Extended Range Arctic Sea Ice Forecast with Convolutional Long-Short Term Memory Networks

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- EU Blue Action project

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  - Our paper has been submitted to MWR

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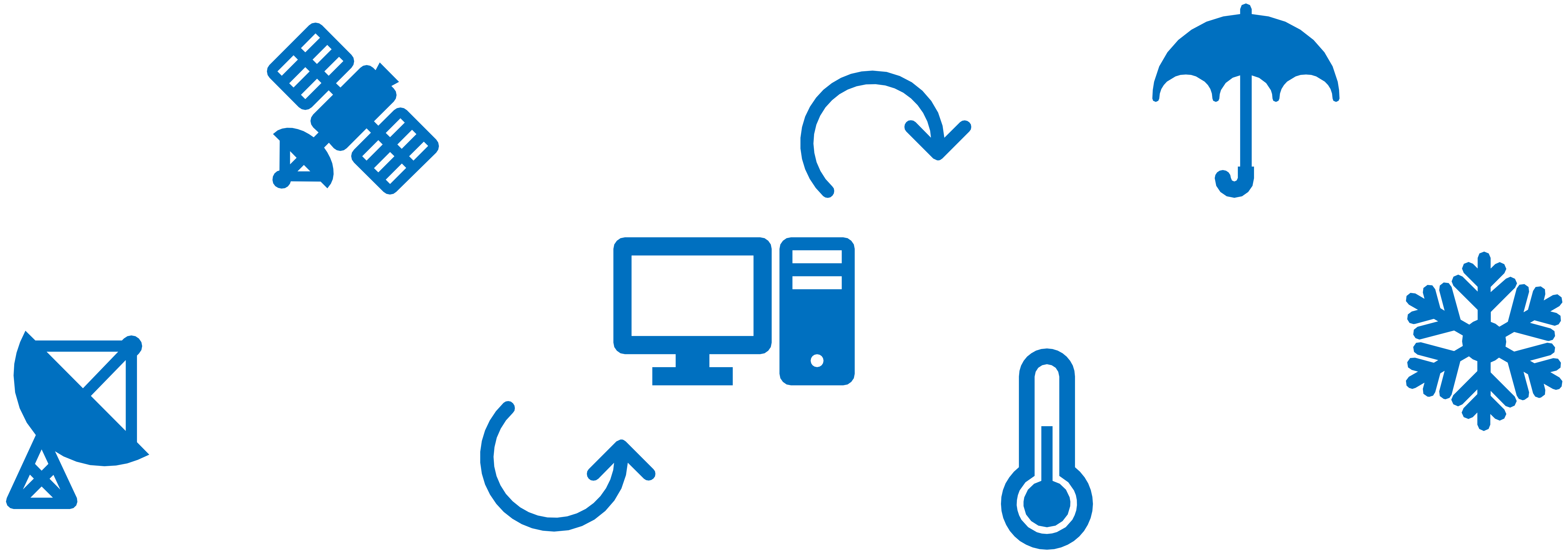
- Weather forecast with deep learning

  - Numerical (model) weather forecast is expensive!

  - Convolutional Long-Short Term Memory (ConvLSTM) is good at tackling spatio-temporal sequence forecasting problem!

  Xingjian, S., Z. Chen, 731 H. Wang, D.-Y. Yeung, W.-K. Wong, and W.-c. Woo, 2015: Convolutional lstm network: A machine learning approach for precipitation nowcasting. Advances in neural information processing systems, 802–810.



PERSPECTIVE

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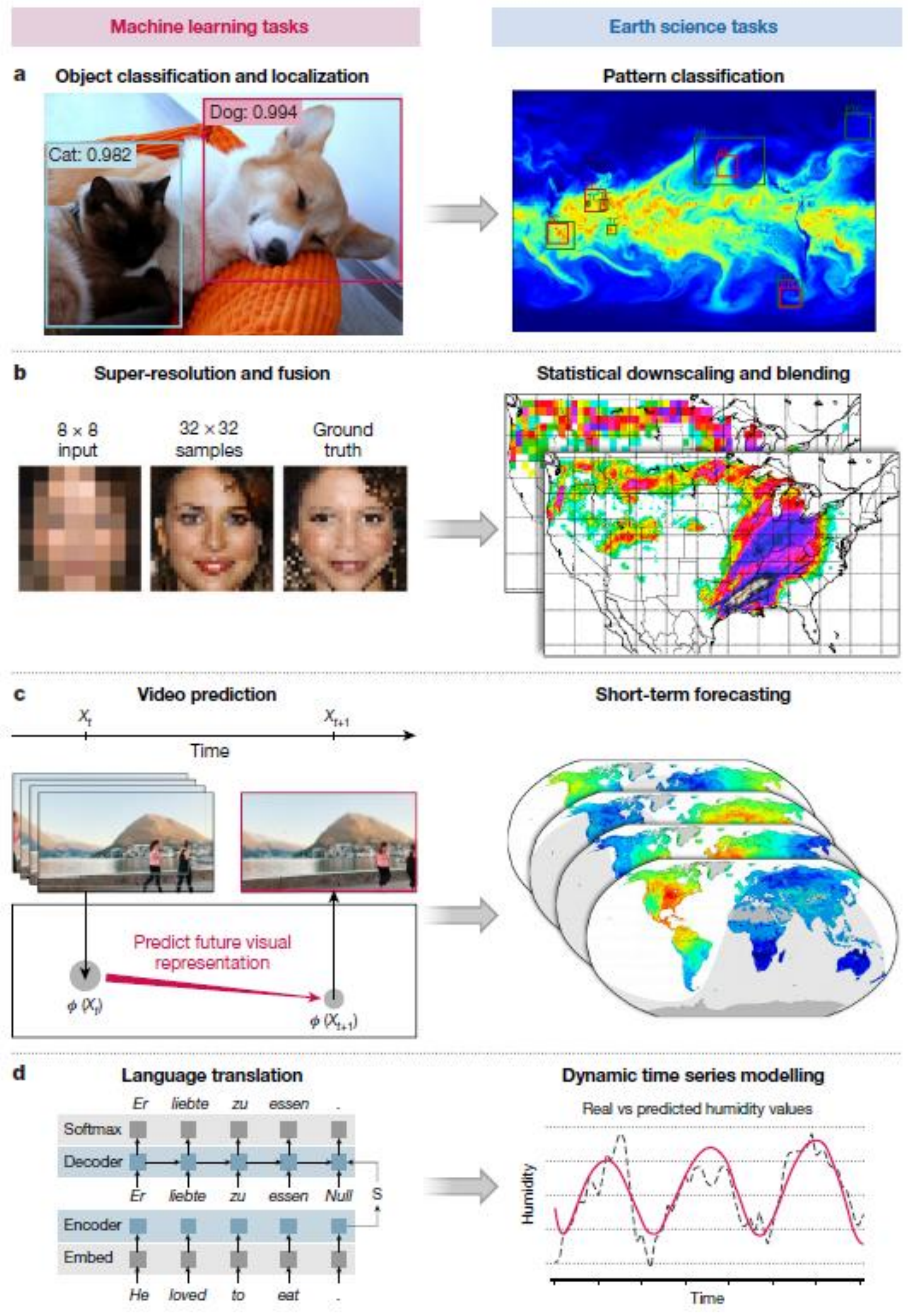
Deep learning and process understanding for data-driven Earth system science

