Hybridizing Knowledge-Based and Machine Learning Models for Climate and Tipping-Point Prediction

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https://awikner.github.io/actm-umd-tamu-prllc

Current Research Threads

- Build on our previous hybrid physics-ML weather forecasting method to allow nonstationarity, and to have appropriate variability, at climatological time scales

- Use ML to forecast bifurcations outside the parameter range of the training data in two scenarios:
  - Future evolution of parameter values is known or hypothesized
  - Parameter values (past and future) are unknown or unspecified

- Noise-emulating regularization to promote stability in iterative ML or hybrid forecasts

Reservoir Computing (RC)

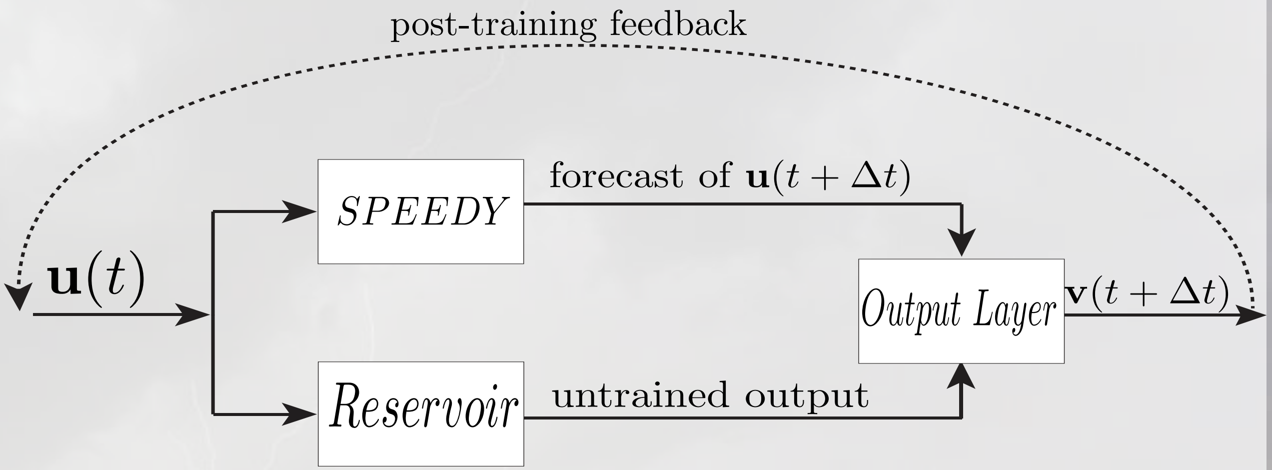
- For ML we use reservoir computing (e.g., Lukoševicius and Jaeger 2009)
  - Recurrent Neural Network – enables memory of time series input
  - Simplified training – only the output layer parameters are trained

- Much faster training than other ML methods allows us to perform a lot of exploratory numerical experiments

- Our hybrid approach can be used with any ML method that is trained to make a short-term forecast
  - Short-term forecasts are cycled iteratively to make a long-term forecast

