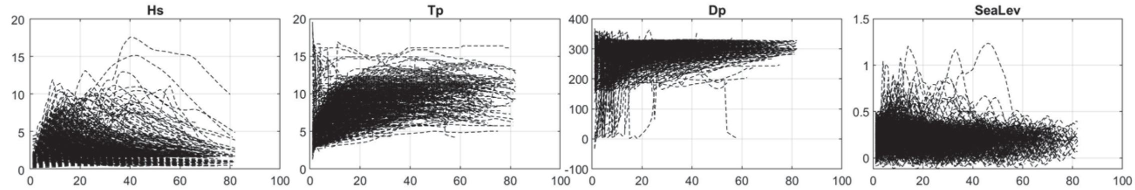

Figure 3. Input parameters for all database storms (units in meters).

The particular shape of the input sequences for the storm, where some values barely change over time requires special attention to data standardization, with respect to mean and standard deviation. The label data (outputs) is also undergoing normalization. This process centers the data on zero using a hyperbolic function. This normalization step helps the model converge faster when using the normalized data (ADELI *et al.*, 2023).
The model is trained with 20,000 epochs, and the learning rate is defined as 10^{-4}. The L2 norm loss function is minimized over the epochs, by mean of the Adam algorithm, by using the mini-batch gradient descent method.
An example of Xbeach-simulated versus surrogate predicted morphological response at Carbet beach for a TC, category 4, with Maximum Hs of almost 6 m offshore, is shown in Figure 4**Erreur ! Source du renvoi introuvable.** Distribution of elevations and elevations' differences, across the domain, are shown together with the cross-shore comparison of both responses at last time step and the forcing inputs. The 2d temporal spatial distribution of erosion-deposition pattern is very well correlated and the final profiles as well.
Some results are shown with regard to the overall BEV (Beach Erosion Volume), computed as the volume of eroded emerged beach (over 0m bathymetric contour), computed along the time.
In Figure 5, a scatterplot with related statistics is presented. It shows the XBeach-simulated versus the surrogate-model predicted Beach Erosion Volume (BEV) for the 40-validation TC cases plus the Hurricane Maria. The colors represent the maximum Hs for each TC and the size of the points increases with time steps. Statistics in the upper left table show the alongshore-median error values averaged across the 40 TC, with brackets giving the min–max values over the TC. The black points (stars) referred to the last time step. The black line indicates the 1:1 line.
As presented, the morphological evolution predictions computed by the convolutional recurrent neural network in all the cases tested are very close to the true values for the entire time interval, with substantial high correlation (with a Brier Skill Score, BSS >0.95 in average) between predictions and "true" responses. Only 2 cases over 40 TC have low values of BSS and RMSD (minimum among them of 0.67, 10 respectively), which represents anyway a *good* classification according to VAN RIJN *et al.*, (2003).

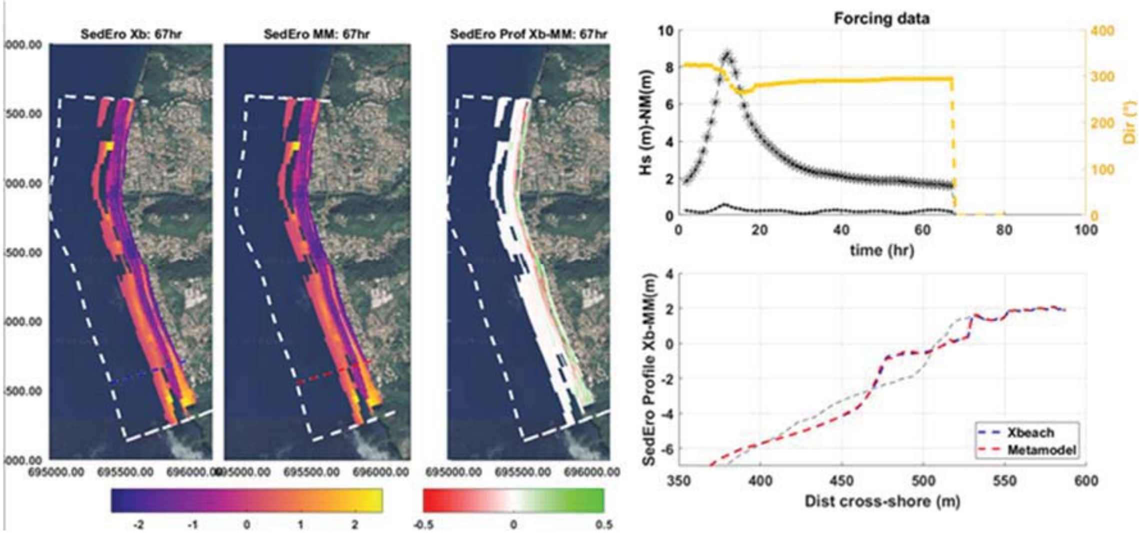

Figure 4. Xbeach-simulated vs surrogate predicted morphological response at le Carbet beach of a TC, category 4. Distribution of elevations and elevations' differences across the domain, cross-shore comparison of both responses at last time step (right down). Input TC characteristics at upper right side.