Markus Reichstein[1,2*], Gustau Camps-Valls[3], Bjorn Stevens[4], Martin Jung[1], Joachim Denzler[2,5], Nuno Carvalhais[1,6] & Prabhat[7]



Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., & Carvalhais, N. (2019). Deep learning and process understanding for data-driven Earth system science. Nature, 566(7743), 195-204.

Research questions

- Can we improve the Arctic sea ice forecast at weather time scales with deep learning techniques (ConvLSTM)?

- Can we quantify the contribution of each predictor to the sea ice forecast with deep neural networks?

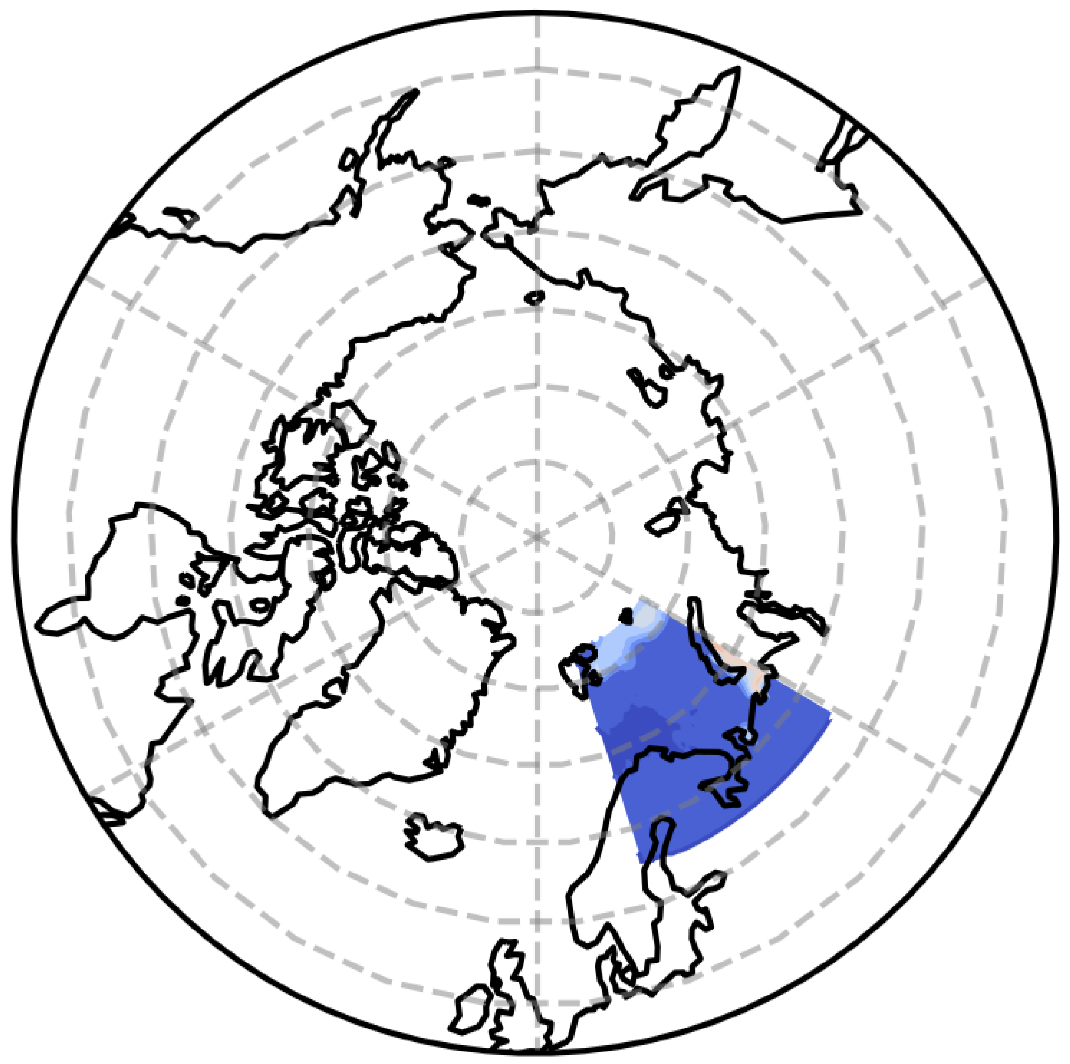
- Is the physical consistency preserved by the deep neural networks during forecast? Can we unbox this blackbox?

- Arctic sea ice forecast

  - Sea ice forecast at weather (weekly) time scales in the Barents Sea

  - Improve the forecast of sea ice with ConvLSTM

  - Atmospheric (SIC, SLP, T2M, Z500, Z850, Sflux, UV10m) and oceanic (OHC) fields from reanalysis products are used in this study



ERA-Interim	1979 - 2016	6 hourly	0.75° x 0.75° x 60 lev
ORAS4	1979 - 2016	monthly	ORCA1