General Hybrid Modeling Approach

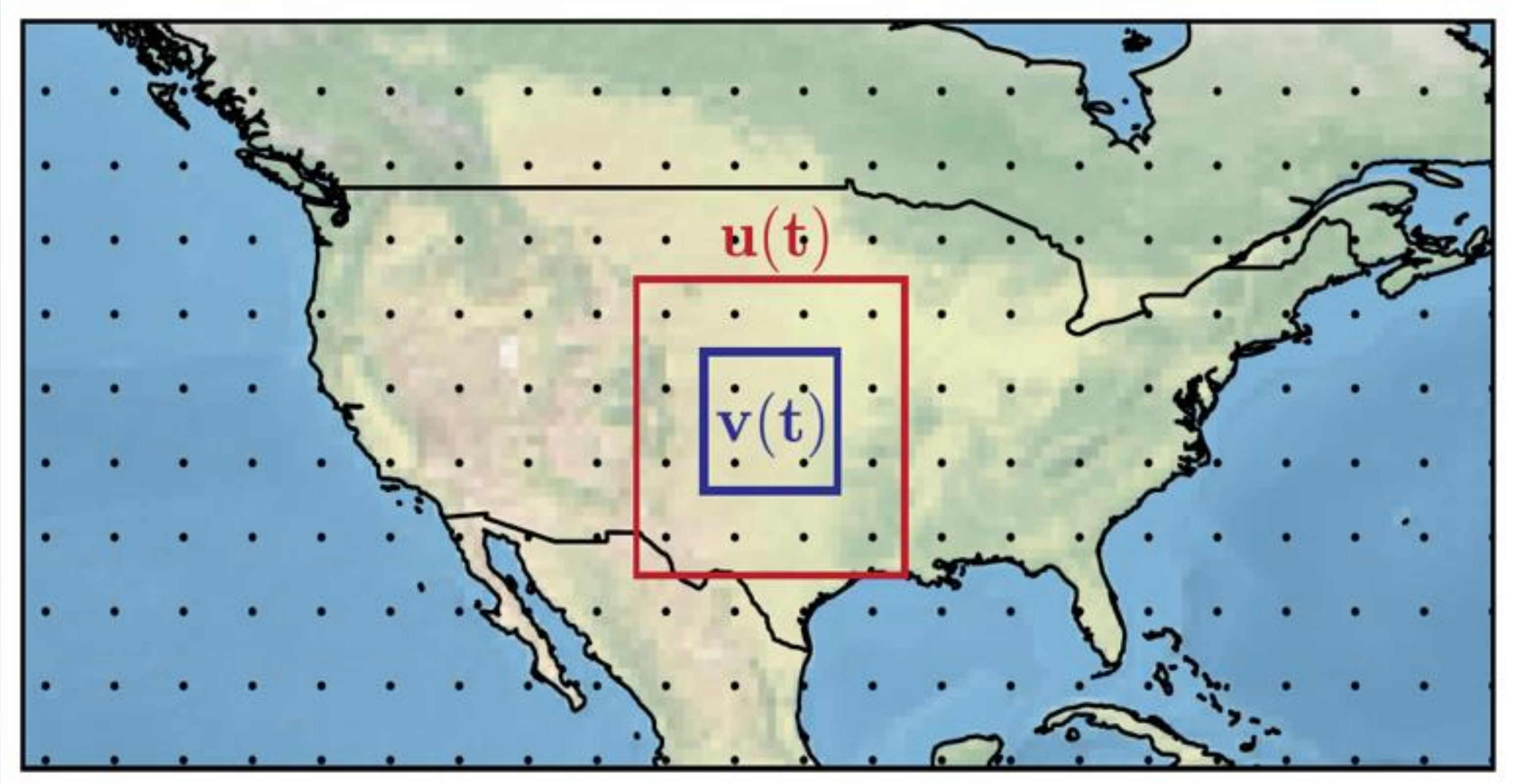
- **Atmospheric state: u**(t)



- **SPEEDY:** AGCM
- **Reservoir:** RNN
- **Output Layer:** trained linear weights
  - **v**(t+Δt) approximates **u**(t+Δt) [or a sub-vector in the parallel version]
- **Parallel version:** ~1000 reservoirs, each forecasts on a separate local region
  - each output layer is independently trained; reservoirs exchange data only post-training

