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 in the ocean and potentially influences ocean uptake of atmospheric carbon dioxide. Prediction of up and downwelling events has been limited to predicting vertical velocities using ocean models, which provide the basis for general inferences about up and downwelling events but, with the exception of sporadic data assimilation schemes that adjust model predictions, are not exclusively based on data. Therefore, ocean models cannot predict these vertical mixing events specifically and realistically. To address this glaring lack of a data driven approach to predicting vertical mixing processes in the ocean, which has immense implications for the study of eddies in the field and beyond, 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.

1 Introduction

Vertical mixing events are characterized by localized high magnitude vertical velocities that persist over time. Vertical mixing events in the ocean are usually driven by Ekman transport near the coast and by mesoscale eddies, ocean eddies with characteristic radius scales on the order of 100 km [McGillicuddy Jr [2016]]. Our study focuses on the waters of the north Atlantic ocean off the continental shelves, where vertical mixing events are caused by eddies.

The availability and quality of satellite altimetry data indicates that mesoscale eddies are ubiquitous in the global ocean [Chelton et al. [2011]]. Upwelling associated with eddy driven high vertical velocities generates visible signals in sea surface temperature, sea surface height and ocean biogeochemistry fields [McGillicuddy Jr [2016]]. Through eddy pumping, cyclonic (anticyclonic) eddies can shift isopycnals upward (downward), unstratify (stratify) the water column, and shoal (deepen) the mixed layer [McGillicuddy Jr [2016]]. The upward eddy pumping brings nutrients closer to the euphotic zone, where they are accessible by phytoplankton and organisms higher up in the food chain (e.g., sharks) [Gaube et al. [2019]].

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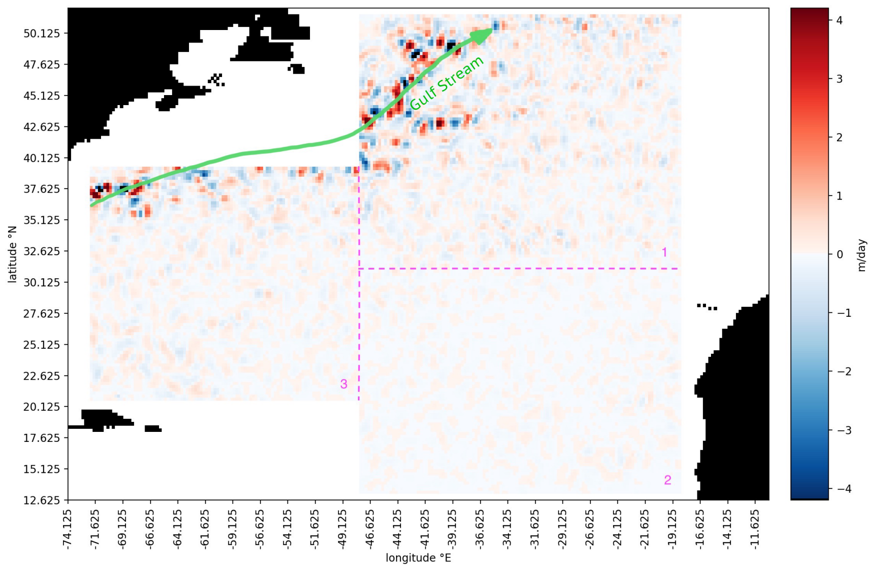

Figure 1: Vertical velocity field in the North Atlantic Ocean on 20 January 1993. Thin dashed purple lines divide subregions 1, 2, and 3.

Deep learning has been used in oceanography as a tool for improving ocean model resolution [Bolton and Zanna [2019]] and estimating ocean-wave conditions [James et al. [2018]], demonstrating that deep learning can be leveraged to make predictions which respect physical principles in oceanography. Our work leverages the work of [Xingjian et al. [2015]] introducing the ConvLSTM. The ConvLSTM uses the basic structure of an LSTM but computes a convolution in place of a dot product, making the network suitable for time series of images. ConvLSTMs have been applied with success in several domains from vehicle traffic prediction [Yuan et al. [2018]] to temperature prediction [Lin et al. [2019]]. Recently, ConvLSTMs have been applied in oceanography for volumetric ocean velocity forecasting [Huang et al. [2020]]. Our work is distinct from [Huang et al. [2020]] in that we focus on vertical ocean velocities as a proxy of vertical mixing events.

2 Data

2.1 Data

Our data comes from Marine Copernicus, the European Program for the establishment of a European capacity for Earth Observation and Monitoring. From Marine Copernicus, we use the Global ARMOR3D L4 Reprocessed dataset (GAL4R), which is a combination of satellite altimetry and in-situ data with 0.25 degree resolution and weekly temporal resolution [Mulet et al. [2012]]. From GAL4R, we use salinity, temperature, and depth, taking depth as an estimation of pressure [Thomson and Emery [2014]]. We study the north Atlantic, using a spatial domain divided into three different regions (Figure 1) to avoid the continental shelf where the satellite altimetry data is less accurate. Satellite altimetry has proven to be a useful tool to study oceanic processes in the deep ocean. Over continental shelves, however, the aliasing of unresolved high-frequency signals of tidal and wind-induced forcing is the source of long-wavelength errors that contaminate altimetry measurements and limit their use in shallow waters [Schlax and Chelton [1994]] [Ray [1998]].