- Weather forecast with ConvLSTM

  - Mathematical expression of ConvLSTM

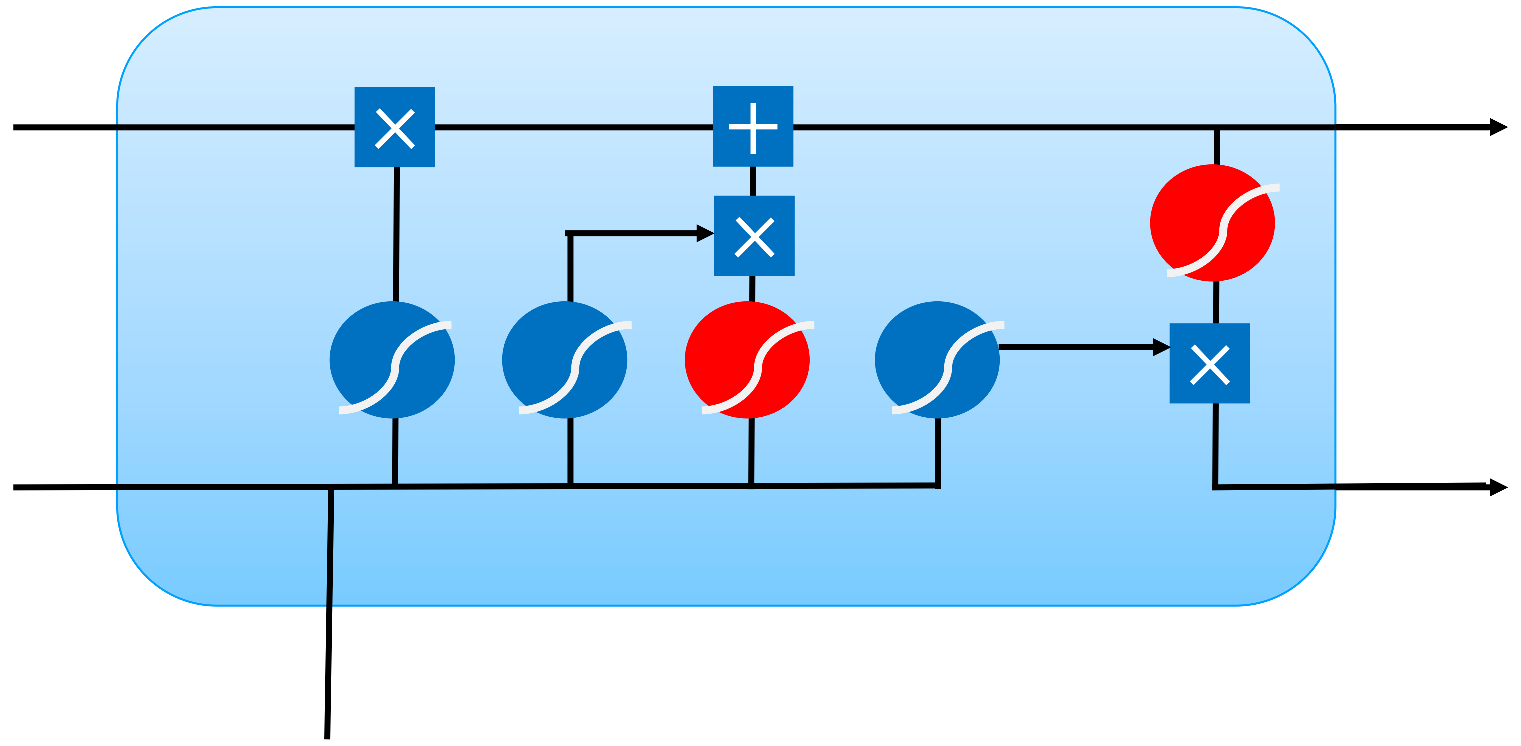
$$i_t = \sigma(W_{xi} * x_t + W_{hi} * h_{t-1} + W_{ci} \circ c_{t-1} + b_i)$$

$$f_t = \sigma(W_{xf} * x_t + W_{hf} * h_{t-1} + W_{cf} \circ c_{t-1} + b_f)$$

$$c_t = f_t \circ c_{t-1} + i_t \circ tanh(W_{xc} * x_t + W_{hc} * h_{t-1} + b_c)$$

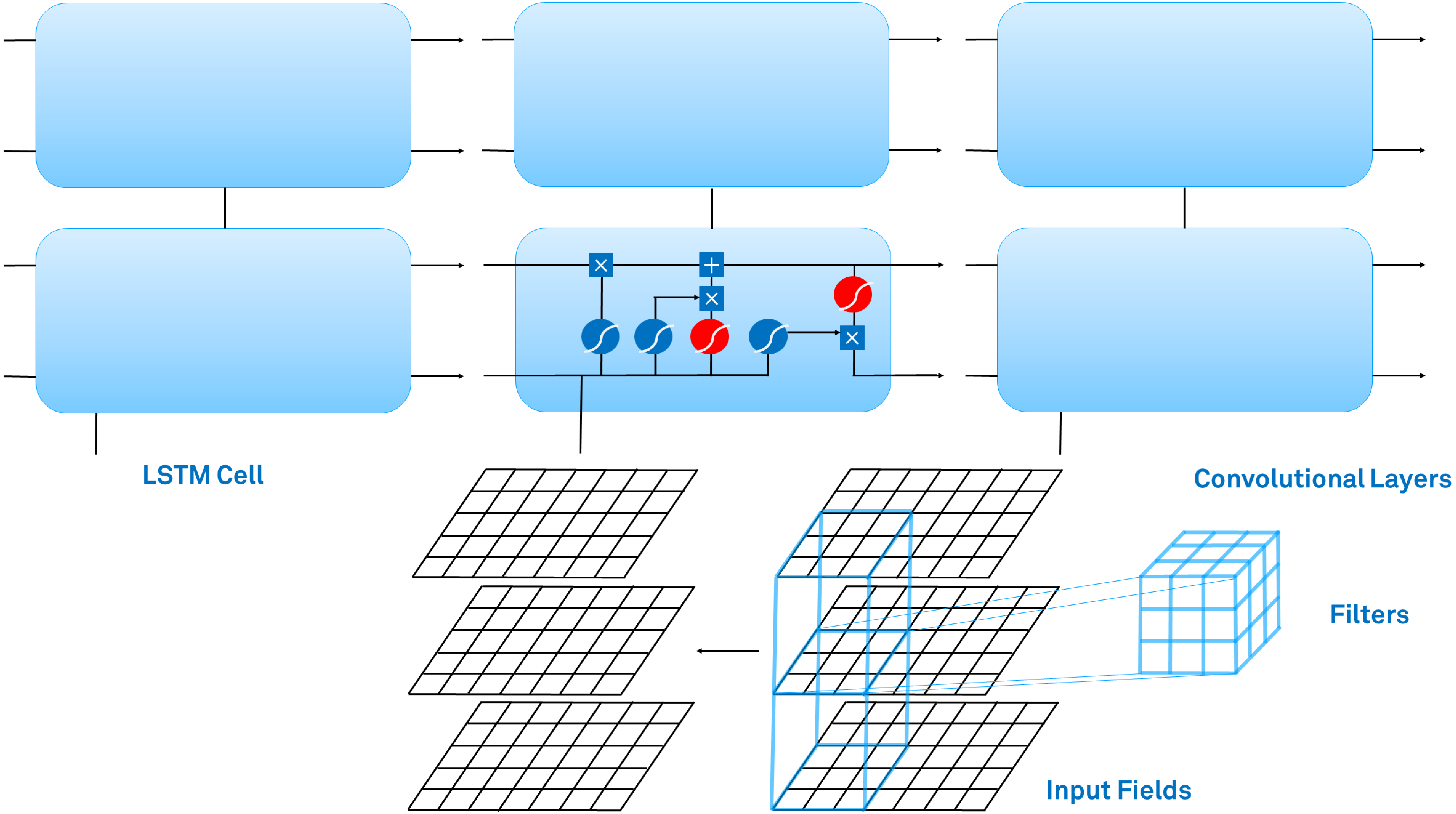
$$o_t = \sigma(W_{xo} * x_t + W_{ho} * h_{t-1} + W_{ct} \circ c_t + b_o)$$

$$h_t = o_t \circ tanh(c_t)$$



With i_t the input gate, f_t the forget gate, c_t the cell state, o_t the output gate, h_t the hidden state, W the weight matrix, x the input, b the bias, o the convolutional operation, * the element-wise product, sigma the sigmoid function and tanh the hyperbolic tangent function.