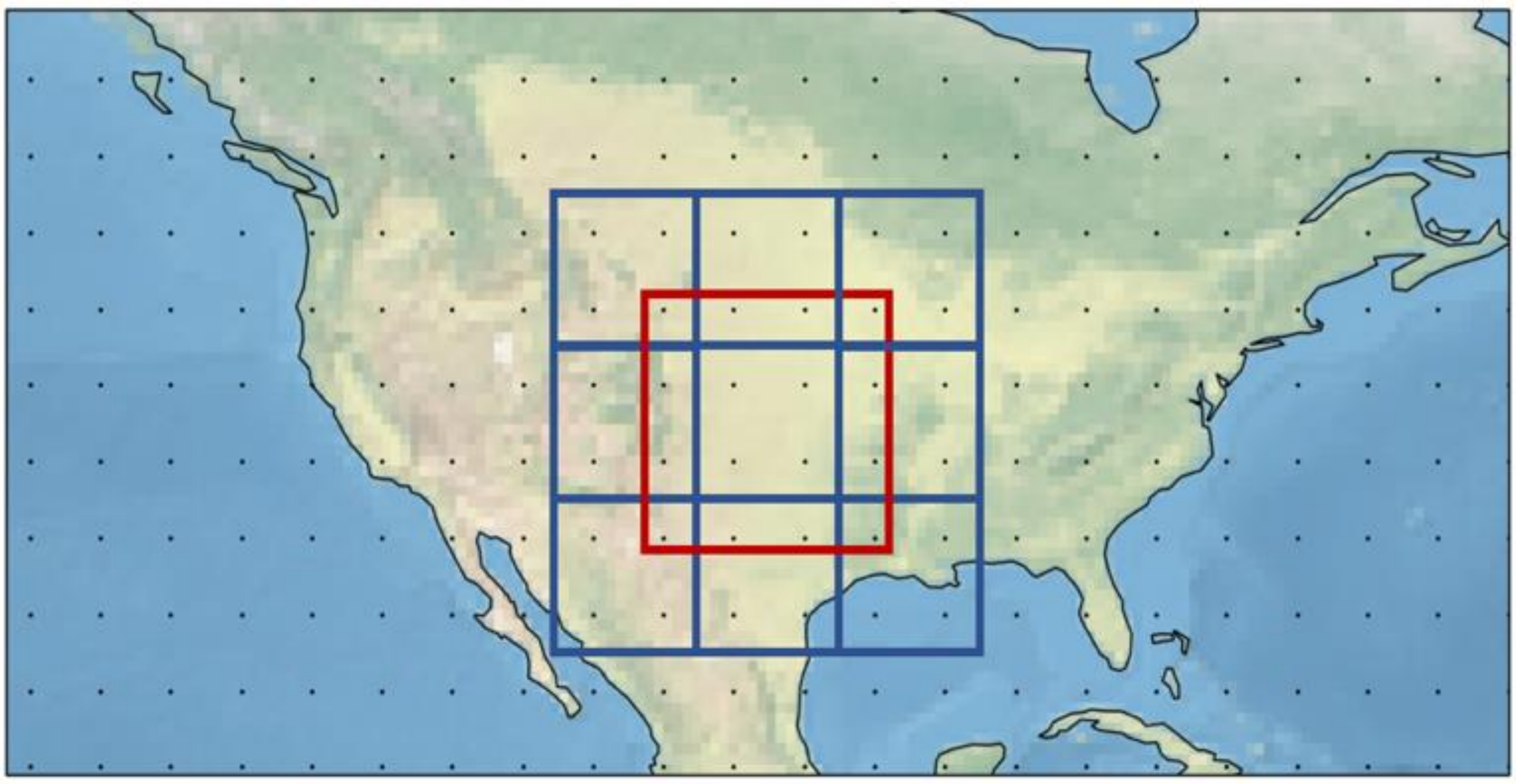
Parallel-Hybrid Training

local input **u**(t), output **v**(t+Δt)



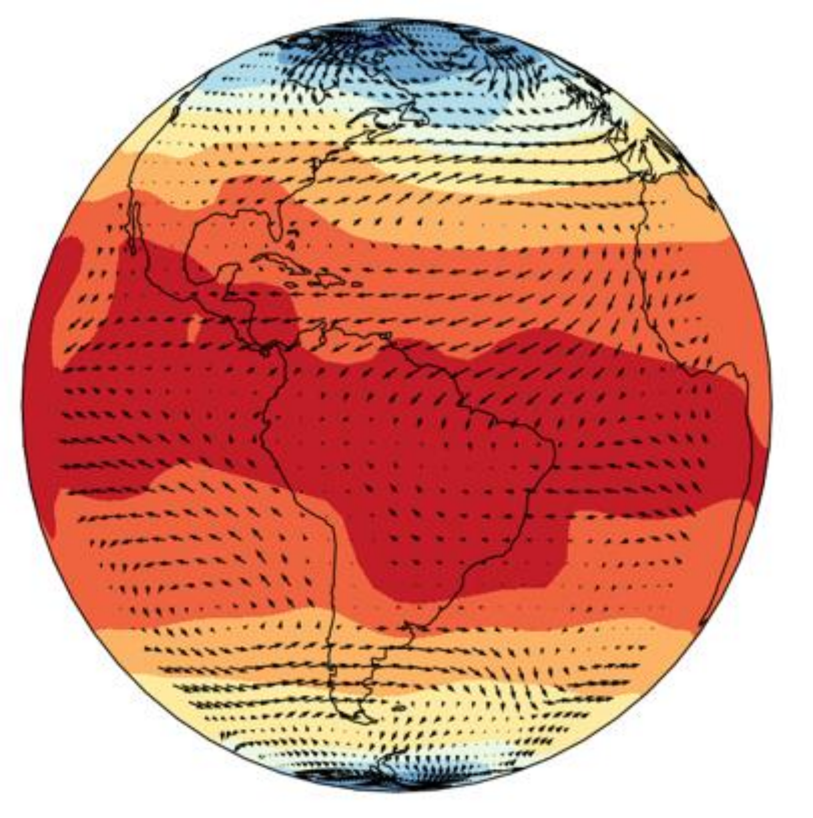
Parallel-Hybrid Post-Training

input from nearby outputs



SPEEDY

- **S**implified **P**arameterizations, primitive **E**quation **DY**namics Version 42 of the International Centre for Theoretical Physics (ICTP)
  - (Molteni 2003, Kucharski 2006)
- Equations
  - Primitive equations
  - Simplified but modern parameterization
- Configuration
  - 8 vertical layers
  - T30 (~300km)
- Been used to test and develop new numerical weather prediction and data assimilation techniques



