

Learning to Predict Spatiotemporal Variability of Climate

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(Shinjae Yoo, Ji Hwan Park, BNL; C. Jiang, Amir Farimani, CMU)

Outline

A Five Minute Climate Tour

A Two Minute Climate Modeling Tour

Prediction and Predictability

Two Kinds of Predictability: External-Forcing Related
Predictability and Natural-Variability Related Predictability

Difficulty with Predicting Natural Variability

Deep Learning Spatio-Temporal Variability of Climate

Difficulty with Predicting Natural Variability with DNNs
⇒ Transfer Learning

Summary and Future Work

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Global Energy Flows W m^{-2}

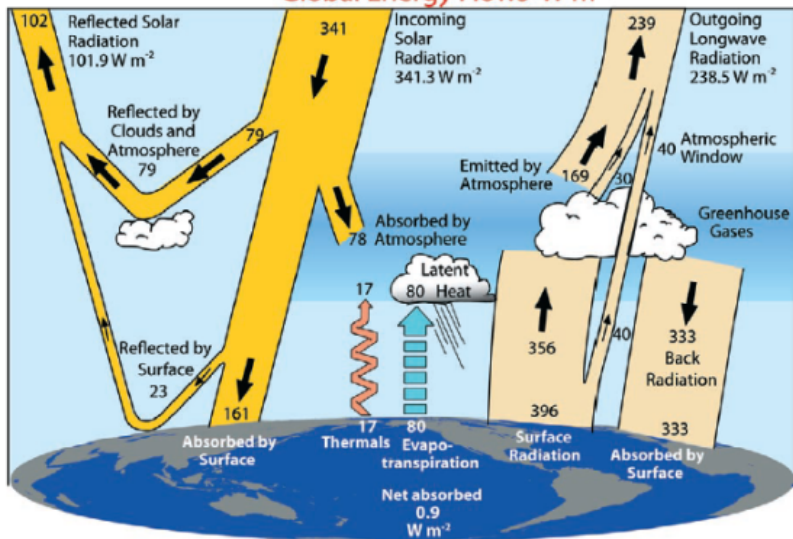
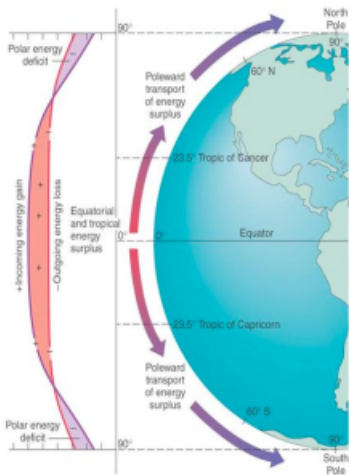


FIG. 1. The global annual mean Earth's energy budget for the Mar 2000 to May 2004 period (W m^{-2}). The broad arrows indicate the schematic flow of energy in proportion to their importance.

(Trenberth et al., 2009)

Poleward Heat Transport



- More Insolation (UV) in Equatorial and Tropical Regions than Polar Regions
- Outgoing IR more uniform
- This Energy Imbalance is Ultimate Driver of Atmospheric and Oceanic Circulation
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Meridional Distribution of Radiative Imbalance

