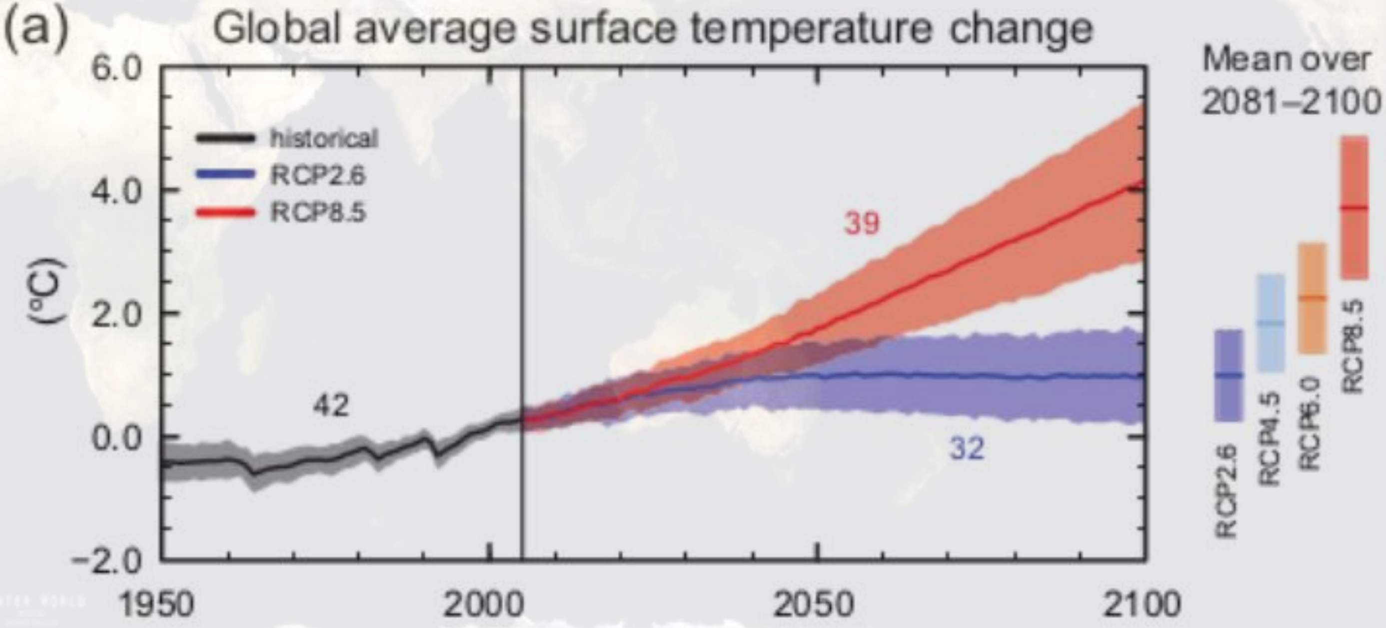
Machine Learning as a tool for Climate Predictability Studies

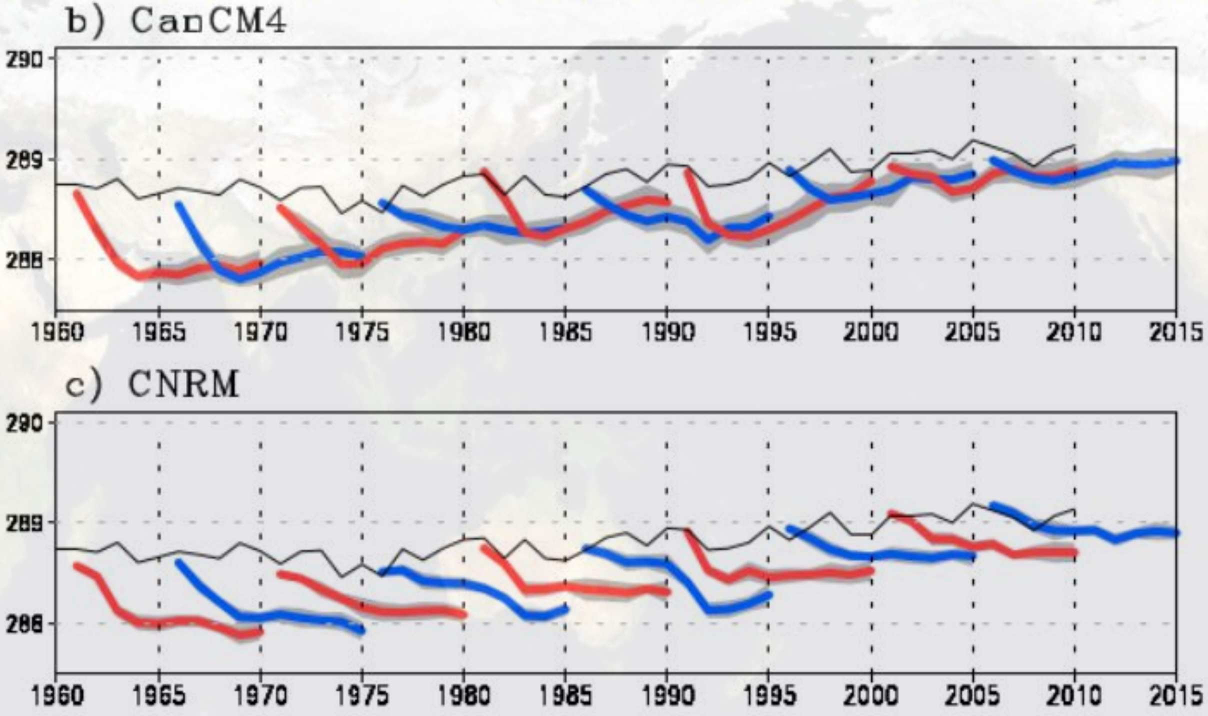
Balu Nadiga, LANL (balu@lanl.gov)
HiLAT-RASM

