Global Coastline Evolution Forecasting from Satellite Imagery using Deep Learning

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Abstract

Coastal zones are under increasing pressures due to climate change and the increasing population densities in coastal areas around the globe. Our ability to accurately forecast the evolution of the coastal zone is of critical importance to coastal managers in the context of risk assessment and mitigation. Recent advances in artificial intelligence and remote sensing enable the development of automatic large-scale analysis methodologies based on observation data. In this work, we make use of a novel satellite-derived shoreline forecasting dataset and two variants of the common Encoder-Decoder neural network, UNet, in order to predict shoreline change based on spatio-temporal information. We analyze the importance of including the spatial context at the prediction step and we find that it greatly enhances model performance. Overall, the UNet and UNetLSTM models presented here achieve significant global forecast correlation scores of 0.66 and 0.77, respectively.

1 Introduction

Coastal zones around the globe are facing increased natural and anthropogenic pressures, and our knowledge of their evolution is critical in many scenarios, including coastal risk assessment and mitigation. Shoreline evolution forecasting is an important element in coastal science which aims at improving our understanding of, and ability to predict, the occurrence and intensity of coastal erosion and its potential impacts on the coast [1, 2]. Much of our current knowledge of coastal evolution originates from the study of a few well-documented coastal sites where frequent field surveys have

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been ongoing for multiple years. However, due to the high cost of in-situ field surveys, the state and evolution of these systems is not known in many areas of the world [3].

Space-borne Earth Observation missions create the potential for studying coastal systems at a global scale and at high temporal frequencies (up-to daily), but present new technical challenges and require the development of new methodologies for information extraction and processing. Machine Learning (ML) is a family of Artificial Intelligence algorithms that aim at automatically approximating the relations between inputs and outputs, by maximizing (or minimizing) an objective function over a labelled dataset of training samples. Recent developments in ML have led to significant advancements in a number of scientific domains [4–11]. Due to the continuous stream of high-dimensional data recorded by multiple EO satellite constellations, ML has seen a wide adoption in RS data processing pipelines, and has been used to augment or completely replace existing image and signal processing-based analysis [12–16].

A large body of work exists in the Coastal Science literature on shoreline forecasting, ranging from physics-based approaches such as process-based morphological models and hybrid shoreline models, to a wide range of data-driven techniques. Deep learning-based models are often found competitive with physics-based and traditional forecasting techniques [1, 17, 18], and offer a number of desirable properties in the context of large-scale shoreline analysis [3, 19]. However, training accurate DL models requires the availability of representative training data which would allow the models to generalize to previously-unseen conditions [20]. In this work, we make use of a novel global-scale dataset of satellite-derived shorelines, and their corresponding shoreline change drivers, in order to train and test a spatio-temporal approach to predicting shoreline change based on Deep Learning. Here, an Encoder-Decoder convolutional neural network (UNet) is extended to include a temporal unit (LSTM) in order to learn the spatio-temporal patterns in shoreline forcing and shoreline response. To our knowledge, this work presents the first steps towards a data-driven method for global shoreline prediction based on spatio-temporal data.

2 Global shorelines dataset

This study makes use of a satellite-derived dataset of global monthly shoreline position time series dataset that spans $\simeq$25 years (1994 to 2019) and covers 6841 coastal points around the globe; in addition to global datasets of shoreline change drivers including coastal waves, sea level anomaly, and regional river discharge. This dataset was presented in [21].

The methodology followed to derive shoreline positions from satellite imagery makes use of Normal Difference Water Index (NDWI) maps in order to segment satellite imagery into land and sea surfaces. Using a NDWI threshold of 0.5, pixels of a single satellite image can be divided into land and sea pixels. The coastline position is then identified as the interface between land and sea. In order to create a time series of global coastline evolution, the Google Earth Engine was used to process a large amount of satellite data from the Landsat 5, 7 and 8 missions. The extracted shorelines are aggregated to a monthly scale using the monthly median shoreline position.

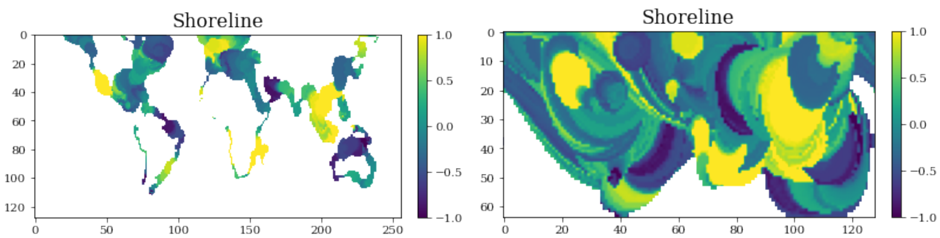
Multiple techniques were used to derive the shoreline change drivers time series. These methods range from satellite altimetry (SSALTO/DUACS) to detect regional sea level anomaly (SLA), to climate reanalysis (ERA5) for wave conditions (i.e. height Hs, period Tp, and direction Dir), and land surface model simulations (ISBA-CTRIP) for river discharge. Additionally, the offshore wave energy flux is computed as $E = Hs^2 \times Tp$ [21] and is included as an additional input.