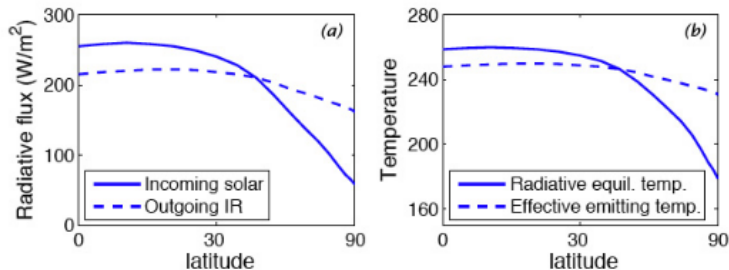
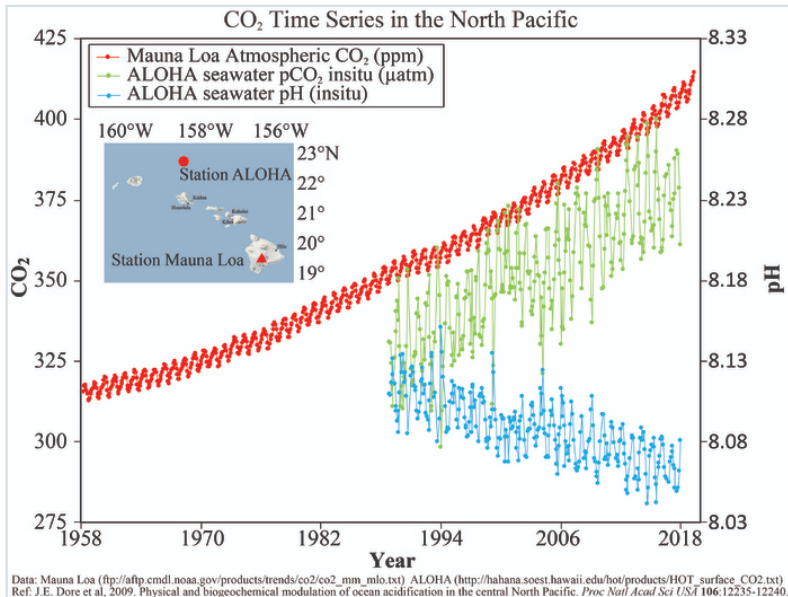
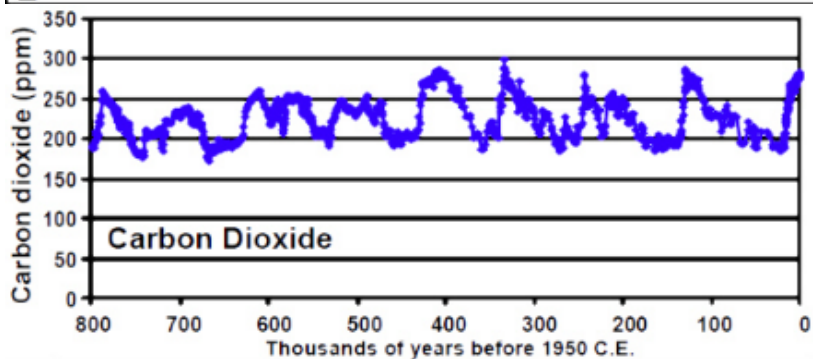
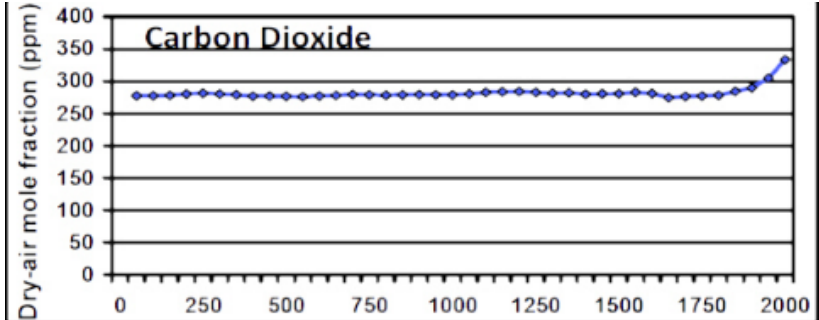


Fig. 11.1 (a) The (approximate) observed net average incoming solar radiation and outgoing infra-red radiation at the top of the atmosphere, as a function of latitude (plotted on a sine scale). (b) The temperatures associated with these fluxes, calculated using $T = (R/\sigma)^{1/4}$, where R is the solar flux for the radiative equilibrium temperature and R is the infra-red flux for the effective emitting temperature. Thus, the solid line is an approximate radiative equilibrium temperature

Vallis, 2006

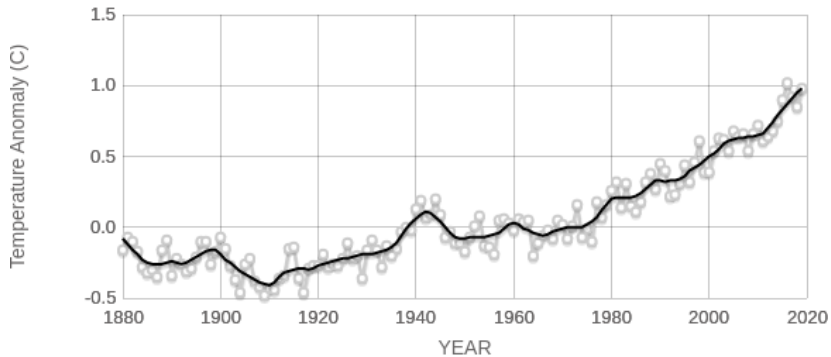
Hawaii Carbon Dioxide Time-Series





(Berkeley Lab)