Models Good at Realizing External-Forcing Related Predictability



IPCC AR5

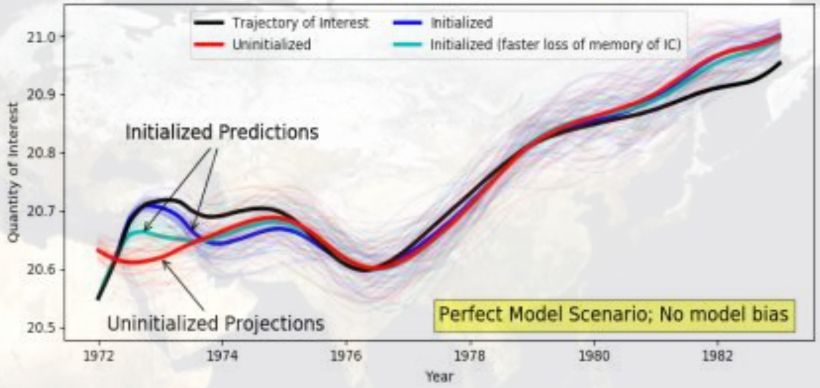
..., *but* Models are Bad at Predictions of Natural Variability

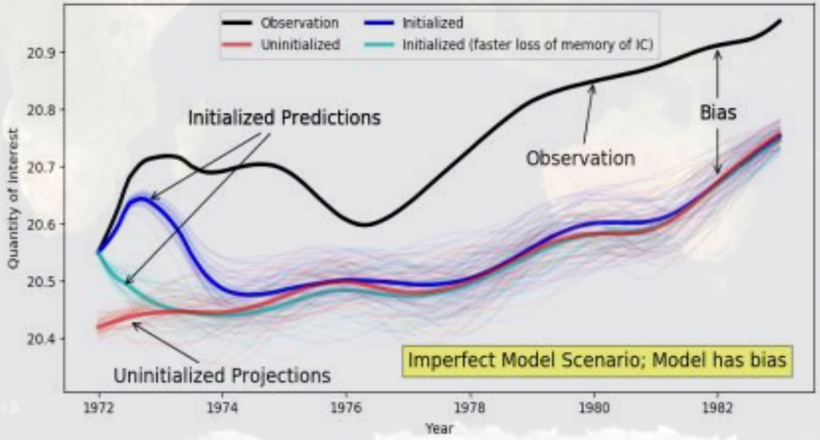


(From Kim et al., 2012)

Initialized Predictions of Various QoIs in Various Models (Surface Temperature in CanCM4 and CNRM) Display a Jump Behavior

Difficulty with Predicting Natural Variability: Model Bias





- Predictability studies are conducted in perfect model settings
- However all climate models are imperfect (have biases)
  - Extremely difficult to model the exact balance (small residual) of myriad (large) processes that lead to the mean state of the climate system and modes of variability
  - Small difference between large numbers

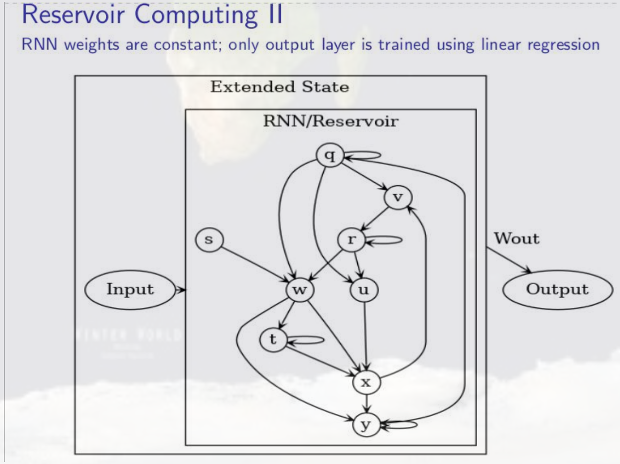
Nadiga et al. "Enhancing skill of initialized decadal predictions using a dynamic model of drift." Geophysical Research Letters 46.16 (2019)

