Deep Learning Forecasting of High Latitude Climate Variability

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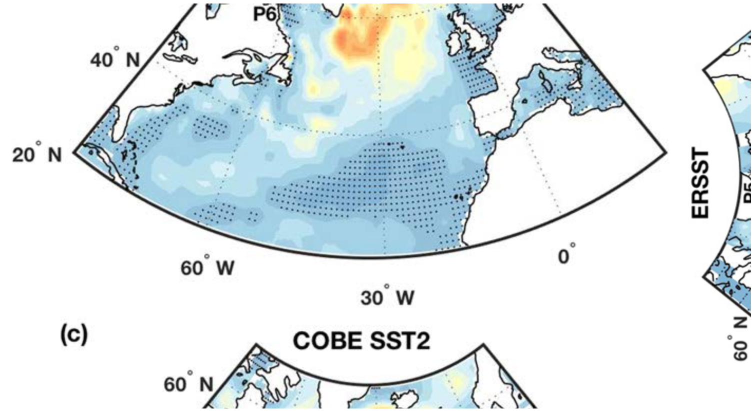
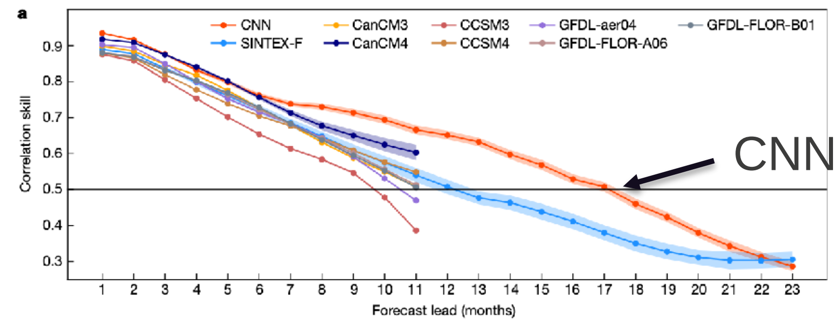
Decorrelation timescale (Buckley et al. 2019)



- large thermal inertia over Subpolar North Atlantic (SPNA)
- affected by the overturning circulation
- **Predictability hotspot**

Hybrid Convolutional Neural Net (CNN) outperforms dynamical ENSO forecast systems (Ham et al. 2019)

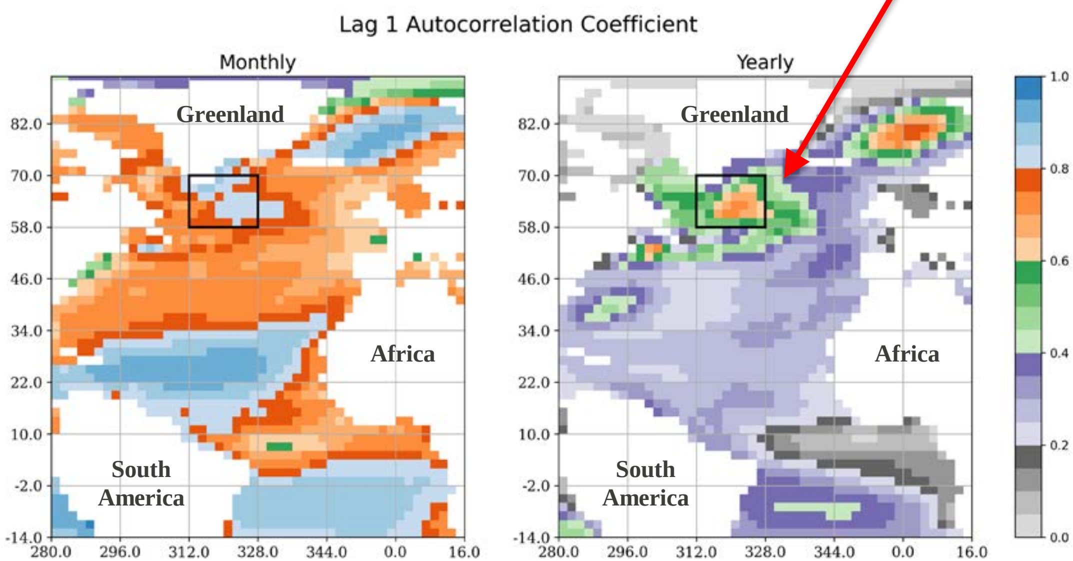


- skillful forecasts up to 18 months
- improves long standing issue of the spring predictability barrier

How well does this DL approach translate to the SPNA prediction problem?