Temperature Response



Source: climate.nasa.gov

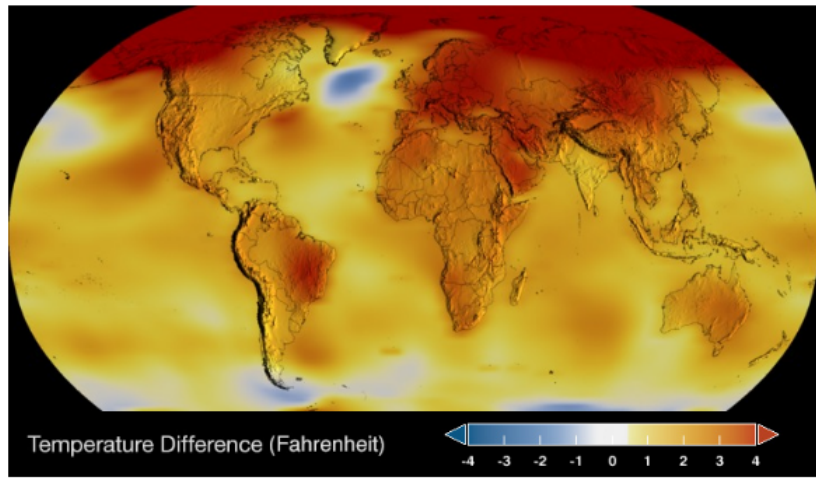
Temperature Response

TIME SERIES: 1884 TO 2019

2019

Data source: NASA/GISS

Credit: NASA Scientific Visualization Studio



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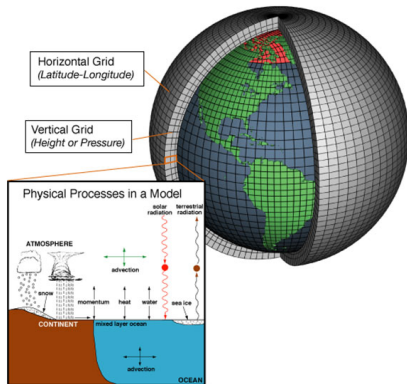
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Summary and Future Work

Earth System Models

- ▶ Built bottom-up by coupling various dynamical, physical, and biogeochemical subsystems
 - ▶ Atmosphere, ocean, sea-ice, land surface and vegetation, biogeochemistry in ocean
 - ▶ Closes carbon cycle
- ▶ Best tool available to understand and model climate and climate change
- ▶ Computationally demanding and requires big infrastructure
- ▶ Prevents it from being used even more widely and in different settings.



http://celebrating200years.noaa.gov/breakthroughs/climate_model/welcome.html

What do Earth System Models *try* to do?

Basically everything that the climate system does: feedbacks, circulation, poleward heat transport, energy balance, energy balance, temperature distribution everywhere, etc.

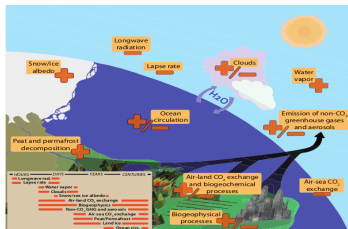
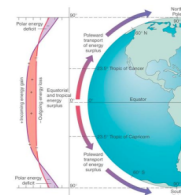


Figure 1.2 | Climate feedbacks and timescales. The climate feedbacks related to increasing CO₂ and rising temperature include negative feedbacks (-) such as LWIR, lapse rate loss (shown in Annex B), and air-sea carbon exchange and positive feedbacks (+) such as water vapor and snow/ice albedo feedbacks. Some feedbacks may be positive or negative (+/-). Clouds, ocean circulation changes, air-land CO₂ exchange, and emissions of non-CO₂ greenhouse gases and aerosols from natural systems. In the smaller box, the large difference in timescales for the various feedbacks is highlighted.

Poleward Heat Transport



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<http://www.nasa.gov/pdf/151207main/earth-energy-budget-060907.pdf>

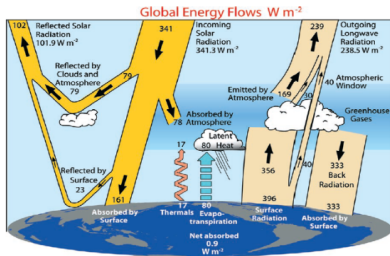
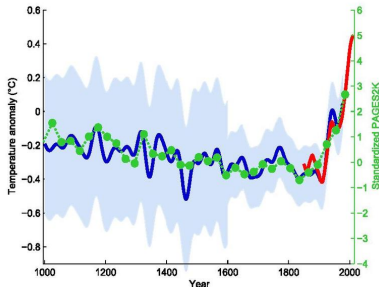


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Prediction and Predictability

“Weather prediction is (then identified with) the process of determining how the weather will change as time advances, and the problem of weather predictability becomes that of ascertaining whether such predictions are possible.”

Climate Prediction and Predictability

“Weather is (often) identified with the complete state of the atmosphere at a particular instant.

