ConvLSTMs for vertical ocean velocity prediction in the North Atlantic

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Abstract

Up and downwelling events in the ocean play a critical role in the vertical mixing of ocean waters. This mixing is of utmost importance in the distribution of biological productivity and uptake of atmospheric carbon dioxide. Prediction of vertical mixing events has been limited to predicting vertical velocities using ocean models, which are not exclusively based on data. To address this glaring lack of a data driven approach to predicting vertical mixing processes in the ocean, we create a dataset of vertical ageostrophic velocities by post processing satellite altimetry data. We train a Convolutional Long Short Term Memory (ConvLSTM) machine learning network on this data to predict future vertical velocities, and evaluate our model's performance. We are able to achieve 4.77 x 10^3 less mean square error loss compared to a naive baseline method after training on 1088 groups of training data. This work lays foundations for the incorporation of deep learning techniques in oceanography at large.

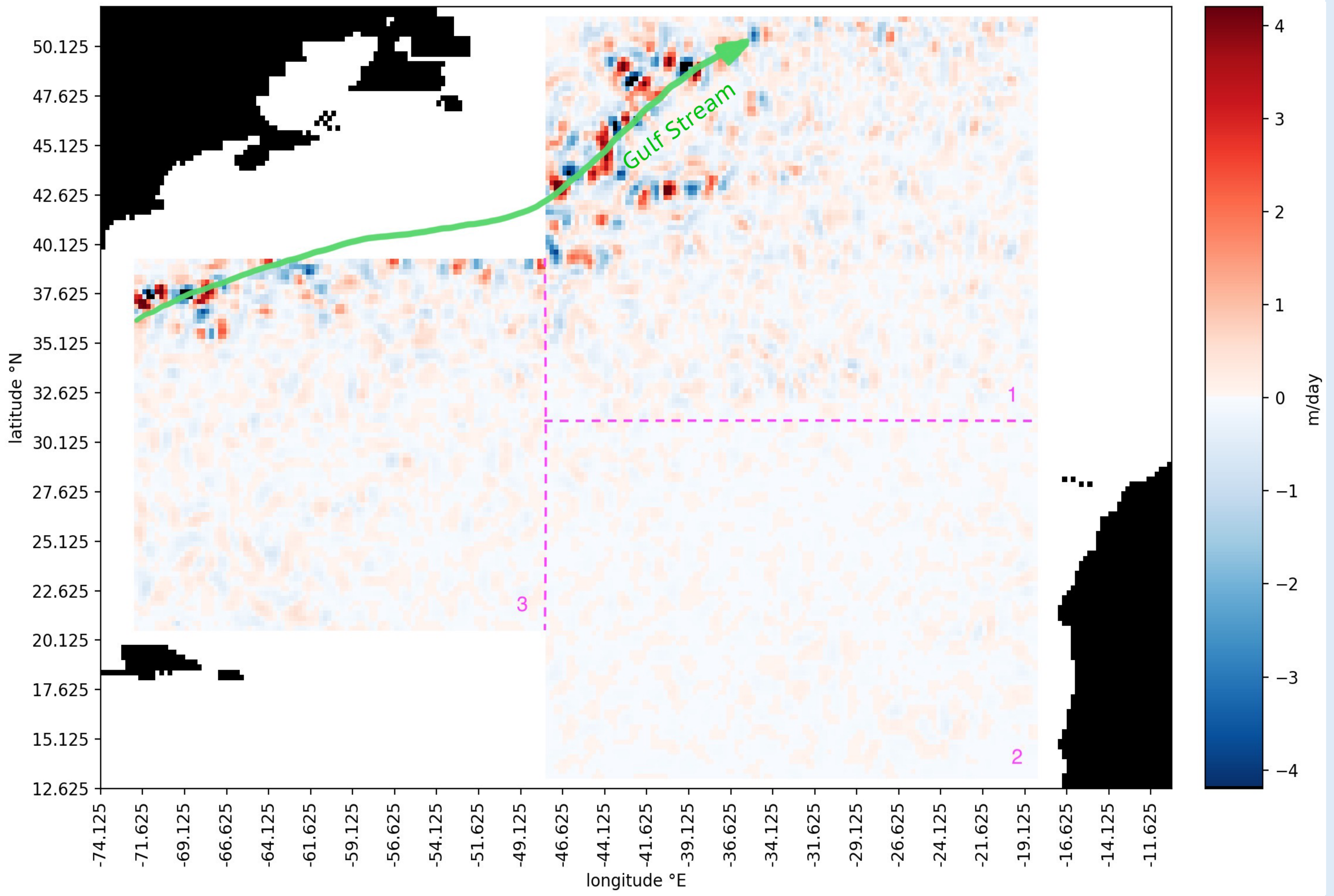

Figure 1: Sample vertical velocity field in the North Atlantic Ocean (20 January 1993). Thin dashed purple lines divide subregions 1, 2, and 3.

