Predicting Future Sea Level From Satellite Altimetry

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This project aims to employ modern machine learning techniques to predict short-term sea level changes.

Specifically, the neural network architecture ConvLSTM[1] is used, enabling us to capture spatiotemporal relationships. This neural network architecture has been developed specifically for geophysical applications and has previously been applied to sea surface temperature, rain forecasting, and ocean wind speed.

The initial area of study is a part of the Southern Atlantic Ocean, as outlined in Figure 1, and the data product is JPL's MEaSUREs Gridded Sea Surface Height Anomalies Version 2205[2], which offers 1/6th degree spatial resolution with a 5-day temporal resolution. The product uses data from TOPEX/Poseidon and the Jason series, along with other satellites for given dates, and is interpolated using Kriging.

The chosen area grid is subdivided both spatially and temporally. The spatial division is shown in Figure 2 and is done by dividing up the grid into 28x28 pixel subsets. The temporal subdivision is achieved by taking each spatial sub-grid and chunking every possible n_{in} + n_{out} combination, where n_{in} is the length of the input time vector and n_{out} the length of the output (target) time vector. Furthermore, ~10 years of data is set aside as validation and test data; see Figure 3.

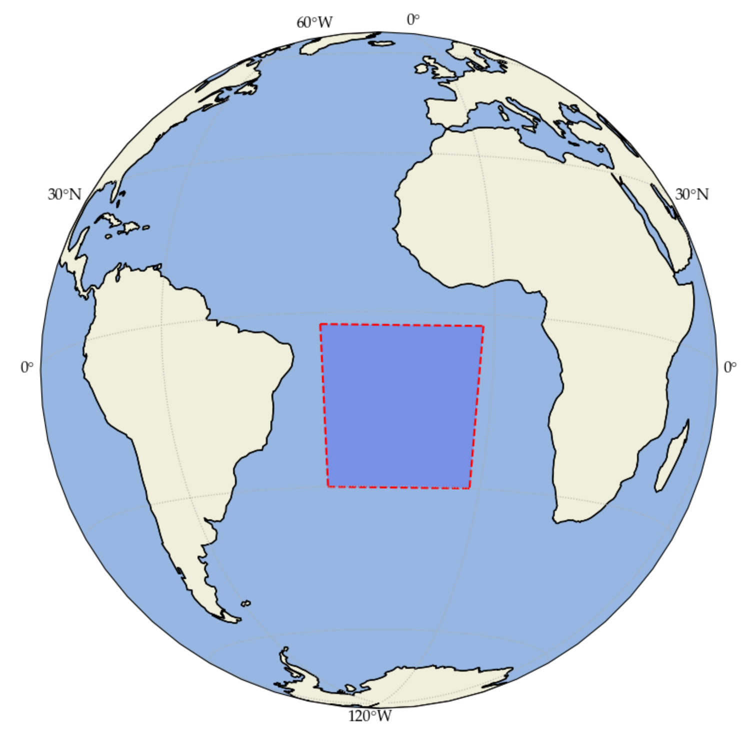

Fig. 1: The initial area of study in the Southern Atlantic Ocean. This area is further subdivided, as shown in Figure 2.

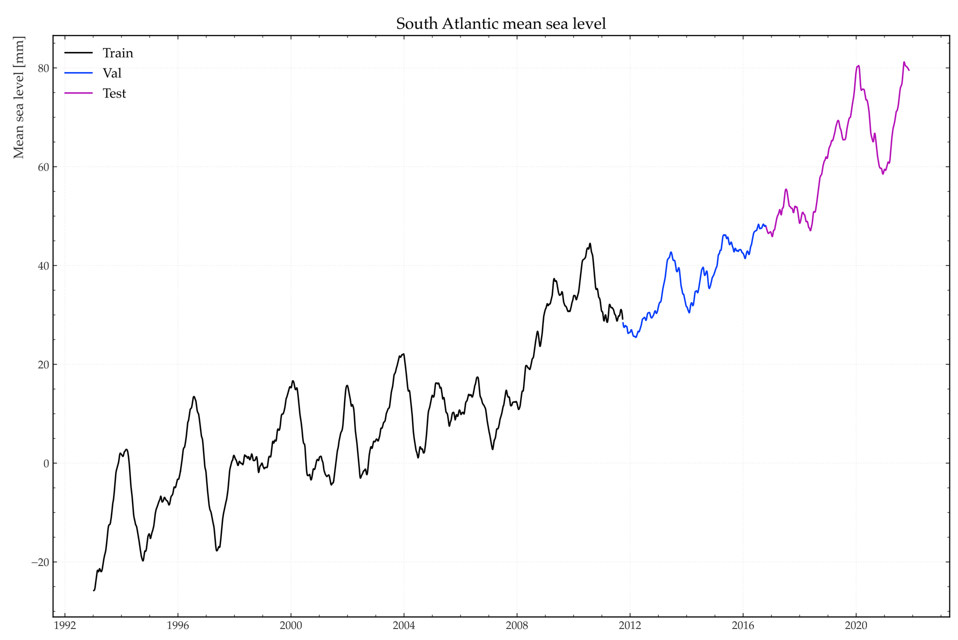

Fig. 3: The mean sea level of the area of study with the train-, validation- and test-set shown. Note that the data has been deseasoned and a smoothing filter of 6 months has been applied.