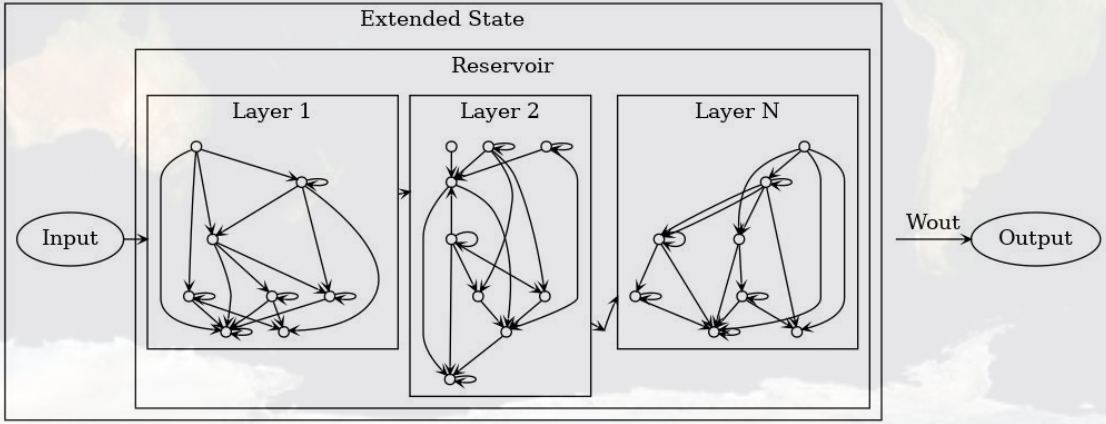
Reduced Order Dynamical Systems and Predictability

- Model order reduction is a necessity to study predictability
  - The actual climate system or its surrogates—comprehensive climate models—are too complicated
  - Interactions span many orders of magnitude
  - Direct studies are too resource intensive, both computationally and otherwise
- The Linear Inverse Modeling (LIM) approach
  - Captures a few essential interactions between dynamical components of the full system
  - Has provided valuable insights into behavior of full system
  - Has been suggested that it captures the bulk if not all of the predictable response in certain systems
  - Has basis in fluctuation-dissipation theorem of statistical mechanics
  - Arises in the context of spectral analysis of the Koopman operator (cf. Dynamic Mode Decomposition)