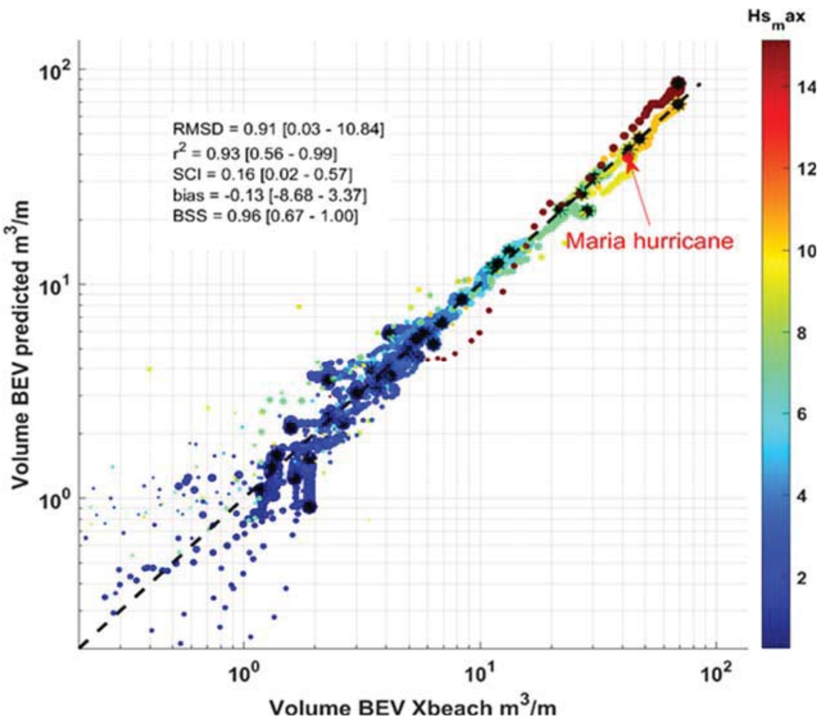

Figure 5. Scatterplot between the XBeach-simulated (x-axis) and DNN-predicted (y-axis) BEV for the validation cases with BEV using the described DNN. The scatterplot, into a log-log plot, shows the validation cases (40 TC, black dots) and the Hurricane Maria (red dot). The colors represent the maximum Hs in the TC and the size of the points increase with time steps. Statistics in the upper left table show the mean overall 48 along-shore profiles, with brackets giving the min–max values. The black points (stars) referred to the last time step. The black line indicates the 1: 1 line.

The speed up the surrogate model with respect to Xbeach (on a multi-core HPC) is of 600x.
New updates are being made by the authors in order to architecture optimisation and increase stability and performance of the model, particularly applying strategy related to early stopping method and regularization techniques (L1 and L2) to introduce coefficients as penalty term to the loss function.

4. Conclusion
This research work focused on building a surrogate model, based on a neural network for predicting beach morphodynamics over time using a database of simulated synthetic TC. The model is a convolutional recurrent neural network (ConvLSTM) enriched by an encoder-decoder architecture (ADELI *et al.,* 2023). This allows the model to consider the entire sequence of data, enabling prediction of the entire erosion-deposition pattern based on the complete history of storm-driven parameters. Overall, the ConvLSTM cell leverages convolutional layers to capture spatial correlations and recurrent layers to capture temporal relationships within the data.
Previous prediction studies primarily relied on machine learning methods, mainly predict dune erosion at a few representative profiles. This machine learning method allows for morphodynamics prediction at several profiles within a large 2d domain of interest, from a Xbeach model. This advancement is achieved by incorporating problem-specific enhancements into the neural network architecture. These formulations not only enable comprehensive prediction but also empower the model to learn spatial and temporal correlations within the data, leading to improved accuracy compared to past efforts.
However, the combination of morphodynamic model with this machine learning method requires particular attention to the quality of the initial calibration of the morphodynamic model, which can affect the beach response to hurricane event and finally the overall metamodel. In this study, the model has only been calibrated and validated on synthetic TC and Maria TC and will be next tested on other historical cyclones.
Also, the wave parameters used in the metamodel is represented by the classical statistical parameters Hs, Tp, Dp, which cannot address the overall complexity of certain wave climate characterized by multiple modes in the shape of the wave spectra. While for TC, the use of wave parameters can still be considered as a correct approximation, the metamodel cannot be directly applied for more complex mixed storm swell.
In addition, to reduce the complexity of our approach, the initial topo-bathymetry is not considered as a variable in the metamodel. Thus, work remains to be done and further tests are needed to assess the sensitivity of the metamodel to the initial bottom elevation.
With certain limitations, the key novelty of this work lies in its ability to generate spatio-temporal predictions across a large geographic domain. Unlike other recent approaches, which focus on directly aggregated predictions of dune or beach erosion (ATHANASIOU *et al.*, 2022, GHARAGOZLOU *et al.*, 2022), ignoring the temporal evolution or spatial

distribution, this model captures the entire temporal evolution across a vast region. The use of this innovative approach constitutes an advance towards improving our ability to predict and understand the consequences of severe weather events on the fragile coastal landscapes of Martinique and the Caribbean region in general.

