A Spatiotemporal Seq2Seq Learning Algorithm for Loop Current Forecasting in GoM

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Objectives

In this research, the Loop Current forecasting in Gulf of Mexico is investigated:

- A spatiotemporal sequence-to-sequence forecasting algorithm is proposed for processing geospatial big data.
- Extensive evaluation and comparative study on a real-world dataset is carried out to verify model capability.

Background

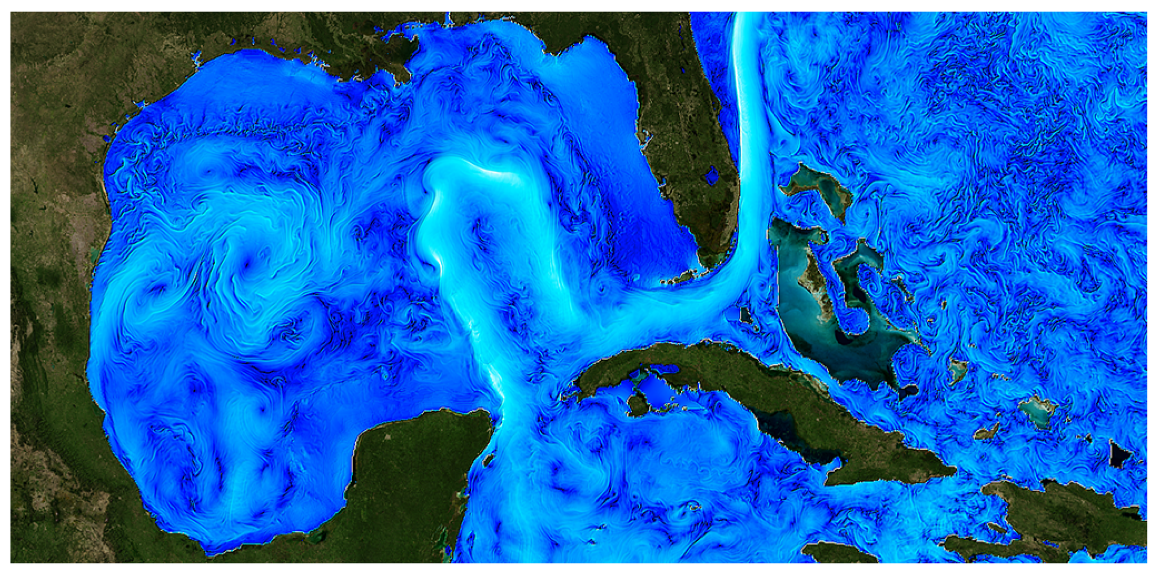


Figure 1:The Loop Current of GoM. Image credit: NAS

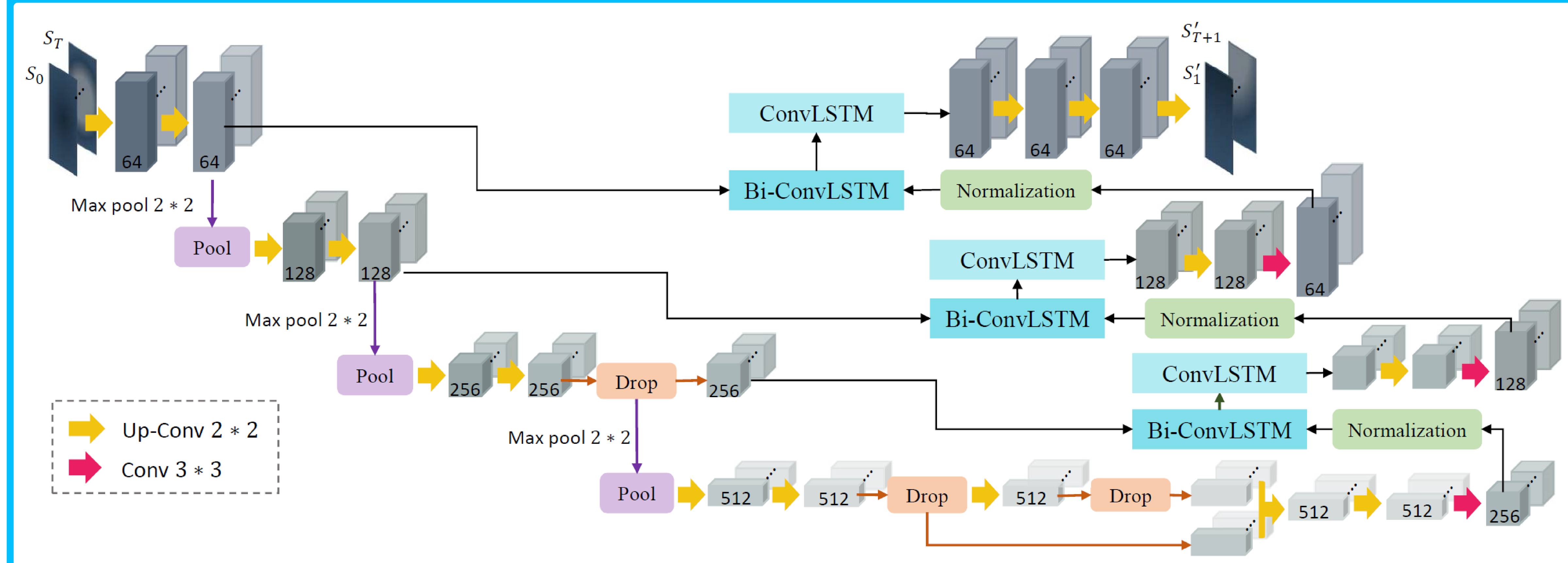
Ever-increasing streams of geospatial big data have attracted researchers utilizing machine learning approaches to extract patterns and insights for understanding, analysis, and prediction. However, current approaches may not be optimal when system behaviour is dominated by spatial or temporal context. Rather than amending classical machine learning, we argue that deep learning, an approach that is able to extract spatio-temporal features automatically, is able to gain more salient temporal understanding of Earth system science problems, improving the predictive ability of seasonal forecasting and modelling of long-range spatial connections across multiple timescales. In this research a spatiotemporal sequence-to-sequence learning algorithm is developed for the long term prediction of the Loop Current System (LCS) and its eddies in Gulf of Mexico (GoM) (Figure 