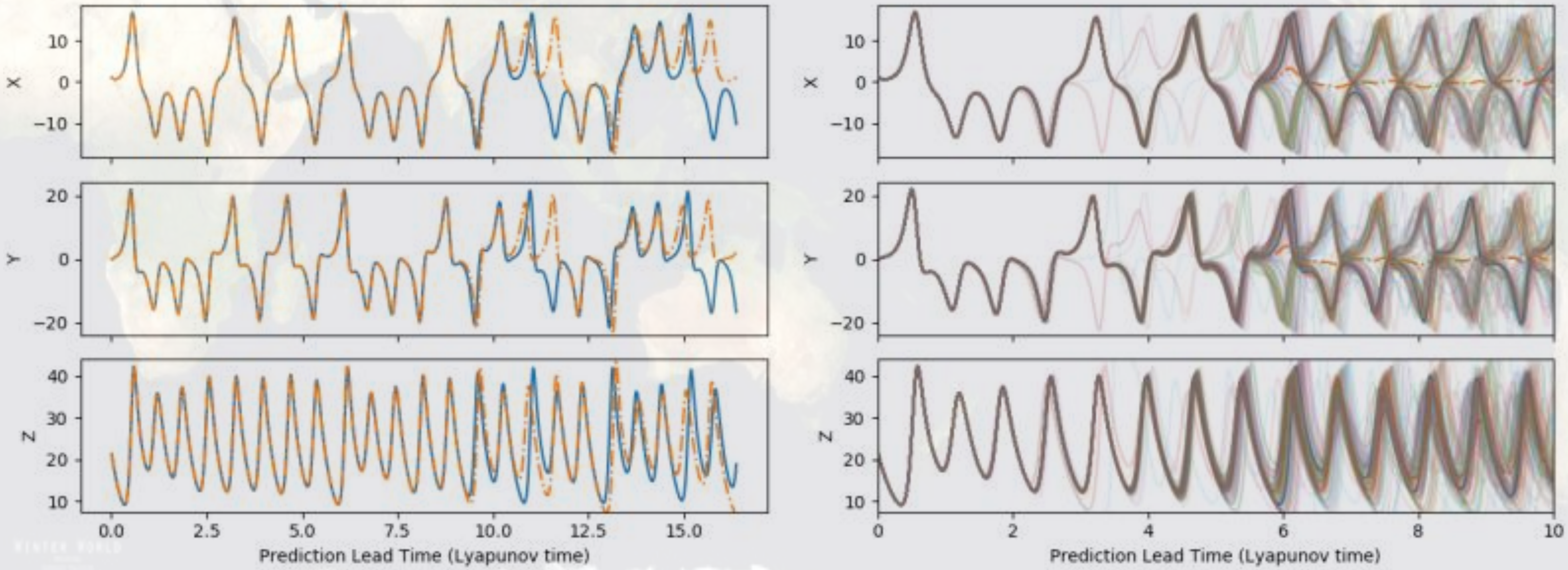
Methods and Architectures

- Classical Statistical Methods (e.g., Linear Inverse Modeling)
- Advanced Statistical Mechanical Methods (e.g., Mori-Zwanzig formalism for memory)
- Deep Learning: MLP, LSTM, PCA-LSTM, convLSTM, Attention, Transformer, Reservoir Computing, etc.





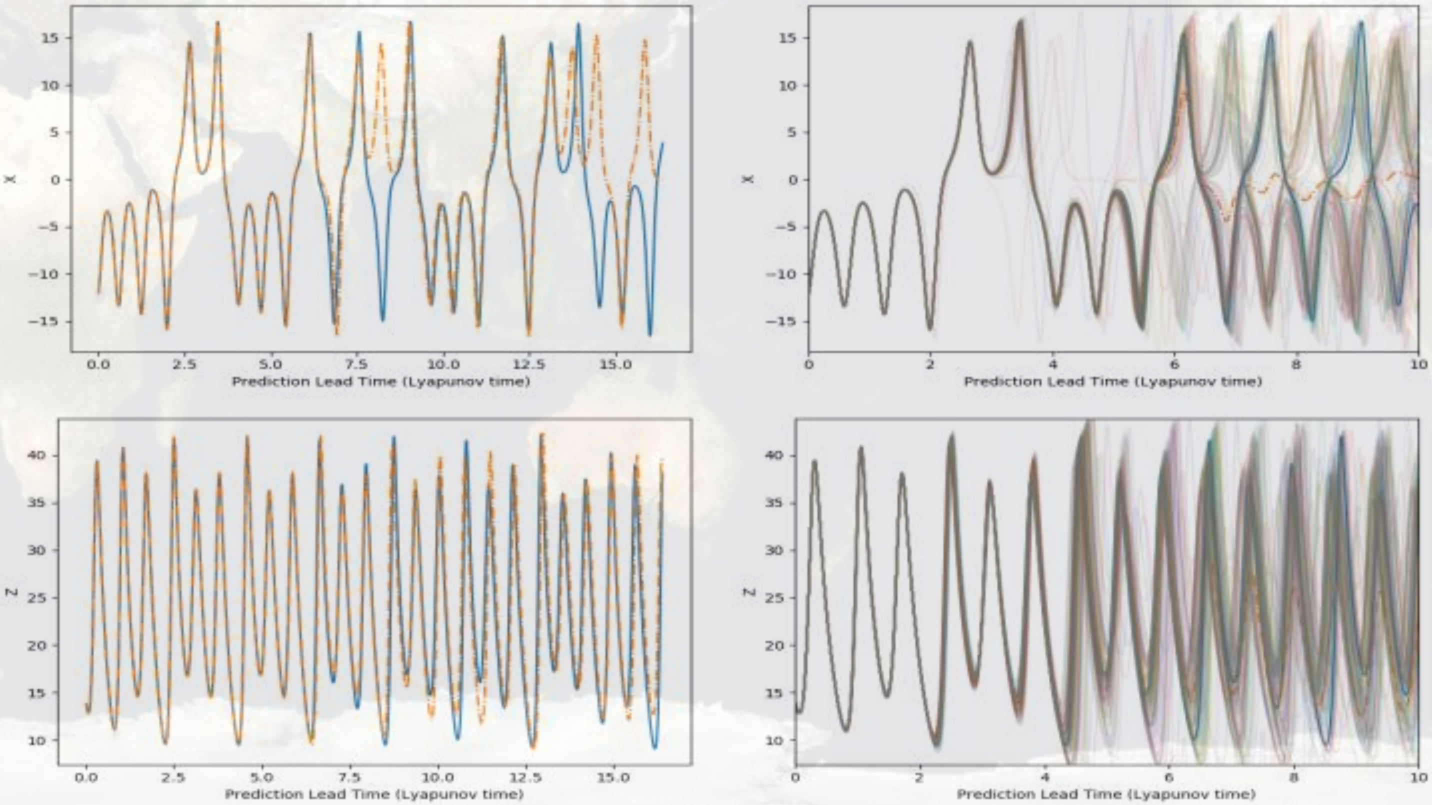
When system is fully observed, RC learns the L63 attractor and predicts for insane lengths of time