Convolutional LSTM



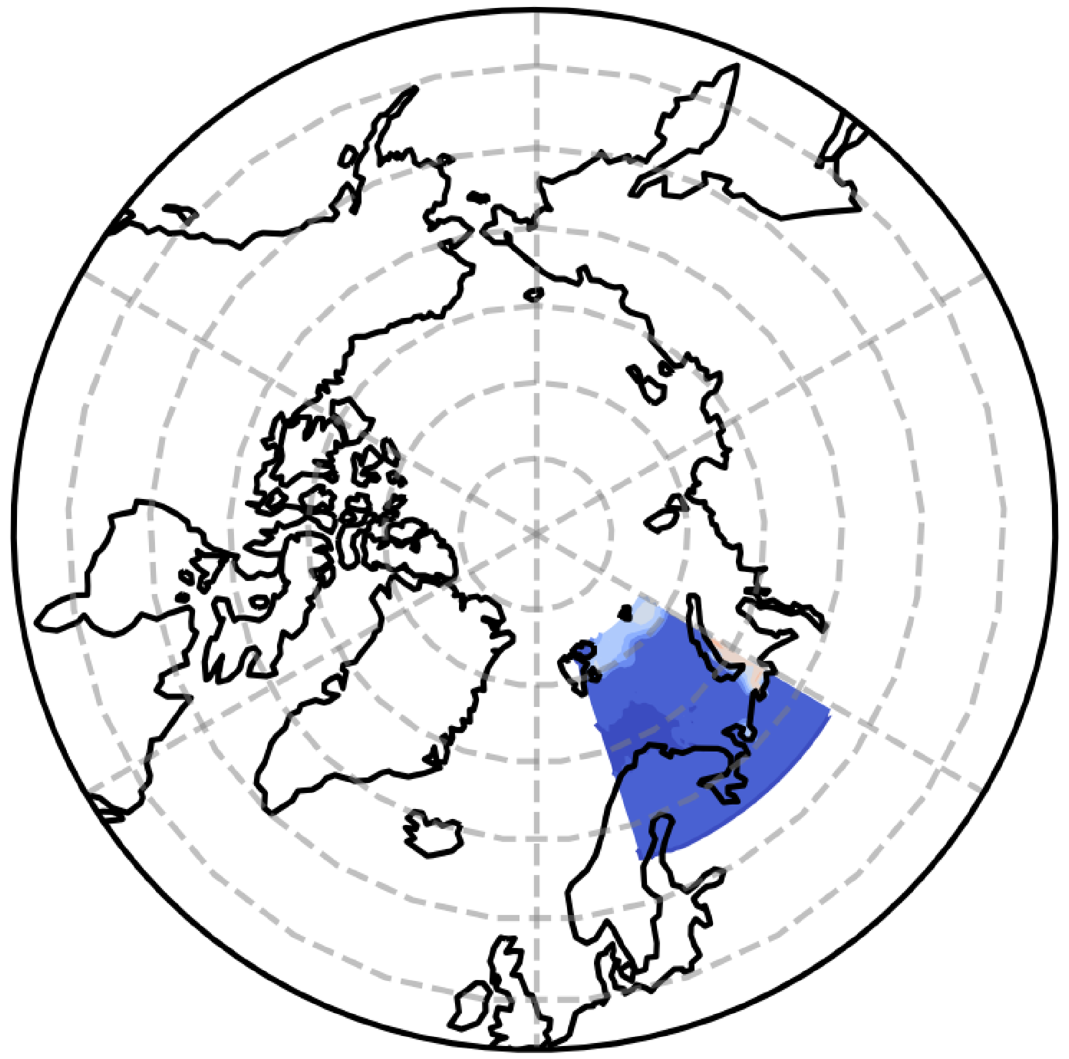
- Setup of ConvLSTM

  - Hyperparameter tuning

Table S1. A brief summary of hyperparameter tuning of ConvLSTM

Method					RMSE (km^2) / 1st week
	Hyperparameter				
	Learning Rate	# Stacked Layers	Filter Size	Epoch	
ConvLSTM	0.02	3	3	1500	54.01
	0.01	***3***	***3***	***1500***	***51.11***
	0.001	3	3	1500	56.79
	0.005	3	3	1500	51.39
	0.01	3	3	1000	54.22
	0.01	***3***	***3***	***2000***	***51.10***
	0.01	5	3	1500	56.93
	0.01	7	3	1500	56.99
	0.01	3	5	1500	56.89
	0.01	3	7	1500	59.09
Climatology					137.91
Persistence					50.17