Finally, a smoothing procedure is applied to all time series in this work in order to retain the interannual to long-term patterns in the shoreline and forcing time series. This filtering also aids in reducing the effects of any potential noise or errors in the satellite-derived data. The smoothing is done using a moving average pass band filter between 9 months and 10 years, where the filtered signal is computed as the signal difference between the lower and upper frequencies' moving averages.

3 Methods

3.1 Spatio-temporal data representation

We develop a synthetic projection of the coastal points onto a 2D grid in order to be used as inputs to the convolutional DL model. First, we create a N×N px grid covering Latitudes of $-60°$ to $60°$ and



(a) 128x256 (b) 64x128

Figure 1: The data representation used as inputs to the spatio-temporal DL model. (a) shows the resulting projection using a larger grid. (b) shows the result of the same projection procedure over a smaller grid size.

Longitudes between $-180°$ and $180°$. The resolution of the spatial dimension is determined according to the target image size. Then, coastal points are sequentially assigned synthetic coordinates from the grid by minimizing the distance between each point's assigned and real coordinates. Example shoreline maps created based on the synthetic projection are presented in Figure 1. Additional example maps of Sla and wave energy are presented in Appendix A.

Our aim behind this procedure is to maintain, as much as possible, the real spatial distribution of points while reducing the sparsity (empty spaces) in the image. The same procedure is repeated to create spatio-temporal maps for the target shorelines as well as for all shoreline change drivers in the global dataset, including SLA, river discharge and the wave parameters (E, Tp, Hs, Dir). The 64×128 images were used to train and test the models presented in this work.

3.2 Neural architecture and training

This work makes use of the common Encoder-Decoder neural architecture UNet [22] in order to capture the spatial patterns in shoreline position at different points in the world. In order to capture the temporal relations in the data, we modify the original UNet architecture by adding a Long Short-Term Memory (LSTM) cell [23] between the encoder and decoder subnetworks. We refer to this architecture as UNetLSTM in the following. The network is passed 7-layered images (of size 64×128 px) as input, representing the different features (SLA, rivdis, E, Tp, Hs, Dir), in addition to the shoreline map at the current time step, and the network is trained to predict the shoreline map of the next month. Furthermore, the complete dataset is split into training, validation and test sets, covering 1994 to 2012, 2012 to 2016, and 2017 to 2019, respectively. Based on this setup, the Adam optimizer [24] is used to train the neural network for 100 epochs using a learning rate of 10^{-5}, a batch size of 16, and RMSE as the loss function.

4 Results

This section presents our experimental results on the use of UNet and UNetLSTM to predict shoreline change at a global scale. In the following, Section 4.1 first examines the impact of including an LSTM cell in the architecture on the network's forecast performance. Then, Section 4.2 examines the impact of utilizing spatial information in the shoreline prediction model. Additionally, Appendix B presents a comparison of the ground truth and predicted time series over a selection of three coastal points.

4.1 Performance comparison

This section presents a comparison of UNet and UNetLSTM accoring to their prediction performances over the three-year test set (2017 to 2019). The models are compared according to their global correlation scores, computed by averaging the correlation score over each coastal point in the dataset. Figures 2 and 3 present maps of the correlation scores of the two models over the test set, and across all points in the global dataset.

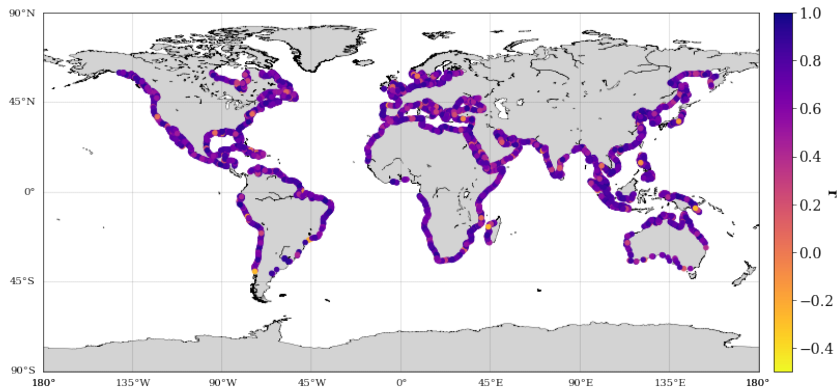


Figure 2: Forecast performance over the test set (3 years) using UNet. ($\overline{r} \simeq 0.66$)