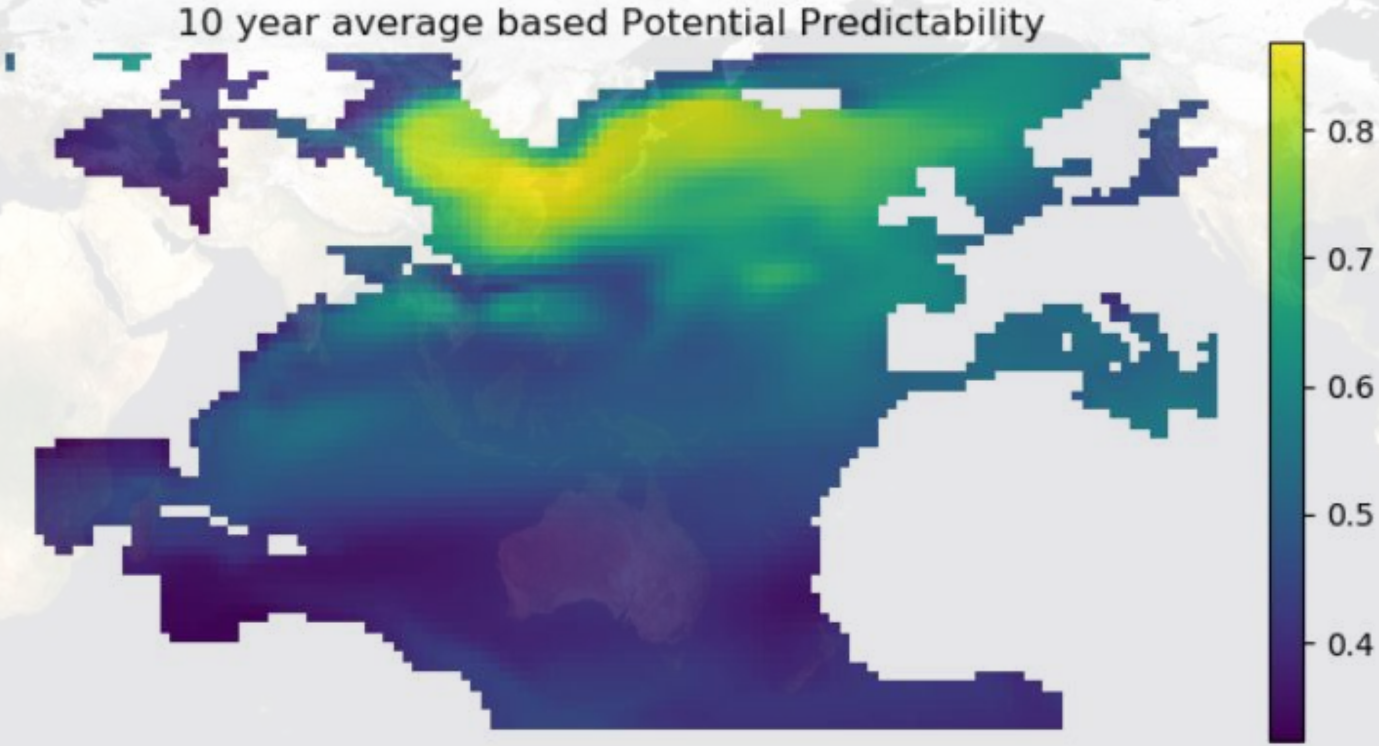
Left: A single prediction. Right: All ensemble members