1). Utilizing sea level anomaly (SLA) data collected over 20 years, movements of the Loop Current (LC) are learned by the proposed model to predict future states—the timing of eddy separations from the extended LC and their positions.

Problem Formulation

Suppose we observe the GoM loop current over a spatial region represented by an $M \times N$ grid which consists of M rows and N columns with P measurements which vary over time. The observations can be represented by a tensor $\mathcal{X} \in \mathcal{R}^{P \times M \times N}$. The spatiotemporal sequence forecasting problem is to predict the most likely length-k sequence in the future given the previous j observations:

$$\tilde{\mathcal{X}}_{t+1}, \cdots, \tilde{\mathcal{X}}_{t+k} = \underset{\mathcal{X}_{t+1}, \cdots, \mathcal{X}_{t+k}}{\operatorname{argmax}} \; p(\mathcal{X}_{t+1}, \cdots, \mathcal{X}_{t+k} | \tilde{\mathcal{X}}_{t-j+1}, \cdots, \tilde{\mathcal{X}}_{t}) \quad (1)$$

LC image sequence prediction: Bi-ConvLSTM U-net



Proposed Method

Encoding: The contracting path of the proposed U-net includes four steps. Each step consists of two convolutional 3×3 filters followed by a 2×2 max pooling function and ReLU. The contracting path extracts progressively image representations and increases the dimension of these representations layer-by-layer. Ultimately, the final layer in the encoding path produces a high dimensional image representation with high semantic information.