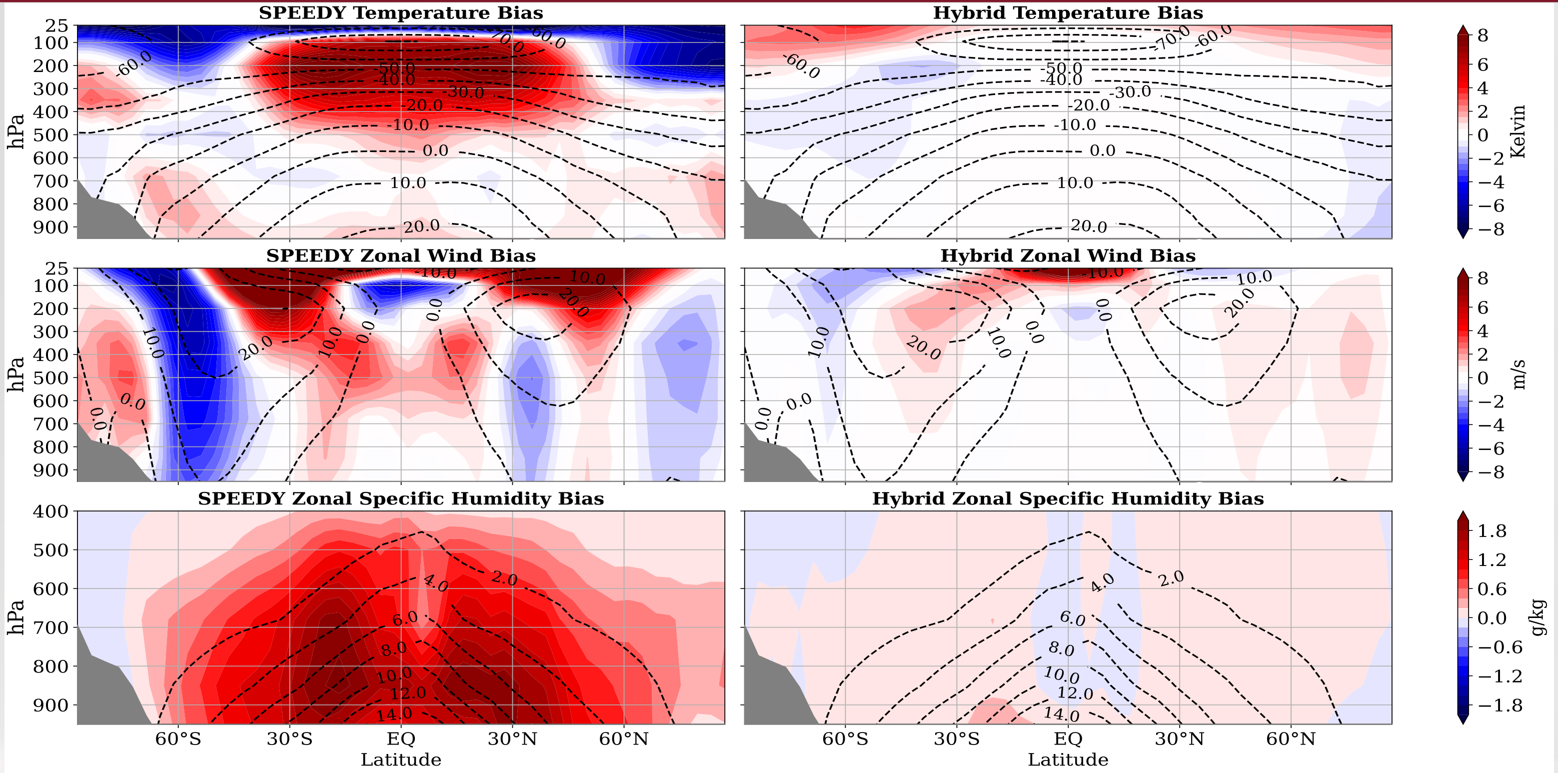
Training

- Regridded ERA-5 Reanalysis data to SPEEDY horizontal and vertical grid
- Used the 5 prognostic variables for SPEEDY
  - Temperature
  - 2 components of the wind
  - Specific Humidity
  - Surface Pressure
- 19 years of data from 1981-1999
- Training minimizes 6 hour forecast error

Climate Simulations

- Ran SPEEDY and the trained hybrid model from Jan 1, 2000 to Dec 31, 2010
  - 11-year free run using a hybrid model optimized for 6-hour forecasts
- Both simulations use climatological surface boundary conditions
- Let each simulation “spin-up” for a year and then calculated climate stats for the ten years from 2001 to 2010
  - Biases are measured by comparing each simulation to ERA 5 for the same period

Climate Simulations Results (Arcomano et al. 2022)



Lower bias indicates better simulation of the 2001-2010 climate represented by ERA5