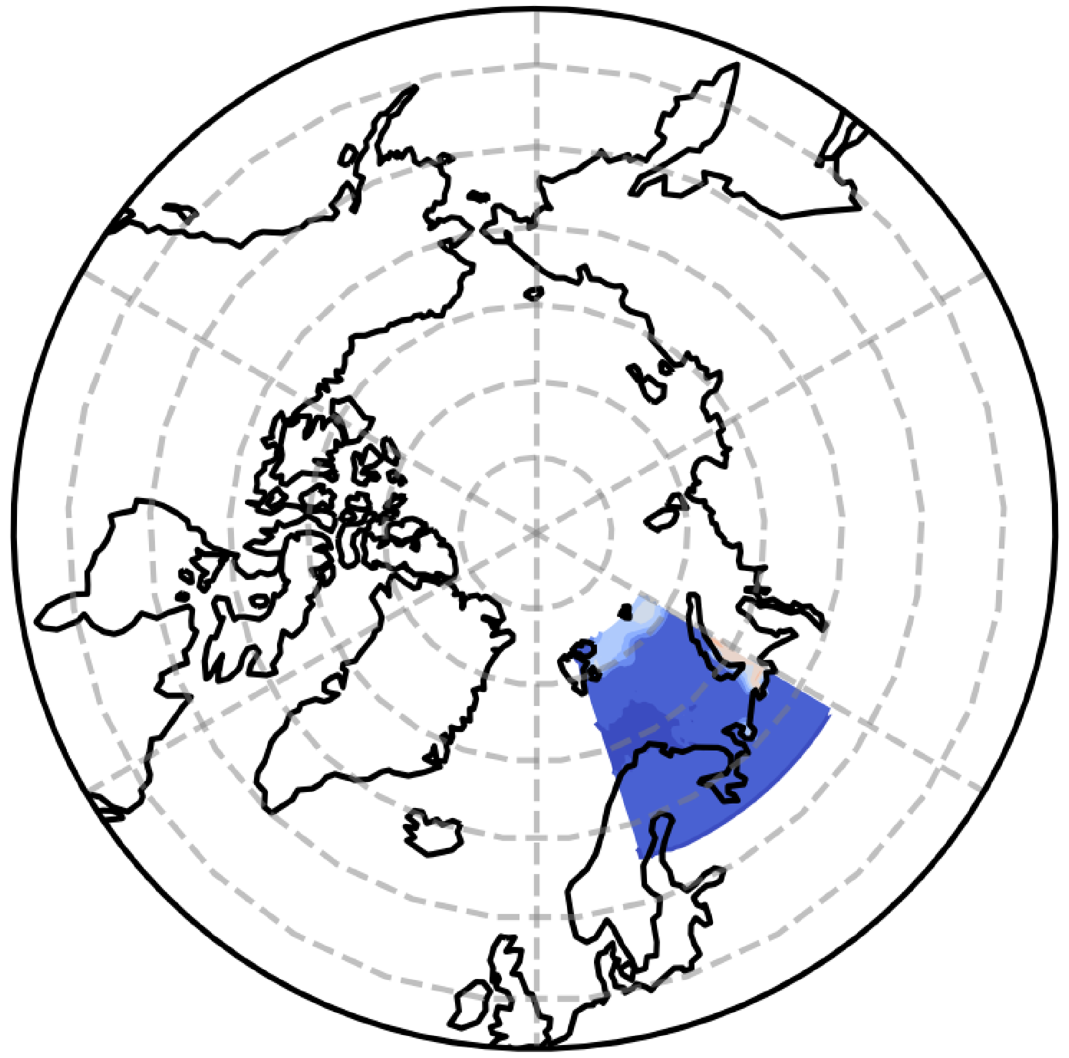
(# Stacked layers are the number of ConvLSTM layers, the sea ice forecast with ConvLSTM is based on SIC and OHC.)

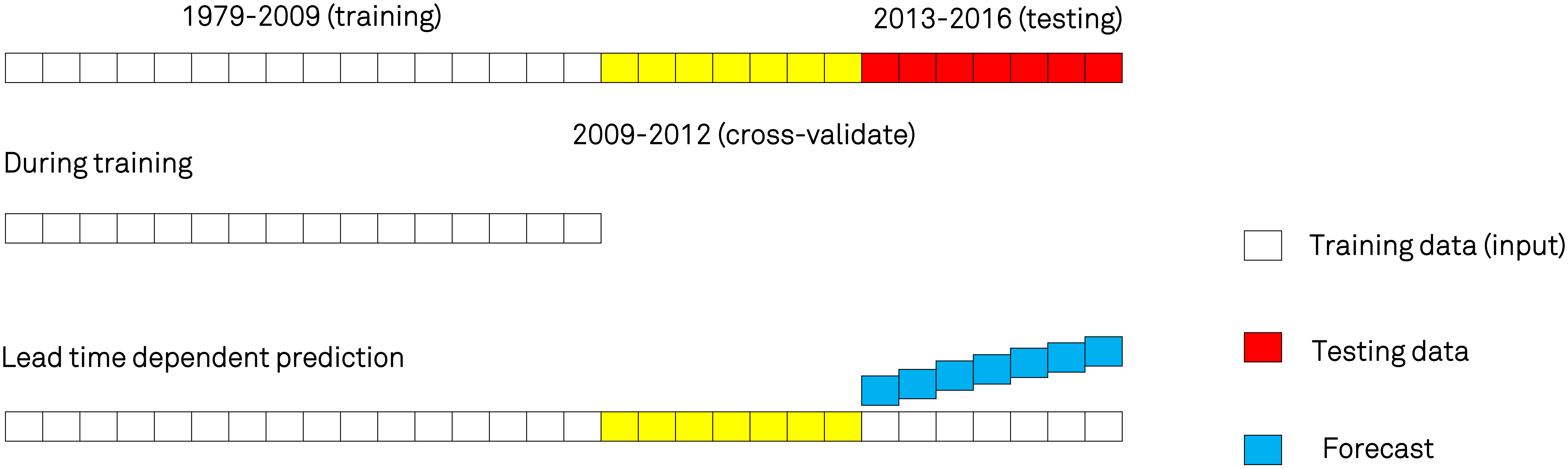


- Deep Learning with ConvLSTM

  - Many-to-One prediction
  (train model with time series and output next step)

  - Forecasts with ConvLSTM are evaluated against climatology, persistence and a generalized linear model with a logit link