5. References

ABDOLALI A., VAN DER WESTHUYSEN A., MA Z., MEHRA A., ROLAND A., MOGHIMI S. (2021). *Evaluating the accuracy and uncertainty of atmospheric and wave model hindcasts during severe events using model ensembles*. Ocean Dynamics 71, 217–235. https://doi.org/10.1007/s10236-020-01426-9

ADELI E., SUN L., WANG J., TAFLANIDIS A.A. (2023). *An advanced spatio-temporal convolutional recurrent neural network for storm surge predictions*. Neural Comput & Applic 35, 18971–18987. https://doi.org/10.1007/s00521-023-08719-2

ATHANASIOU P., VAN DONGEREN A., GIARDINO A., VOUSDOUKAS M., ANTOLINEZ J.A.A., RANASINGHE R. (2022). *Estimating dune erosion at the regional scale using a meta-model based on neural networks*. Nat. Hazards Earth Syst. Sci. 22, 3897–3915. https://doi.org/10.5194/nhess-22-3897-2022

BLOEMENDAAL N., HAIGH I.D., DE MOEL H., MUIS S., HAARSMA R.J., AERTS J.C.J.H. (2020). *Generation of a global synthetic tropical cyclone hazard dataset using STORM*. Sci Data 7, 40. https://doi.org/10.1038/s41597-020-0381-2

FILIPPINI A.G., DE BRYE S., PERRIER V., MARCHE F., RICCHIUTO M., LANNES D., BONNETON P. (2018). *UHAINA : A parallel high performance unstructured adaptive near-shore wave model,* in: XVèmes Journées, La Rochelle. Presented at the Journées Nationales Génie Côtier - Génie Civil, Editions Paralia, pp. 47–56. https://doi.org/10.5150/jngcgc.2018.006

GHARAGOZLOU A., ANDERSON D.L., GORSKI J.F., DIETRICH J.C. (2022). *Emulator for eroded beach and dune profiles due to storms*. JGR Earth Surface 127, e2022JF006620. https://doi.org/10.1029/2022JF006620

KNAPP K.R., DIAMOND H.J., KOSSIN J.P., KRUK M.C., SCHRECK C.J. (2018). *International best track archive for climate stewardship (IBTrACS) project*, Version 4. https://doi.org/10.25921/82TY-9E16

LÓPEZ I., ARAGONÉS L., VILLACAMPA Y., SERRA J.C. (2017). *Neural network for determining the characteristic points of the bars*. Ocean Engineering 136, 141–151. https://doi.org/10.1016/j.oceaneng.2017.03.033

POELHEKKE L., JÄGER W.S., VAN DONGEREN A., PLOMARITIS T.A., MCCALL R., FERREIRA Ó.) (2016. *Predicting coastal hazards for sandy coasts with a Bayesian Network*. Coastal Engineering 118, 21–34. https://doi.org/10.1016/j.coastaleng.2016.08.011

ROELVINK D., VAN DONGEREN A., MCCALL R., HOONHOUT B., VAN ROOIJEN A., VAN GEER P., DE VET L., NEDERHOFF K., QUATAERT E. (2015).

XBeach technical reference: *Kingsday release*. Model description and reference guide to functionalities, 1–141.

SANTOS V.M., WAHL T., LONG J.W., PASSERI D.L., PLANT N.G. (2019). *Combining numerical and statistical models to predict storm - induced dune erosion.* JGR Earth Surface 124, 1817–1834. https://doi.org/10.1029/2019JF005016

SUTSKEVER I., VINYALS O., LE Q.V. (2014). *Sequence to sequence learning with neural networks*. https://doi.org/10.48550/ARXIV.1409.3215

VAN GENT M.R.A., VAN DEN BOOGAARD H.F.P., POZUETA B., MEDINA J.R. (2007). *Neural network modelling of wave overtopping at coastal structures*. Coastal Engineering 54, 586–593. https://doi.org/10.1016/j.coastaleng.2006.12.001

VAN RIJN L.C., WALSTRA D.J.R., GRASMEIJER B., SUTHERLAND J., PAN S., SIERRA J.P. (2003). *The predictability of cross-shore bed evolution of sandy beaches at the time scale of storms and seasons using process-based Profile models*. Coastal Engineering 47, 295–327. https://doi.org/10.1016/S0378-3839(02)00120-5