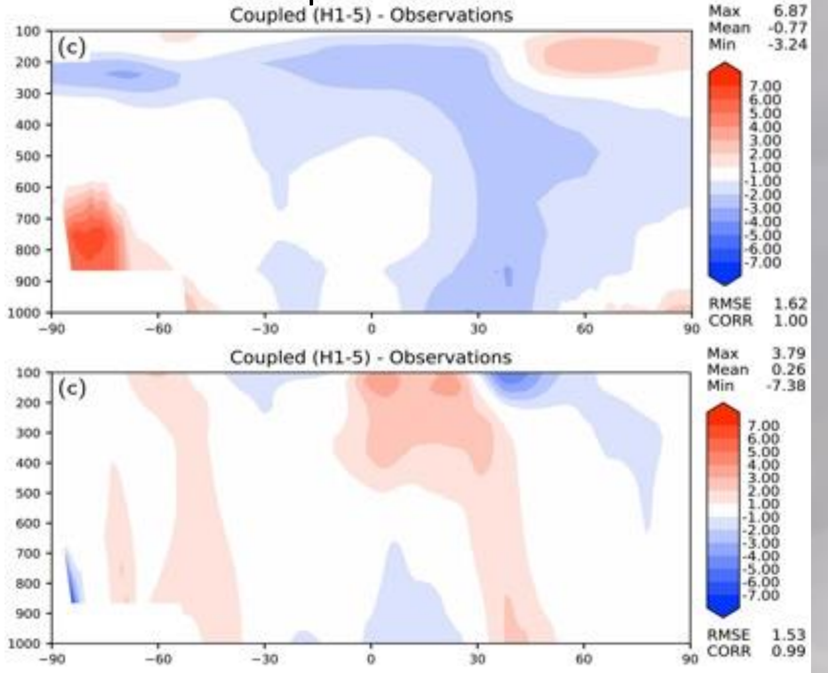
Comparison with Coupled Ocean-Atmosphere Model

- Energy Exascale Earth System Model
  - Fully coupled Earth system model
  - Run on ~6000 CPU cores
- Our Hybrid Model
  - Climatological boundary conditions
  - Once trained can be run using desktop
    - 10 year simulation ~2 hours

	Temperature			
Model	Min Bias	Max Bias	Mean Bias	RMSE
E3SM	-3.24	6.87	-0.77	1.62
Hybrid	-0.92	2.38	0.19	0.49
SPEEDY	-6.56	7.11	0.83	3.22

	Zonal Wind			
Model	Min Bias	Max Bias	Mean Bias	RMSE
E3SM	-7.38	3.79	-0.26	1.53
Hybrid	-1.73	1.83	0.12	0.60
SPEEDY	-6.93	20.7	0.63	2.30

E3SM Coupled Model Version 1



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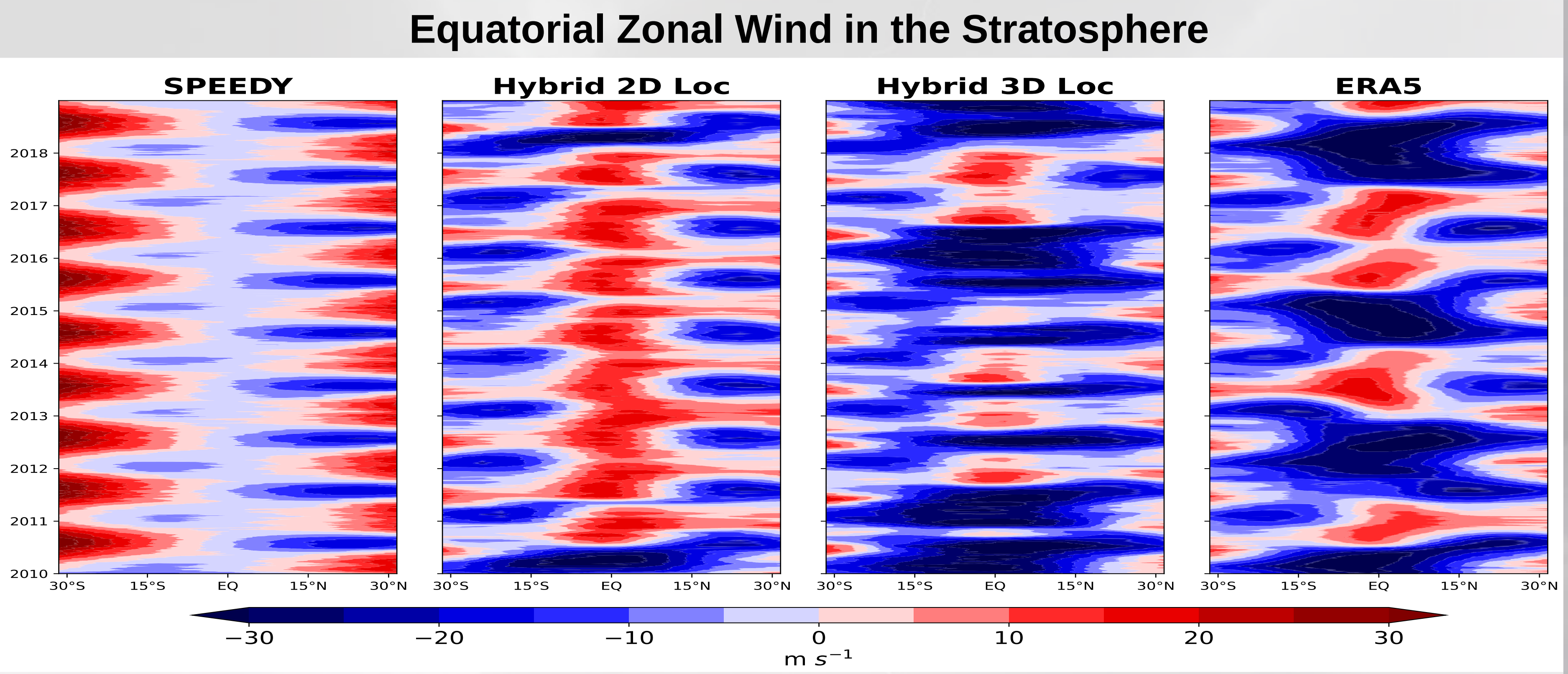
Current Work