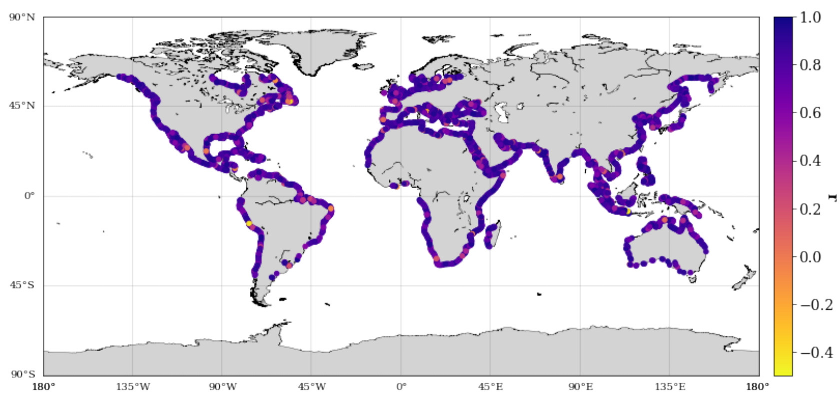


Figure 3: Forecast performance over the test set (3 years) using UNetLSTM. ($\overline{r} \simeq 0.77$)

While UNetLSTM achieves overall higher performance scores, we note the significant accuracy demonstrated by the traditional (non-recurrent) UNet architecture over the test set. These results also suggest that both models produce low-quality forecasts at similar coastal points. We hypothesize that this consistent deterioration in model performance at those areas is due to data-related limitations (e.g. noise, error) rather than the network itself.

Overall, these results demonstrate how the inclusion of both the spatial and temporal dimensions of the data improves the ability of the neural network to forecast global shoreline change, as demonstrated by the generally higher correlations of UNetLSTM around the globe in Figure 3, in addition to the higher average correlation score (0.77 compared to 0.66).

4.2 Spatial dependencies

The experiment presented here examines the impact of taking the real spatial distribution of the coastal points into account on the model's ability to produce accurate shoreline forecasts. To this end, we vary the distance function used when assigning synthetic coordinates to coastal points. In the realistic case (Figure 3), the haversine distance is used in order to embed the real distribution of points into the synthetic projection. Then, a random synthetic projection is created by replacing the haversine distance function with a random number generator. Since the coastal points are distributed randomly in this dataset, the model's ability to exploit any real spatial dependencies in the data should be hindered.

Figure 4 presents the shoreline prediction results of UNetLSTM using a non-realistic spatial projection. A comparison with the results shown in Figure 3 confirms that taking the spatial context of coastal points into account does greatly enhance the ability of the network to model shoreline change, achieving a significant global correlation improvement from 0.46 to 0.77.

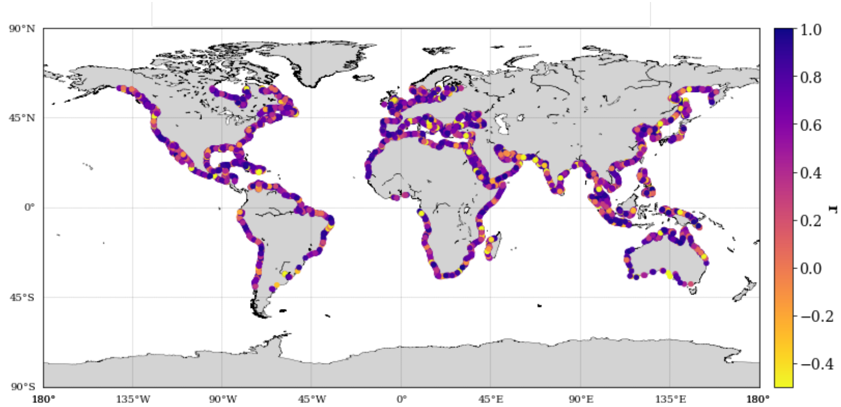


Figure 4: Forecast performance over the test set (3 years) using UNetLSTM and a non-realistic synthetic map projection ($\overline{r} \simeq 0.46$).