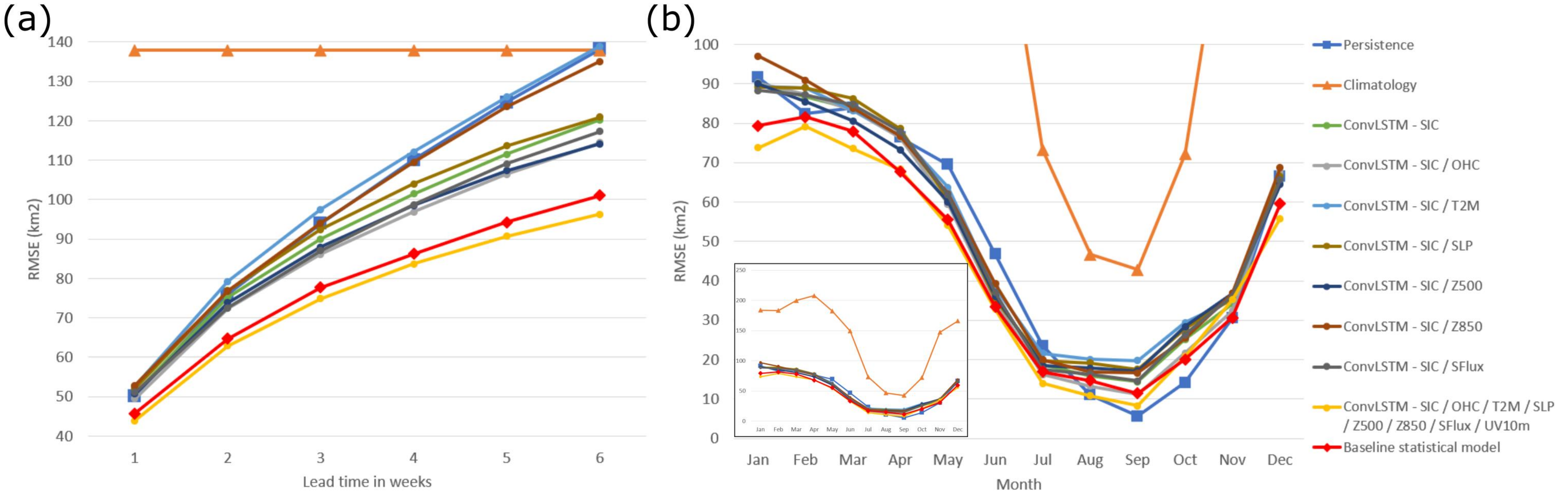




- Sea ice forecast with ConvLSTM

  - Lead time dependent constrained forecast (using multiple fields to forecast SIC)

$$RMSE = \frac{1}{t}\Sigma_{t=1}^{t}\sqrt{\frac{1}{xy}\Sigma_{x=1,y=1}^{x,y}(sic_{predict} - sic_{observe})}$$

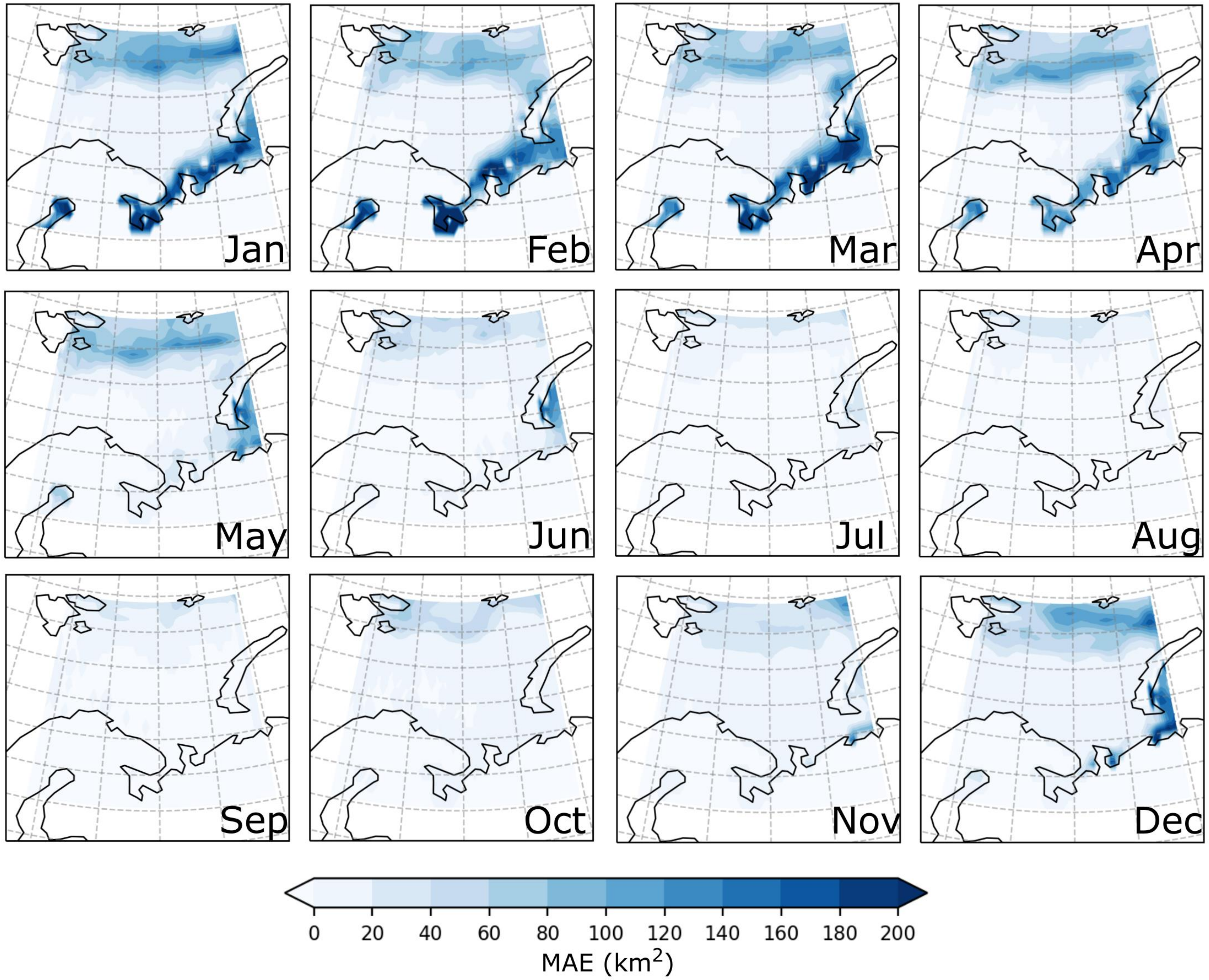


RMSE of (a) the constrained forecast of SIC with a lead time up to 6 weeks and (b) the constrained forecast of SIC for the first week in each month with ConvLSTM using different predictors against persistence, climatology and the baseline statistical model. The unit is square kilometer per grid cell.