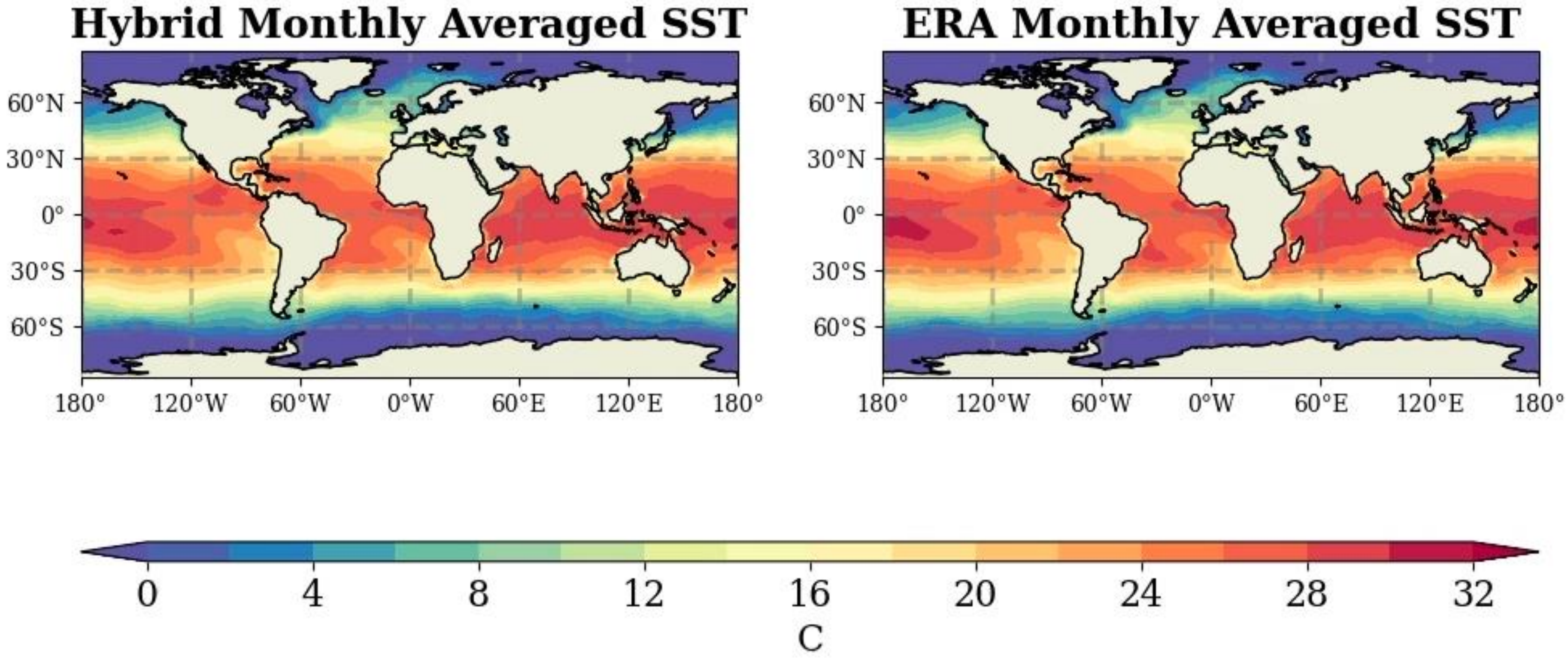
- Add vertical localization
  - Going from a 2-d grid of ML reservoirs to a 3-d grid
  - Improves year to year variability for the stratosphere

- Allow nonstationarity of boundary conditions
  - Two way coupling of the atmosphere to the ocean, sea ice, etc.
  - First approach: using ML-component to forecast sea surface temperatures (SSTs)

Vertical Localization: Preliminary Result



Ocean-Atmosphere Coupling: Preliminary Result



Conclusions

- Hybrid physics-ML atmospheric model allows fast simulation of climate scenarios
  - Could run large ensemble of simulations within a scenario

- Ongoing work to make the hybrid model more suitable for nonstationary scenarios
  - Vertical localization, slab ocean model in SPEEDY

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- Ongoing research on tipping points and stability
  - Will transition from toy models to earth-system hybrid