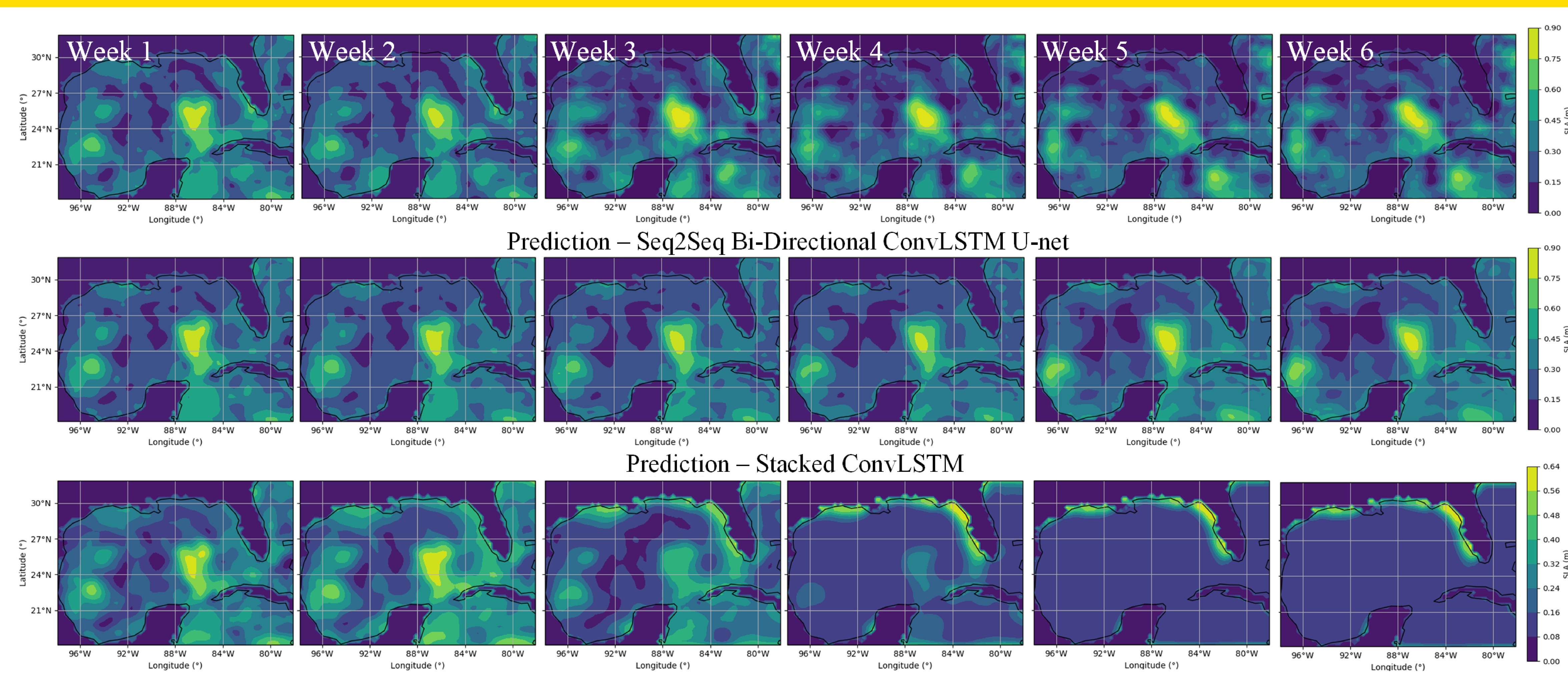
Decoding: Each step starts with performing an up-sampling function over the output of the previous layer. We employ Bi-ConvLSTM [1] to process two kinds of feature maps, i.e. feature maps copied from the encoding part and the output of the up-convolution. The expanding path increases the size of the feature maps layer by layer to reach the original size of the input image after the final layer.

Two level ConvLSTMs: In the first level, Bi-ConvLSTM uses two ConvLSTMs to process the input data into two directions of forward and backward paths, and then makes a decision for the current input by dealing with the data dependencies in both directions. Each of the forward and backward ConvLSTM can be considered as a standard one. The output Z_t of the Bi-ConvLSTM considering bidirectional spatio-temporal information of each image is calculated as:

$$Z_t = tanh(W_y^{\vec{\mathcal{H}}} * \vec{\mathcal{H}}_t + W_y^{\overleftarrow{\mathcal{H}}} * \overleftarrow{\mathcal{H}}_t + b) \quad (2)$$

In the second level, a ConvLSTM layer is stacked on the Bi-ConvLSTM to model well the spatiotemporal relationships of image sequences.