The network is trained on sequences of length n_{in}, and is asked to predict n_{out} timesteps. The error in prediction is used to adjust the weights of the network.

These are early stages, where much focus is on getting the network to work. Thus n_{in} = 10 and n_{out} = 10, which means the input is 50 days and the output is 50 days. As can be seen in Figure 4, this does not produce very useful outputs, as the network tends to just persist, yielding the lowest error.

Much work is ongoing to increase the power of the network, see the box "Future work".

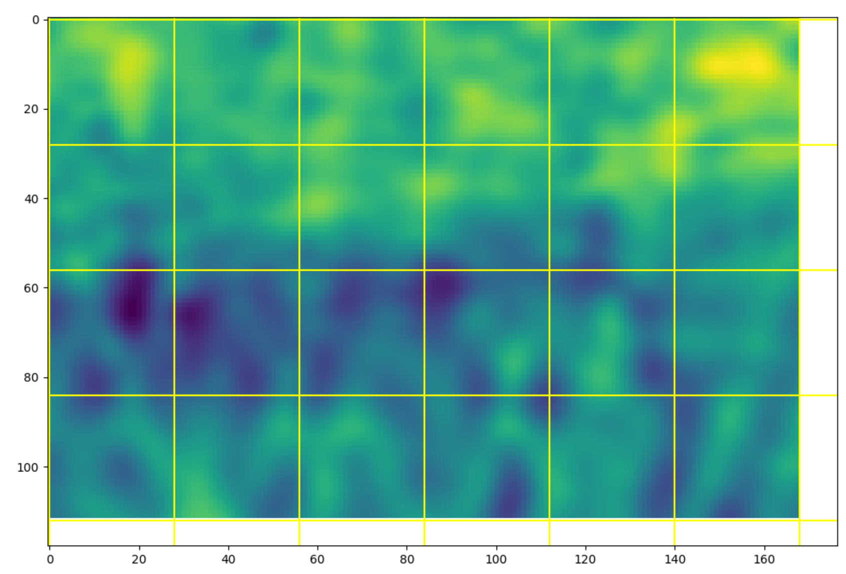

Fig. 2: The area of study is subdivided into 28x28 "images". This is done to save on resources as the larger the "image" the more GPU RAM one needs. This grid shows the MEsSUREs sea-level anomaly values for an arbitrary date, with the subdivision indicated by the yellow lines.

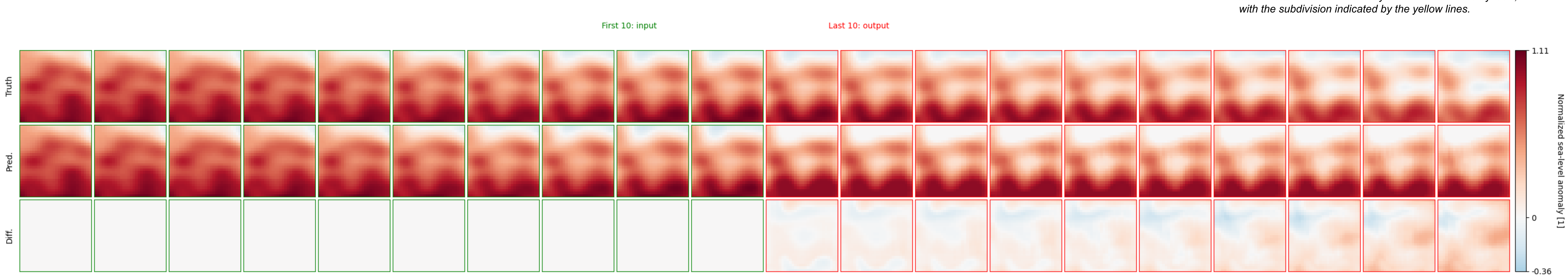

Fig. 4: An example prediction. First row is the ground truth, next row shows input (the first 10 columns) which gives a prediction (the last 10 columns) and the last row is the difference between ground truth and prediction.

References

1) Shi, X., Chen, Z., Wang, H., Yeung, D., Wong, W. and Woo, W., 2022. Convolutional LSTM Network: A Machine Learning Approach for Precipitation Nowcasting. [online] arXiv.org. Available at: <https://arxiv.org/abs/1506.04214v2> [Accessed 28 August 2022].

2) Fournier S., Willis J., Killett E., Qu Z. and Zlotnicki V.. 2022. SEA_SURFACE_HEIGHT_ALT_GRIDS_L4_2SATS_5DAY_6THDEG_V_JPL2205. Ver. 2205. PO.DAAC, CA, USA. Dataset accessed [2022-08-01] at https://doi.org/10.5067/SLREF-CDRV3

Future work

The MEaSUREs dataset is heavily interpolated, which may impede the network's ability to learn physics inherent in the data. Thus a change to another product, e.g. AVISO, is underway.

The techniques of physics-informed neural networks should be able to help the network learn, by adding to the loss function terms that require it to respect some physics-based equation relevant to the problem. This area is being researched.

The subdivisions should probably overlap. This might help the network figure out boundary conditions between two sets of "images".

Outliers such as ENSO should be removed from the data, as their inherent randomness can cause the network to become confused. A potential way of removing ENSO has been identified and is being evaluated.