5 Discussion & Conclusion

This communication aims at demonstrating the benefit and potential performance improvements that can be achieved by accounting for the spatial context of coastal points when predicting shoreline change, in addition to their local behavior as is generally done in similar shoreline studies. The experiments presented here made use of a traditional neural architecture, UNet, as well as a modified UNetLSTM variant of the network, to predict interannual to long-term shoreline change at a global scale. The models achieve global correlation scores of 0.66-0.77, with the spatio-temporal model (UNetLSTM) demonstrating the best performance of the models tested.

This work focuses on examining the performance and impact of a spatio-temporal approach for shoreline prediction. Future development of the work should benchmark more recent neural architectures at this task. For instance, diffusion-based models have been proposed in the video frame prediction literature [25], and can be used in order to more explicitly motivate the model to capture local-scale events such as storms, while taking into account global patterns such as climatic modes, in order to forecast shoreline change. Furthermore, another important aspect to be considered in the context of this work is the interpretability of the proposed model. While this work demonstrates the benefit of a spatio-temporal approach for shoreline prediction, the DL model used is considered a black-box which lacks interpretability. Future work in data-driven techniques for shoreline prediction should consider different DL explanation techniques [26, 27], or otherwise use interpretable machine learning [28].

Overall, the models presented in this work show promising performance and motivate further research on the use of Remote Sensing and Deep Learning for coastal evolution analysis. To our knowledge, the UNetLSTM model presented here can be considered the current state-of-the-art in data-driven shoreline modelling at a global scale.

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A Input variable maps

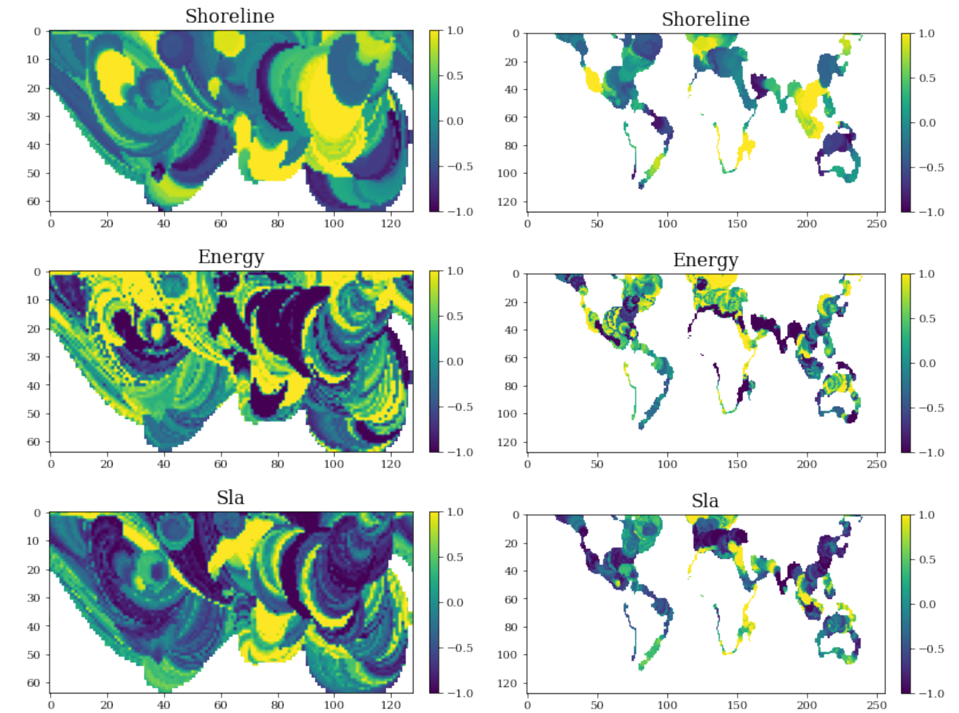

Figure 5: The map representation based on the synthetic projection using images of size 64×128 (left) and 128×256 (right) for shoreline, wave energy and sea level anomaly

B Time series comparison

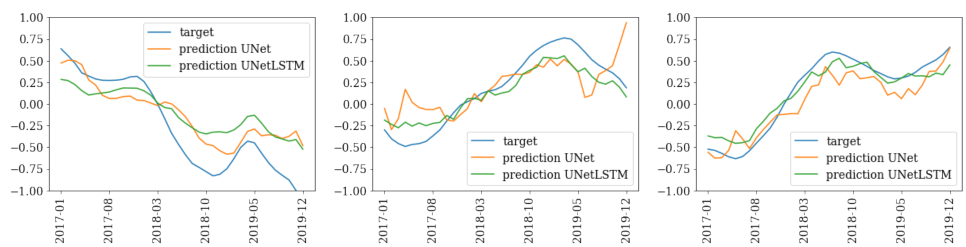

Figure 6: A visualization of the target and predicted time series produced by UNet and UNetLSTM at a selection of coastal points.