- Sea ice forecast with ConvLSTM

  - MAE of constrained forecast with SIC and OHC

$$MAE = \frac{1}{t}\Sigma_{t=1}^{t}|sic_{predict} - sic_{observe}|$$



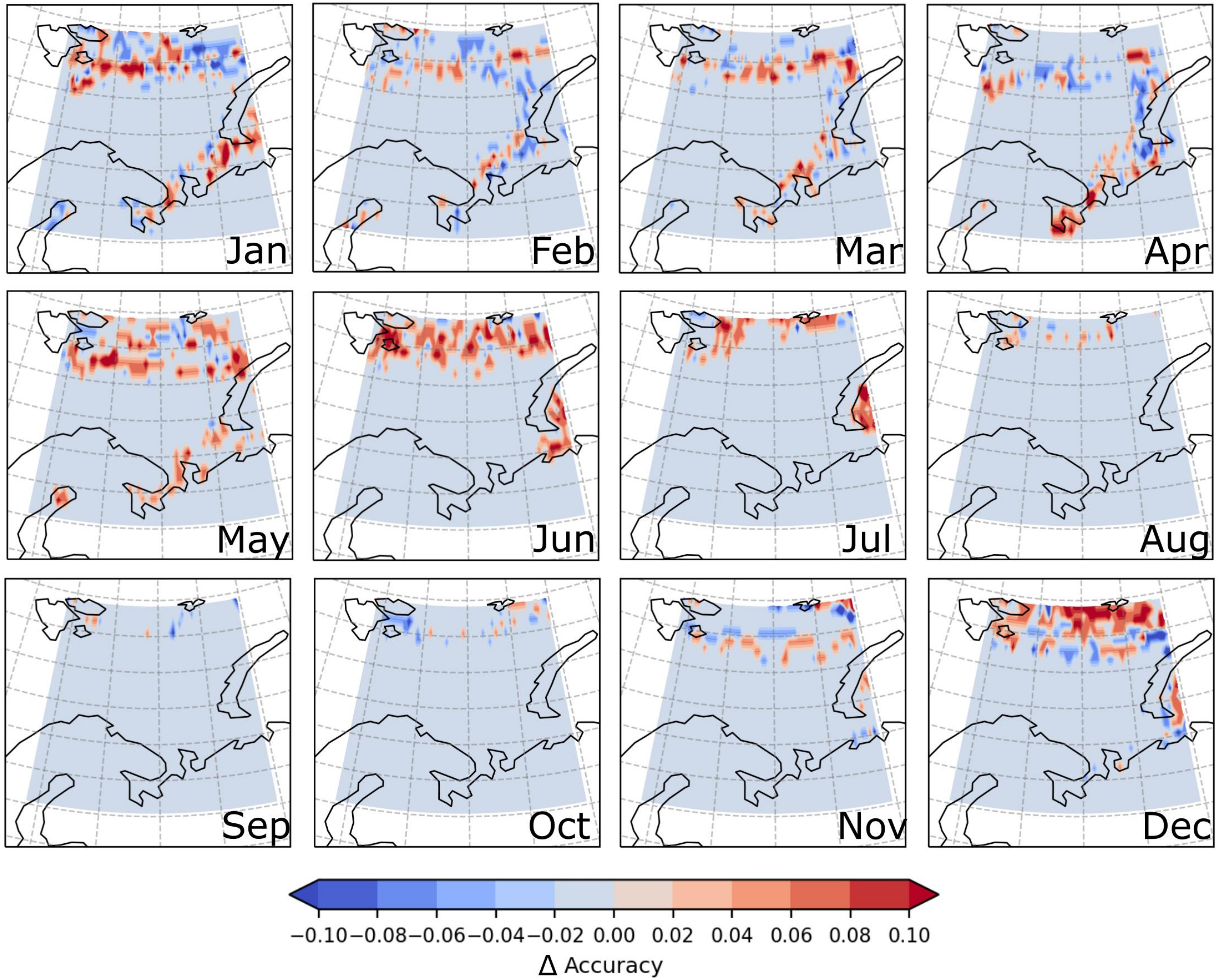
MAE of the constrained forecast of SIC for the first week in each month with ConvLSTM using SIC and OHC

- Sea ice forecast with ConvLSTM

  - Accuracy score of constrained forecast with SIC and OHC

  Accu_convlstm – Accu_persist

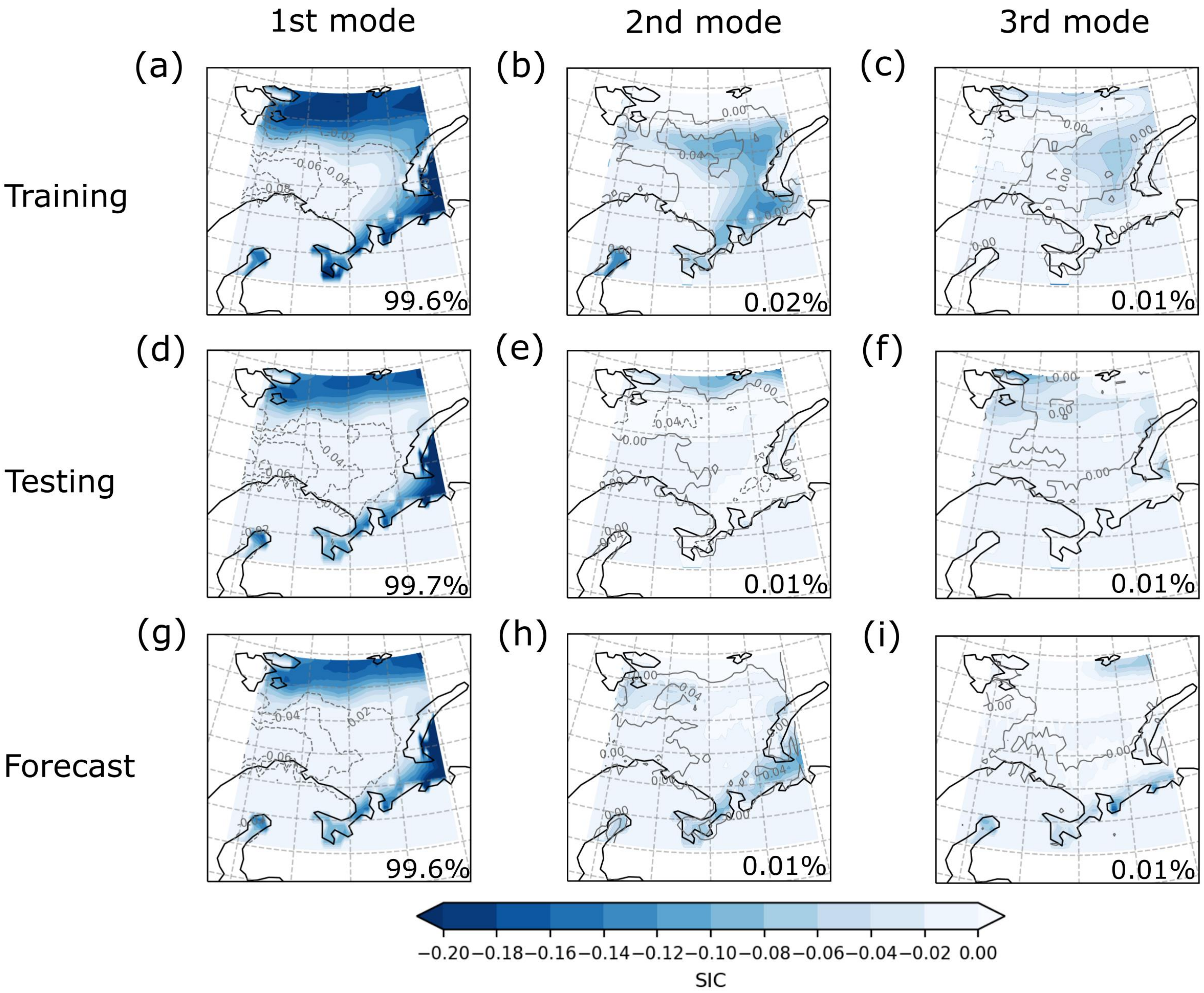
$$Accuracy = \frac{Correct\ predictions}{All\ predictions}$$



Difference of the accuracy score of the constrained forecast of SIC for the first week in each month between ConvLSTM and persistence. The SIC forecast with ConvLSTM uses SIC and OHC fields.