With partial obs. predictions good for much shorter periods

Top: Learning with X only (Y only is similar). Bottom: Learning with Z only

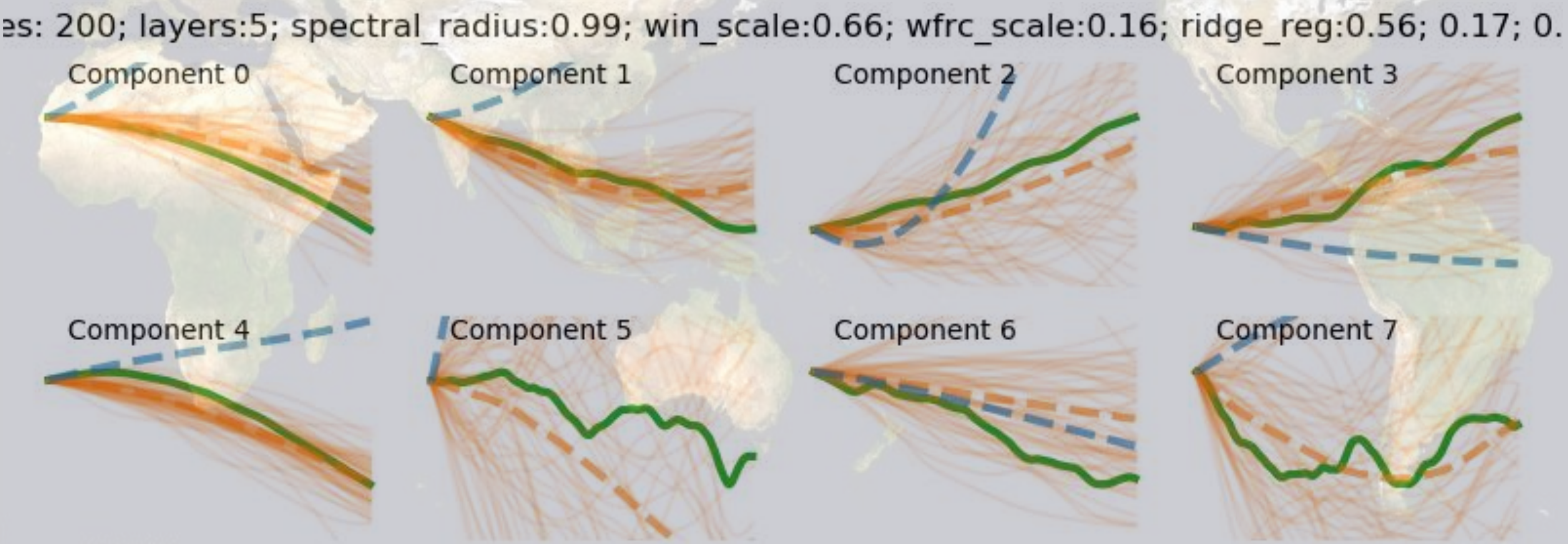


Prediction of SST in the North Atlantic



Potential Predictability as the ratio of variances of N-year average and 1-year average of SST

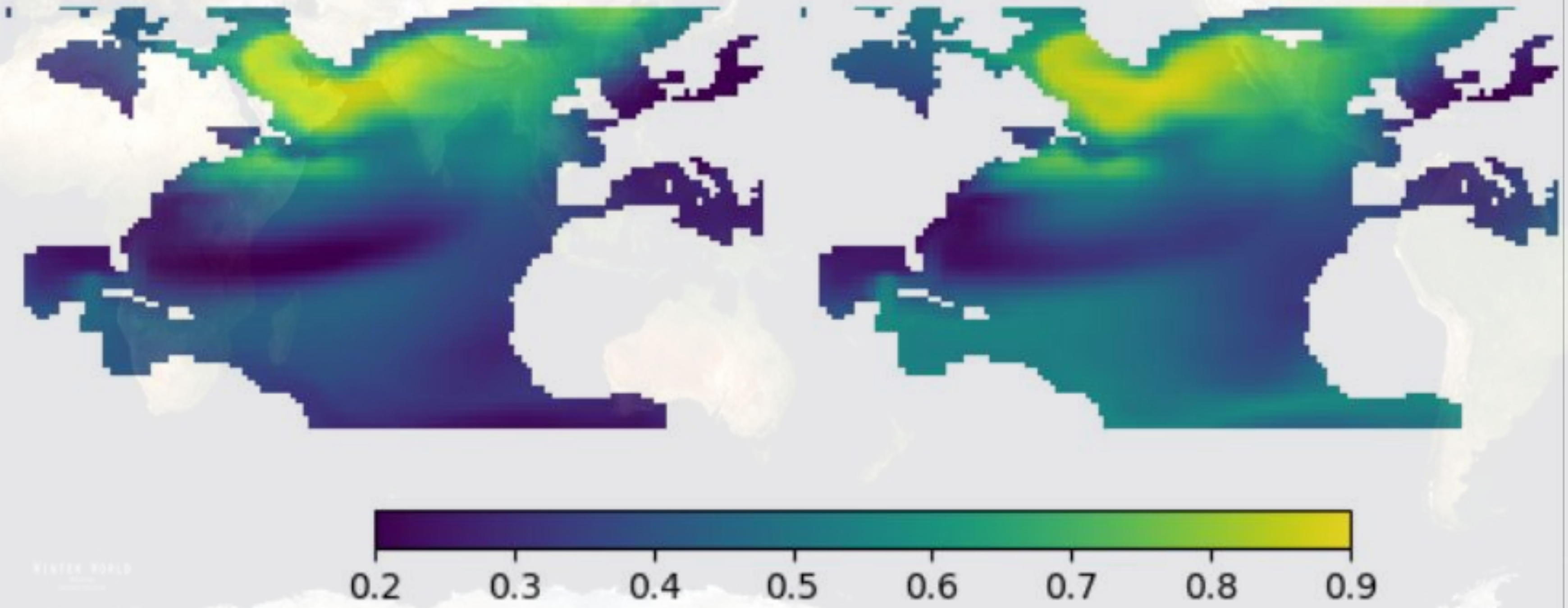
Predicting Evolution of Internal Variability