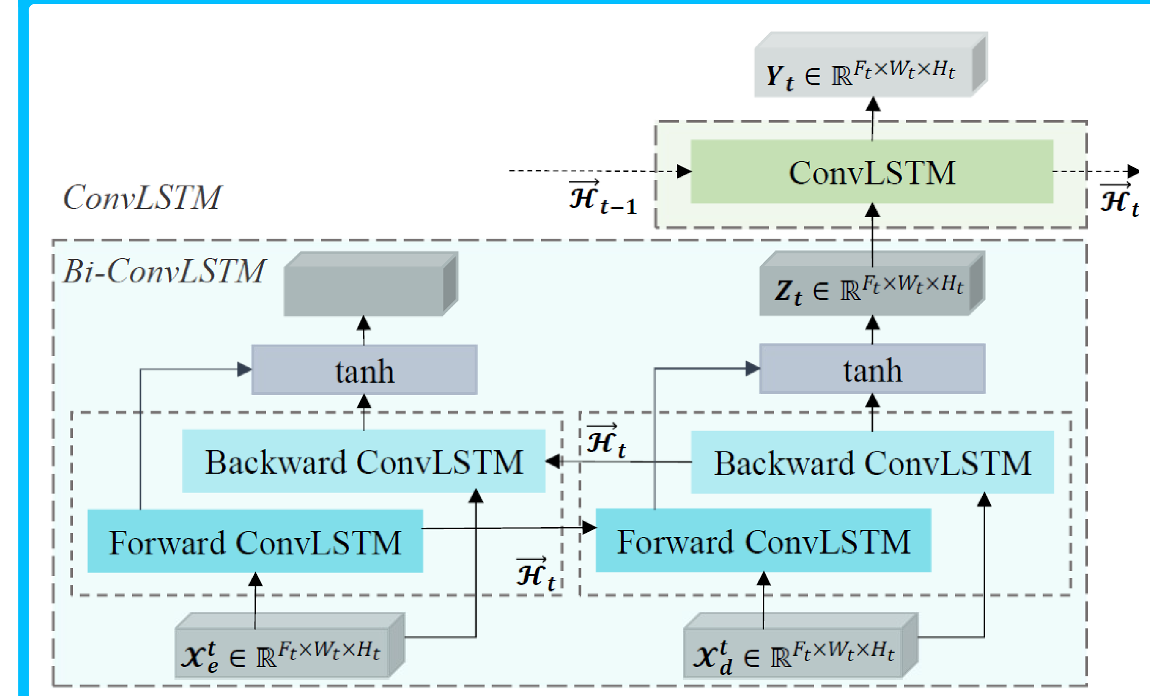
Results



The Mean and Standard Deviation of MSE of LC Prediction

# of Weeks ahead	1	2	3	4	5	6	7	8
Proposed Model	0.0028±*0.0003*	0.0072±*0.0010*	0.0100±*0.0014*	0.01310±*0.0019*	0.0158±*0.0026*	0.0181±*0.0035*	0.0204±*0.0046*	0.0227±*0.0049*
ConvLSTM [2]	0.0132±*0.0045*	0.0497±*0.0175*	0.0812±*0.0274*	0.1087±*0.0363*	0.1233±*0.0431*	0.1253±*0.0445*	0.1259±*0.0444*	0.1260±*0.0445*

Bi-Directional ConvLSTM



Dataset

The study area chosen is bounded by a box of $18^o - 32^o$N and $76.5^o - 98^o$W. The daily sea level anomaly data with a resolution of $1/25^o$ for a time period from January 1993 to January 2018 was provided by the AVISO/Altimetry Center. The sea surface height (SSH) data was normalized and was subsampled to weekly from the period from year 1993 to 2012 (1305 weeks). The resolution of SSH satellite data of the selected GOM region is 87x57. More details of the dataset can be referred to [3].

Conclusion and Future Work

This work proposed a Spatio-Temporal Learning Algorithm for image-structured time series modeling. Experiments on spatio-temporal prediction tasks demonstrate that our proposed model was able to generate satisfactory predictions from the ground truth image.

Future work will focus on hybrid modelling techniques—coupling physical process models with the versatility of data-driven machine learning. For example, a motion field of the LC can be learned with data-driven methods, and the motion field can be further processed with a physical model to predict future states.

Acknowledgements

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References

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