Data

- Data is from Marine Copernicus, a combination of satellite altimetry and in-situ data with 0.25 degree resolution and weekly temporal resolution [1].
- We use salinity, temperature, and depth as input for the program developed by [2] which computes the vertical velocity field to create a weekly dataset of vertical velocities in the north Atlantic Ocean from 1993 to 2018.
- Data is divided in the same three regions (Fig. 1) in order to keep the training process computationally reasonable

Methods

- The data is organized into groups of 6 consecutive weeks with the first 5 weeks as the input data and the sixth week as the label (Fig. 3).
- Given our five consecutive 2-D inputs mapping to a single 2-D output, we use a many-to-one style ConvLSTM [3] with 6 filters, each sized 6x6, followed by a single convolutional layer with 1 filter sized 3x3. We use a mean square error (MSE) loss.
- To benchmark our model's performance we use a naive method taking the vertical velocities in the fifth week as a prediction of the vertical velocities in the sixth week. The naive method is trained and evaluated on the same data.

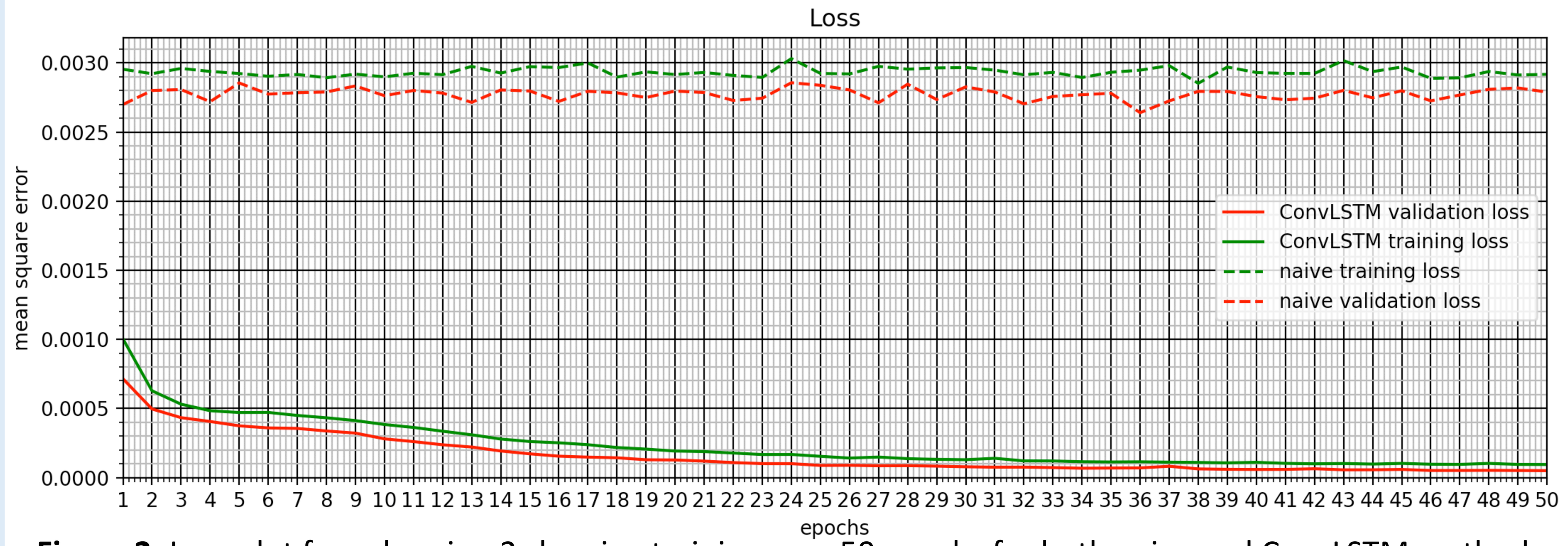

Figure 2: Loss plot for subregion 2 showing training over 50 epochs for both naive and ConvLSTM method. The ConvLSTM immediately outperforms the naive method, and continues to improve over training time.