A CNN based model to predict SST over the SPNA Box

- in an **idealized setting** (CESM preindustrial control simulation)
- using **SST** & upper **ocean heat content** from the larger Atlantic sector as shown



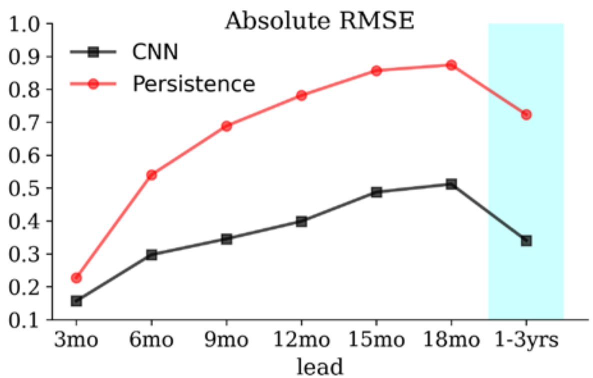
An example model architecture

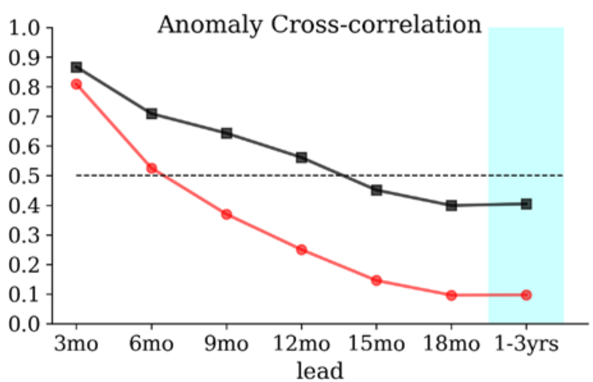
Layer	i/p channel	o/p channel	Kernel	# Parameters (21721)
input	3x56x48			
Convolution	3	10	7x7	1480
Tanh	10	10		
MaxPool	10	10	2x2	
Convolution	10	10	5x5	2510
TanH	10	10		
MaxPool	10	10	2x2	
Convolution	10	10	3x3	910
TanH				
Linear	10	10	12x14	16810
Linear	10	1	30x1	11

- Predictors: 3-6 consecutive months of (prior) SST and OHC maps @ 2x2 degrees
- (Train, Validate, Test) : 1500, 200, 100 years

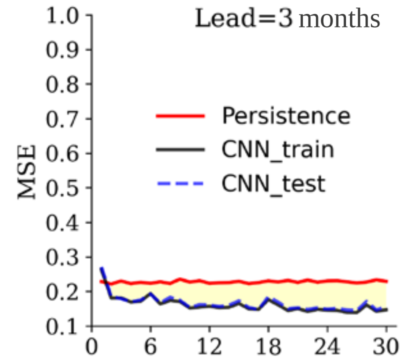
Conclusions and Future Work

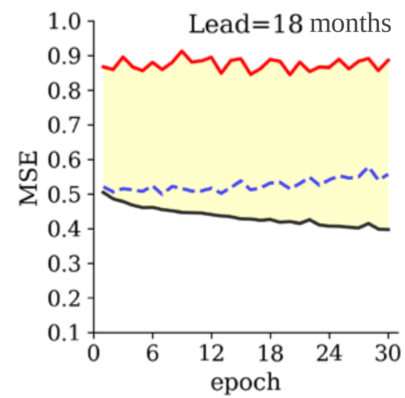
it translates well for seasonal predictions; not so much for multi-year predictions





tendency to overfit the training data for longer leads





Future work:

1. Comparison with other standard benchmarks
2. Testing of more complex architectures
3. Use of transfer learning for real-time forecasts
4. Interpret results/gain physical insights

Thank you