References

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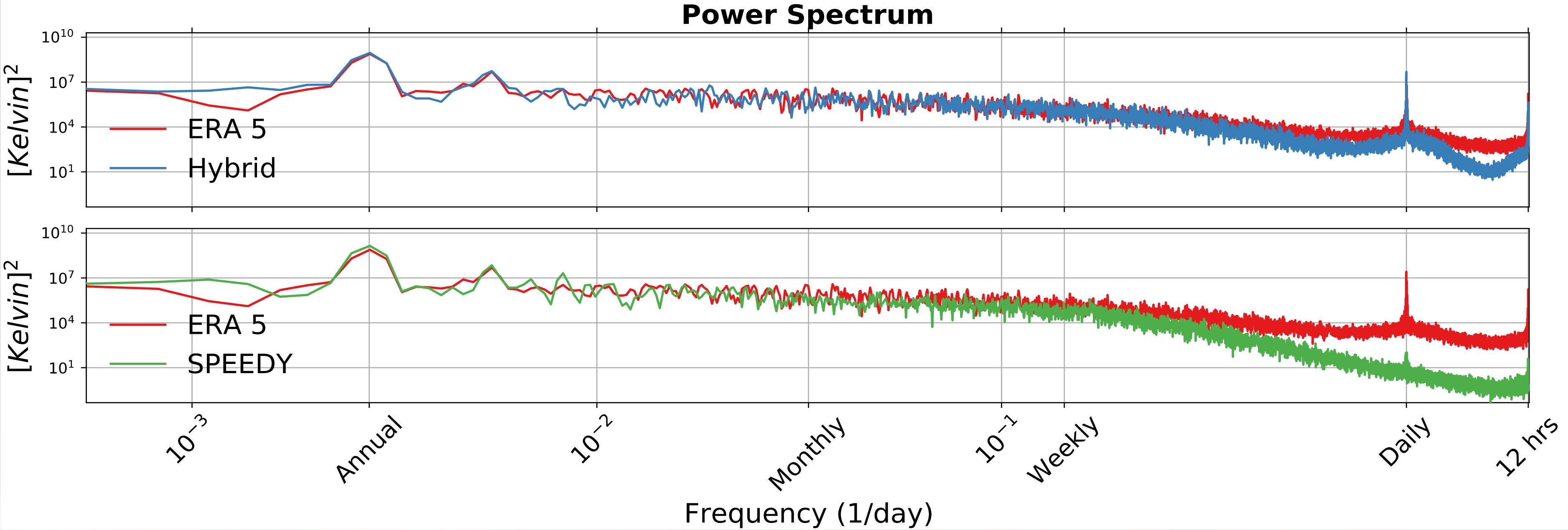
2.) Pathak, J., Wikner, A., Fussell, R., Chandra, S., Hunt, B. R., Girvan, M., and Ott, E. (2018). Hybrid forecasting of chaotic processes: Using machine learning in conjunction with a knowledge-based model

3.) Molteni,F.,2003:Atmospheric simulations using a GCM with simplified physical parameterizations. I. Model climatology and variability in multi-decadal experiments. *Clim. Dyn.,* **20,** 175-191.