Region	ConvLSTM MSE (test data)	Naïve MSE (test data)	Percent difference
1	1.76 x 10^{-2}	6.79 x 10^{-1}	3.76 x 10^3
2	3.59 x 10^{-5}	2.2 x 10^3	6.03 x 10^3
3	1.44 x 10^{-3}	6.65 x 10^{-2}	4.52 x 10^3
Average (3 regions)	6.36 x 10^{-3}	2.49 x 10^{-1}	4.77 x 10^3

Table 1: Summary of performance on testing data for the ConvLSTM model and the naive baseline method. In each region, the ConvLSTM model outperforms the naive baseline method by over 1000%. This result indicates that the ConvLSTM model is learning more than just the structure of the vertical velocity data and making predictions.

Results

- We achieve a final model with average MSE loss of 6.36 x 10^{-2} across the three regions, compared to an average MSE loss of 2.49 x 10^{-1} with our naive method, a 4.77 x 10^3% improvement [Tab. 1, Fig 2].
- We study the spatial variability of the model's performance by examining snapshots (ground truth), predictions of the snapshots (predictions), and anomalies (predictions minus ground truth) of vertical ocean velocities for test data in subregion 1 (Fig. 4).
- We observe that the ConvLSTM approach to vertical velocity prediction in the most energetic subregion of the North Atlantic reproduces the spatial variability successfully.

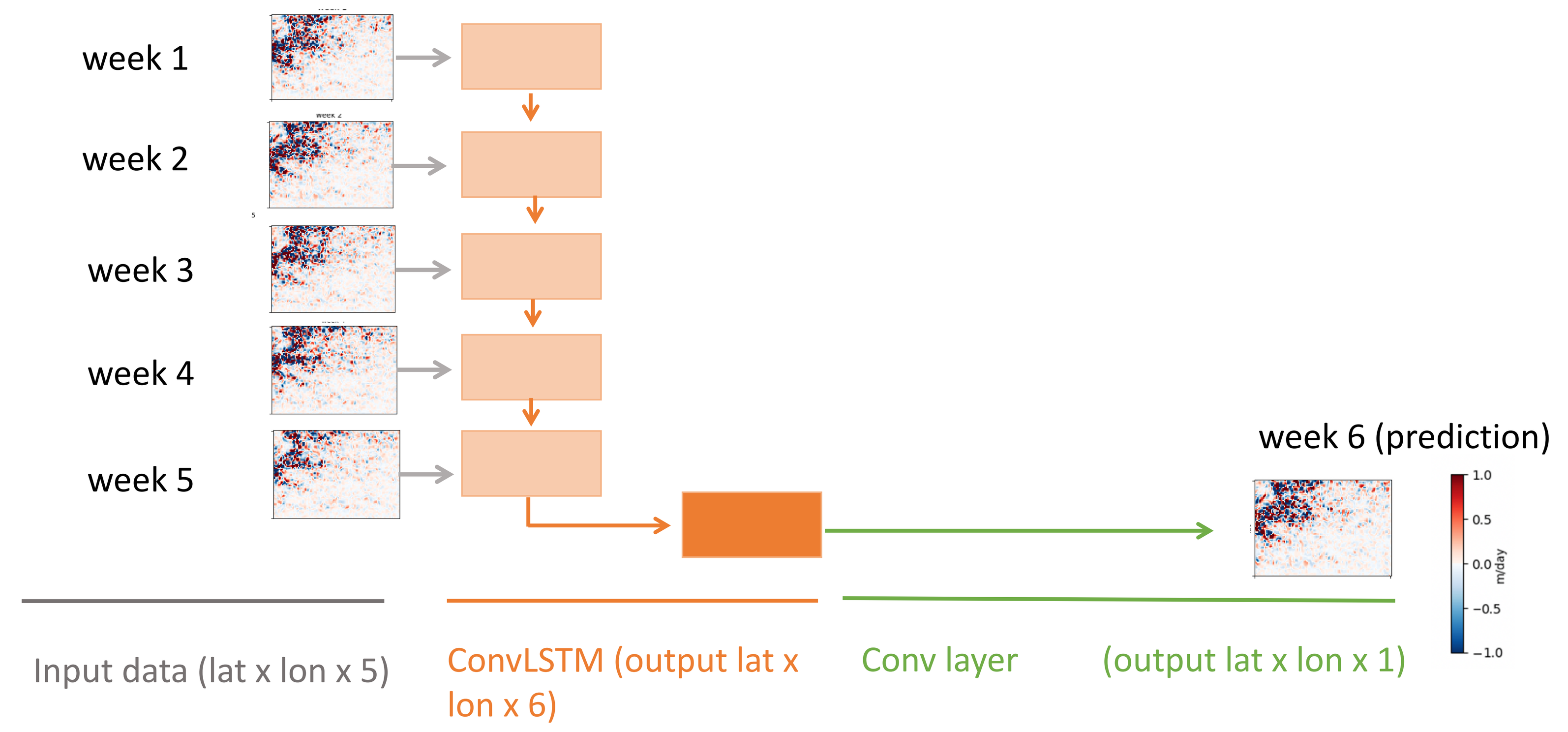

Figure 3: Schematic of ConvLSTM method including ConvLSTM and Convolutional layer. Future work on this study includes doing a hyper parameter search for best network architecture and extending the scope of our predictions beyond one week in the future.