Green: Truth; Dashed Blue: Linear Inverse Modeling; Dashed Orange: ensemble-mean of ML-based model
Thin Orange: individual members of ML-based ensemble

Reservoir Computing vs. Linear Inverse Modeling

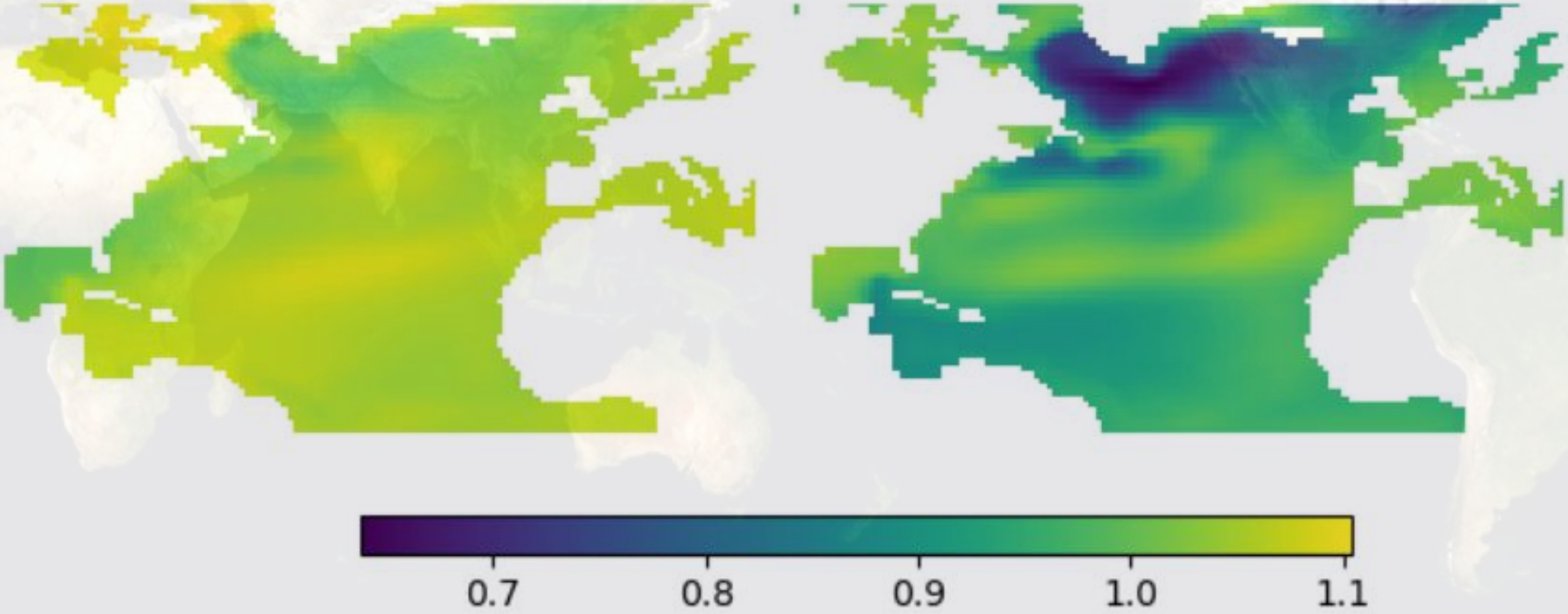
Learning from Long Runs of Data. 800 years split 80:20



Anomaly Correlation (Higher values ⇒ Higher skill)