2.2 Post processing

Vertical ocean velocities needed to study up and down welling events cannot be measured and indirect methods are needed to estimate them. We use salinity, temperature, and depth to calculate seawater density. We use this density data as input for the program developed by [Vélez-Belchí and Tintoré [2001]]. This program computes the vertical velocity field via the quasi-geostrophic omega equation from ocean density data to create a weekly dataset of vertical velocities in the north Atlantic Ocean.

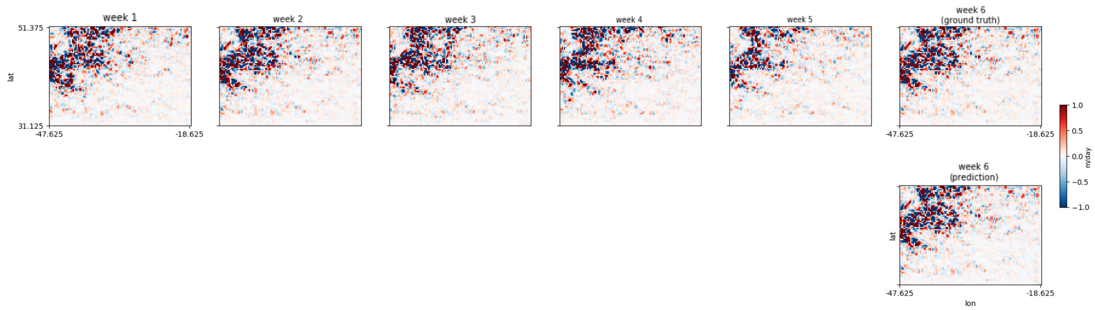

Figure 2: Sample input data (weeks 1-5), label (week 6 - ground truth), and prediction (week 6 - prediction) after 50 epochs of training. This data comes from the test dataset from subregion 1.

3 Methods

For this study we focus on the vertical velocities on the surface of the ocean; thus our data has a matrix depth of 1. The data is divided in the same three regions (Figure 1) in order to keep the training process computationally reasonable, with overlapping regions of size 10 pixels (2.5 degrees) added for reconstruction. This results in subregion 1 spanning 47.625°W to 18.375°W and -31.125°N to 51.625°N, subregion 2 spanning 47.625°W to 18.375°W and 13.125°N to 33.625°N, and subregion 3 spanning 72.125°W to 45.125°W and 21.125°N to 39.875°N with sizes 117 x 82, 117 x 82, and 108 x 77 respectively. 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 (Figure 2). For all three regions the data from January 1993 to December 2013 is used as training data and the data from January 2014 to June 2016 is used as validation data during training, and the data from June 2016 to December 2018 is reserved for testing the model after training, creating a 81.1% training, 9.6% validation, 9.5% testing split. Given this split, we are left with 1088 groups of 6 weeks as training samples and 254 groups of 6 as testing samples.

Given our five consecutive 2-D inputs mapping to a single 2-D output, we use a many-to-one style ConvLSTM with 6 filters, each sized 6x6, followed by a single convolutional layer with 1 filter sized 3x3. At each step, we use padding to keep the height and width of our data uniform. We use a mean square error (MSE) loss and the Adam optimizer with learning rate 0.001. We trained our ConvLSTM for 50 epochs and test the model on the reserved testing data after training.

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 run on the same training, validation, for 50 epochs and evaluated on the same testing data reserved for evaluating the ConvLSTM method.

4 Results and future work

4.1 Results

We achieve a final model with an average MSE loss of 6.36×10^{-2} across the three regions, compared to an average MSE loss of 2.49×10^{-1} with our naive method, a 4.77×10^{3}% improvement [Table 1]. We observe little overfitting and model performance continues to make improvements through the end of training, leveling out significantly around epoch 10 (Figure 3). Noteworthy, MSE in region 2 is three orders of magnitude less than MSE in regions 1 and 3. That finding is in agreement with the significant differences in the Eddy Kinetic Energy that is found in eastern boundary currents such as the Canary Islands southward flow in region 2, less than 100 cm^2 s^{-2} [Zhou et al. [2000]], and western boundary currents such as the Gulf Stream that flows along the northwestern areas of regions 1 and 3, more than 3000 cm^2 s^{-2} [Richardson [1983]]. Also, this finding give us a frame of reference to better understand the scales of the errors we can expect when applying ConvLSTM to very different oceanic flows we observe in the Atlantic Ocean.