- Sea ice forecast with ConvLSTM

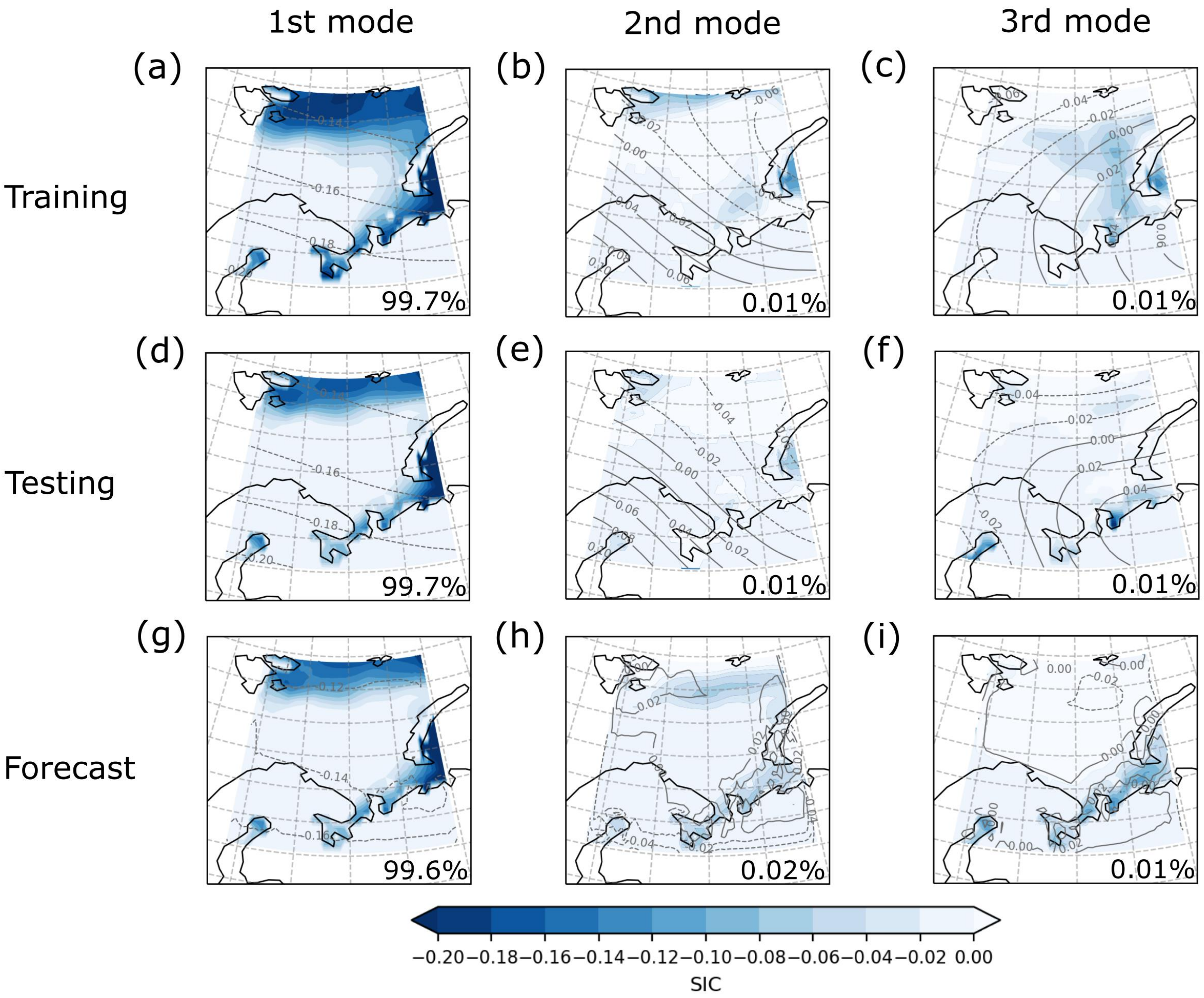
  - Physical consistency of operational forecast with SIC and OHC (using multiple fields to forecast SIC and all the other input fields)



Covariance map of SIC and OHC for the (a, d, g) first, (b, e, h) second and (c, f, i) third SVD modes in (a, b, c) training (d, e, f) testing and (g, h, i) forecast data for the first week. The SVD was performed on the covariance matrix of normalized SIC and OHC.

- Sea ice forecast with ConvLSTM

  - Physical consistency of operational forecast with SIC and Z500



Covariance map of SIC and Z500 for the (a, d, g) first, (b, e, h) second and (c, f, i) third SVD modes in (a, b, c) training (d, e, f) testing and (g, h, i) forecast data for the first week. The SVD was performed on the covariance matrix of normalized SIC and Z500.

Bring home messages

- Weather forecast with ConvLSTM

  -> Complex non-linear weather forecast tasks (temporal-spatial sequence prediction) can be tackled by ConvLSTM

- Sensitivity tests with ConvLSTM

  -> Predictability with certain predictors can be evaluated using ConvLSTM

  -> Energy balance related fields have strong impact on the predictability of sea ice

- Physical consistency

  -> Depending on the input fields, physical consistency between input fields can be preserved during forecast with ConvLSTM.

Reference

Chi, J., & Kim, H. C. (2017). Prediction of Arctic Sea Ice Concentration Using a Fully Data Driven Deep Neural Network. Remote Sensing, 9(12), 1305.

Kim, S., Hong, S., Joh, M., & Song, S. K. (2017). DeepRain: ConvLSTM network for precipitation prediction using multichannel radar data. arXiv preprint arXiv:1711.02316.

Kim, S., Kim, H., Lee, J., Yoon, S., Kahou, S. E., Kashinath, K., & Prabhat, M. (2019, January). Deep-Hurricane-Tracker: Tracking and Forecasting Extreme Climate Events. In 2019 IEEE Winter Conference on Applications of Computer Vision (WACV) (pp. 1761-1769). IEEE.

Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., & Carvalhais, N. (2019). Deep learning and process understanding for data-driven Earth system science. Nature, 566(7743), 195-204.

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