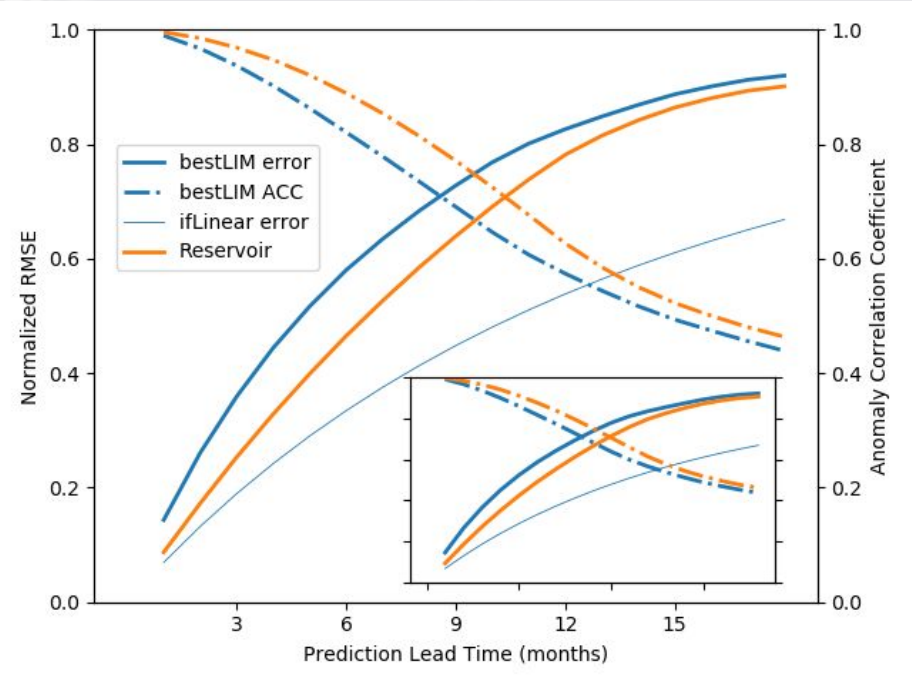
Reservoir Computing vs. Linear Inverse Modeling

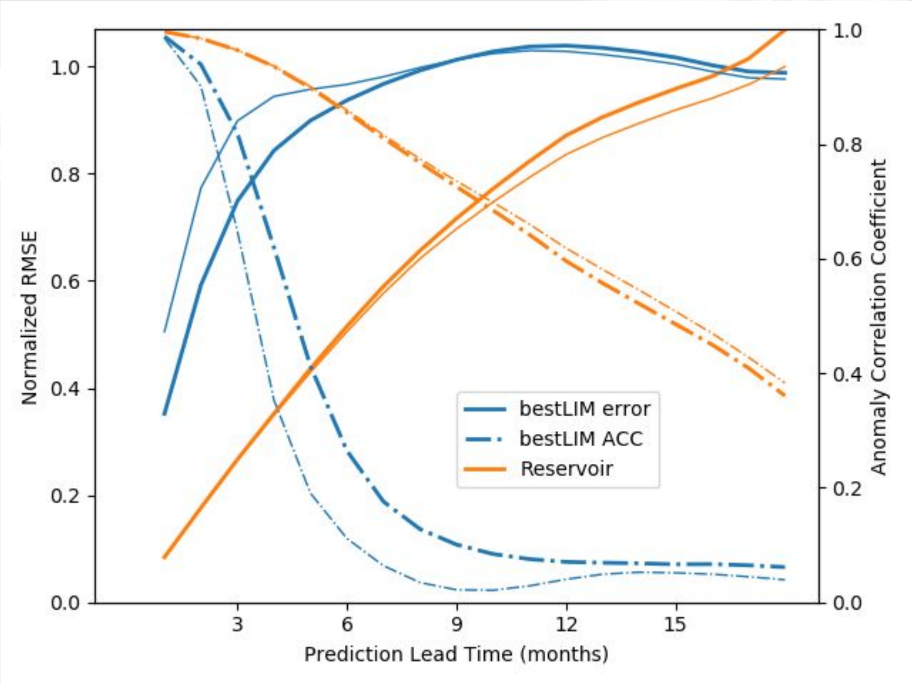
Learning from Limited Data. 13 year segments split as 88:12



Normalized RMSE (Lower values $\Rightarrow$ Higher skill)

RC Vastly OutPerforms LIM





Training with lots of data
Main: 20 EOFs; Inset: 30 EOFs
RC slightly better than LIM

Training with limited data
Thick: 20 EOFs; Thin: 30 EOFs
RC vastly better than LIM

Summary and Future Work

- Currently LIMs are the main reduced order dynamics workhorse for predictability studies
- What do data driven methods have to offer in this setting?
- Reservoir Computing based prediction system developed for an Earth System Model (Think weighted sum and nonlinearity)
- RC vastly outperforms LIM
- The system and the predictions need to be analyzed to identify predictable patterns and establish predictability
- Application to observations and CMIP
- Predictability studies conducted in perfect model settings suggest that predictability extends to the decadal timescale
- In reality, however predictive skill vanishes much much faster. How much can we expect ML to improve skill?