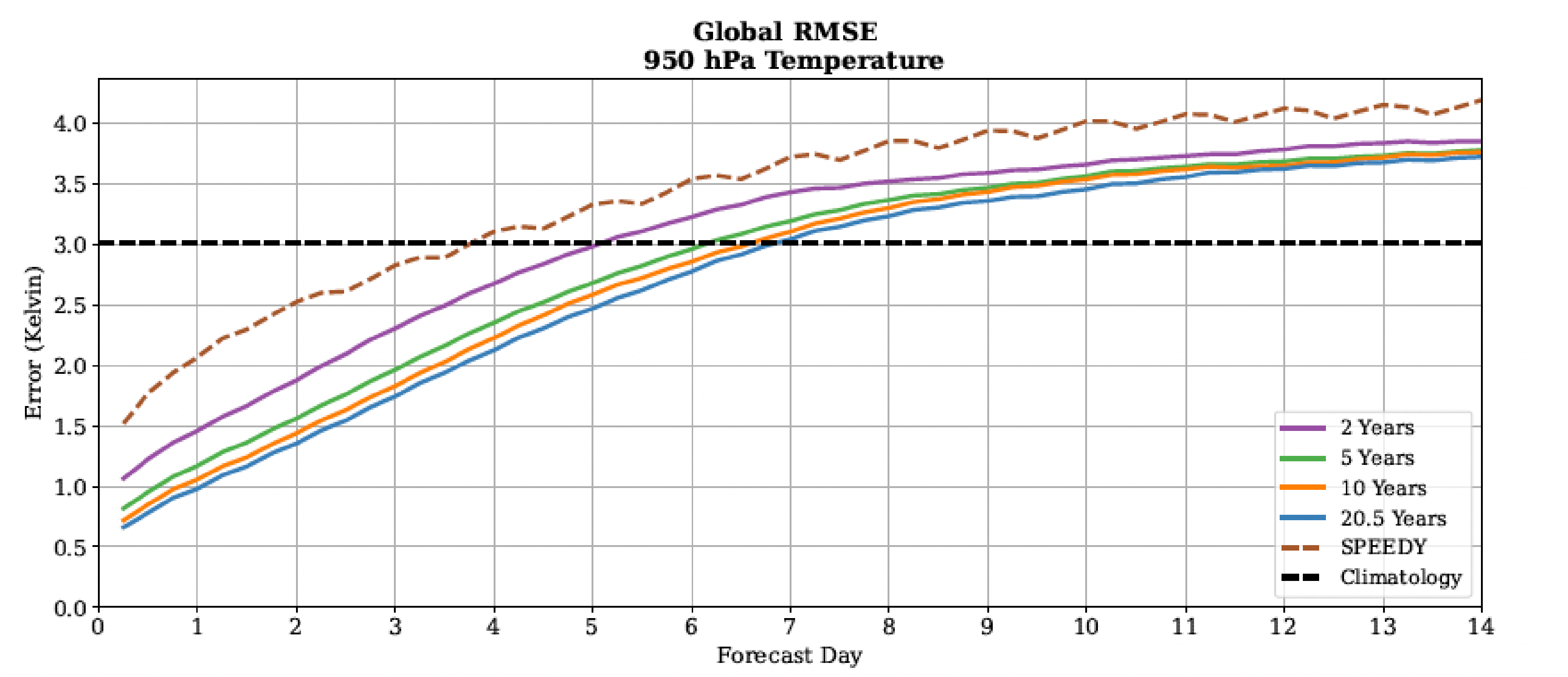
4.) Kucharski,F.,F.Molteni,and A.Bracco,2006:Decadal interactions between the western tropical Pacific and the North Atlantic Oscillation. *Clim. Dyn.,* **26,** 79-91.

Climate Dynamics

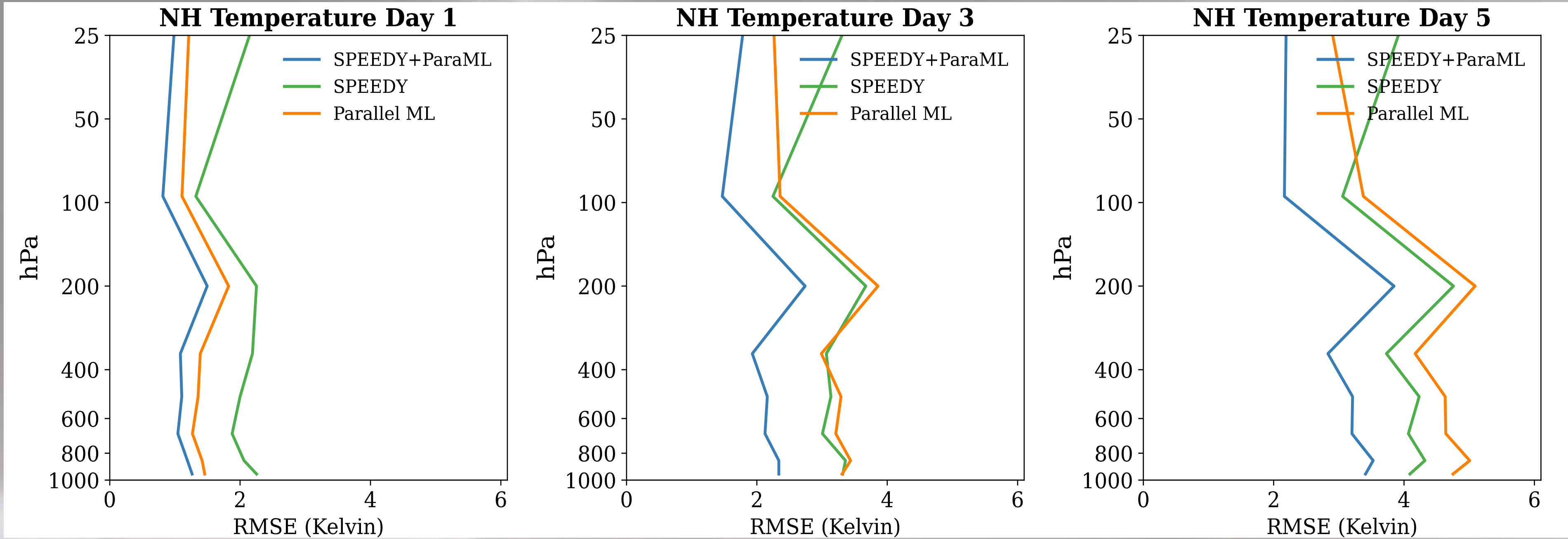


Significant improvement in short timescale variability

RMSE as a Function of Training Data



RMSE as a Function of Training Data



Ocean Atmosphere Coupling