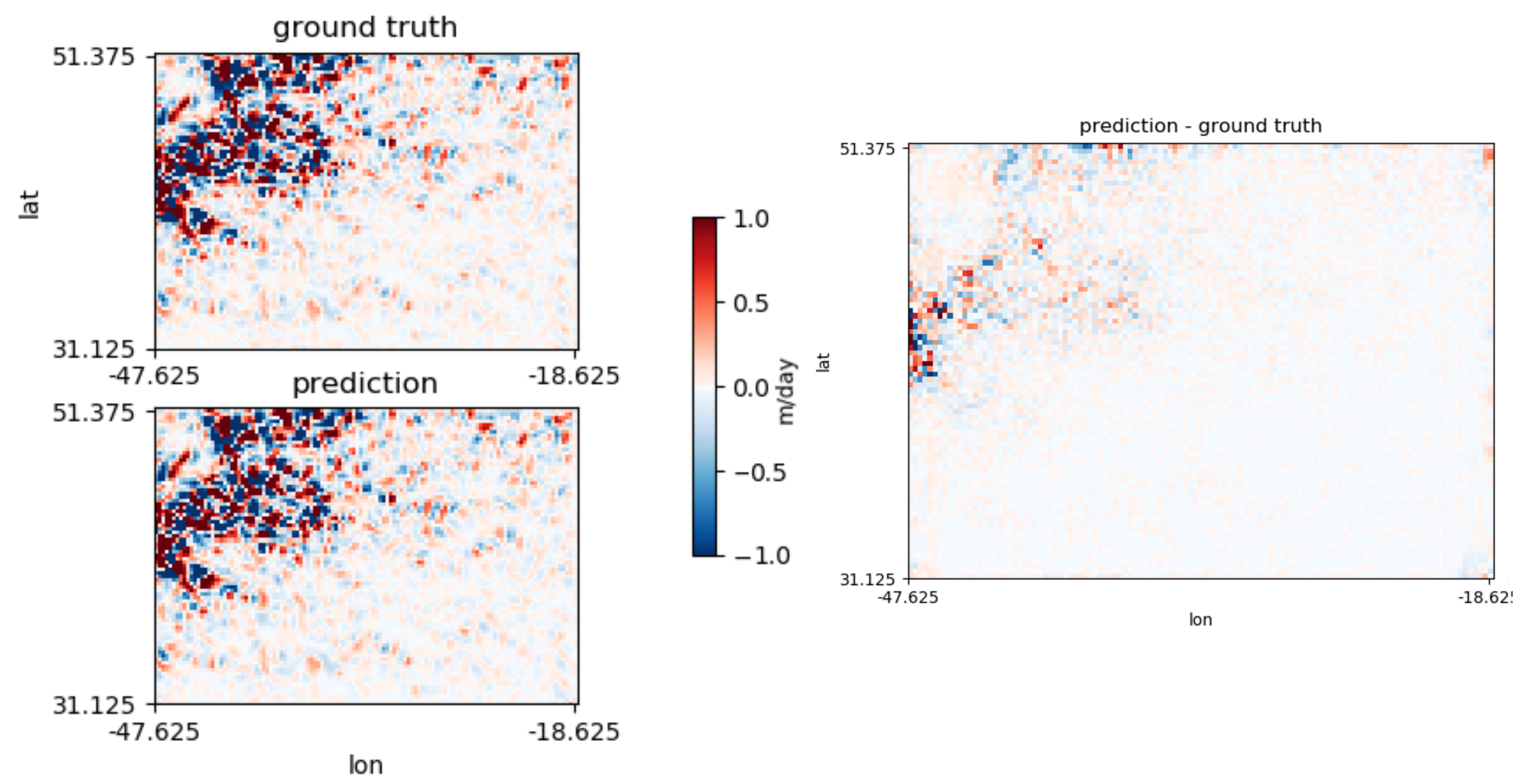

Figure 4: Left: More detailed look at ground truth versus prediction as shown in (Figure 2). Right: At every grid point ground truth is subtracted from the prediction, producing anomalies. Highest anomalies correspond to most extreme vertical velocities.

References

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