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

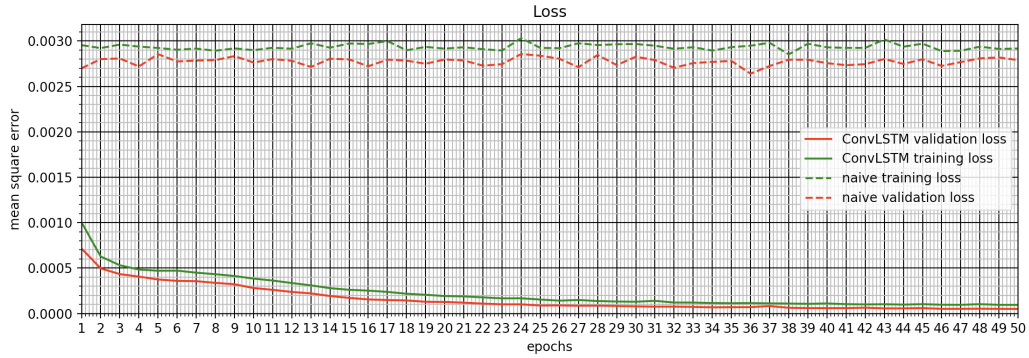

Figure 3: Loss plot for subregion 2 showing training over 50 epochs for both naive and ConvLSTM method. The ConvLSTM immediate outperforms the naive method, and continues to improve over training time.

Region	ConvLSTM MSE (test data)	Naive 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.

ocean velocities for test data in subregion 1 (Figure 4). Overall, we observe that the ConvLSTM approach to vertical velocity prediction in the most energetic subregion of the North Atlantic reproduces the spatial variability successfully. The maximum anomalies represent $\sim$1/4 of the maximum vertical velocities in the southwestern boundary of the Gulf Stream. Nevertheless, these anomalies rapidly decrease to $\sim$1/8 of the maximum vertical velocities as the Gulf Stream meanders to the mid-Atlantic. Away from the turbulent region of the Gulf Stream , anomalies of vertical velocities are negligible, although the small scale of these scales merits a closer examination that is out of the scope of this exploratory work.

4.2 Future Work

Future work on this study includes doing a hyper parameter search for best network architecture.

This work lays solid foundations to extend the scope of our predictions beyond one week in the future. Specifically, this work sets the stage for extending predictions to time scales of two weeks, which will be of paramount importance to predict the short term effect of tropical depressions and hurricanes Xingjian et al. [2015] on the vertical mixing of the water column. As we predict further into the future, from weekly to monthly and from monthly to seasonal time scales, we will analyze the drop-off of our model's performance.

In terms of the spatial domain of out data, we plan to extend our study beyond the surface North Atlantic to include the southern Atlantic and additionally deeper layers of the ocean. Finally, we plan to use clustering algorithms to identify vertical mixing events, localized high velocities that persist over time, in our data.

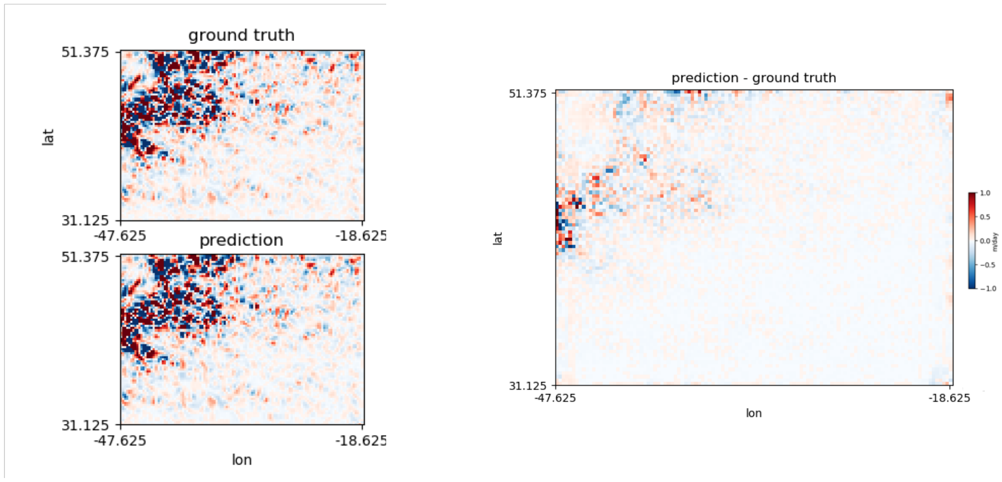

Figure 4: Left: More detailed look at ground truth versus prediction as shown in (Figure 2). Right: At every grid point ground truth is subtracted from the prediction, producing anomalies. Highest anomalies correspond to most extreme vertical velocities.

Broader Impact

Our work aims to contribute to the oceanographic community by creating a dataset of vertical ocean velocity that covers the North Atlantic region at large and contributing to better understand vertical mixing events. By validating the application of deep learning to observational ocean data inference, this study offers a new scientific paradigm in oceanography and a set of tools for the observational oceanographic community. That is, this work is a proof of concept on how to merge data-driven methods that use observational oceanographic data with physical knowledge of the physics of the ocean. Many of the broader impact questions are not particularly applicable to our work, since our work does not rely on human-related data nor does its application have direct human consequence.

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