...We may therefore define climate as a set of statistics of the ensemble of all states during a long but finite span. Climate prediction then becomes the process of determining how these statistics will change as the beginning and end of the time span advance and climatic predictability is concerned with whether such climatic prediction is possible”

Lorenz, E. N. (1975). Climate predictability, The physical basis of climate and climate modelling (vol. 16, pp. 132–136), Garp publication series: WMO.

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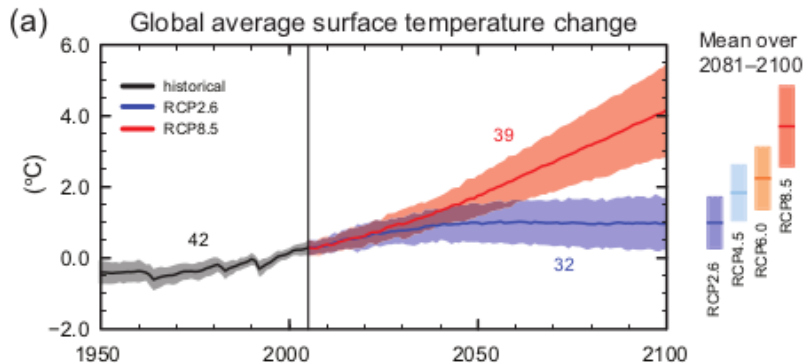
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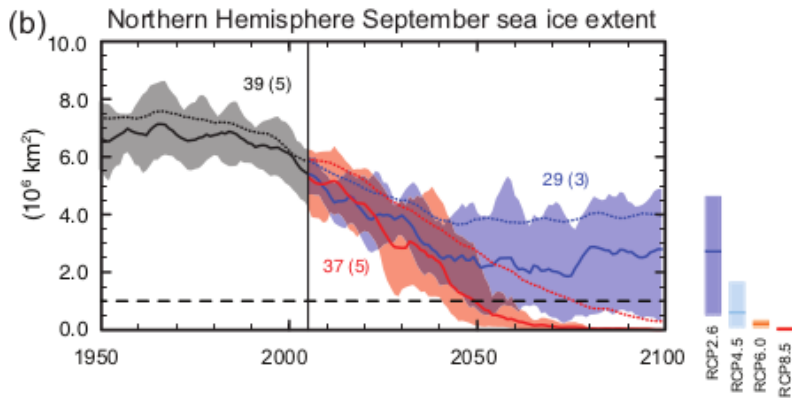
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Models Good at Realizing External-Forcing Related Predictability (IPCC AR5)



Note that as much as 93% of excess heat due to GHGs is taken up by the world oceans!

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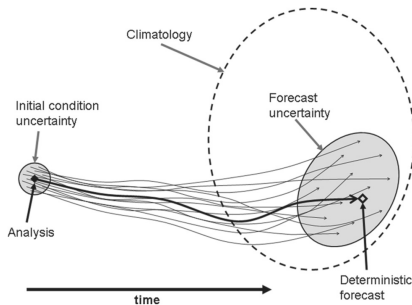
Summary and Future Work

Chaotic Nature of Natural Variability

(Lorenz, 1969; Griffies and Bryan, 1997, etc.)

- ▶ Conduct initial condition ensemble simulations with climate model

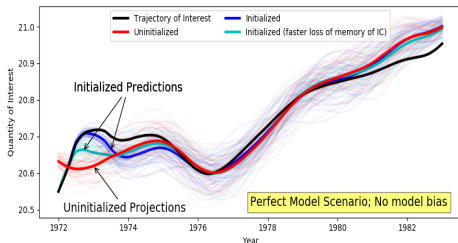
- ▶ Obtain forecast dist. $P(\mathbf{v}|\boldsymbol{\theta})$ ($\boldsymbol{\theta}$ is obs.) and climatological dist. $P(\mathbf{v})$



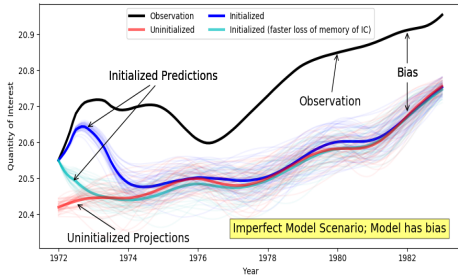
(Swinbank et al. (2016) Cambridge University Press)

- ▶ Conduct analysis of forecast error covariance Σ_F and climatological covariance Σ_C (assuming normal dist.)
 - ▶ Canonical Correlation Analysis
 - ▶ Discriminant Analysis
 - ▶ Predictive Component Analysis

Difficulty with Predicting Natural Variability: Model Bias



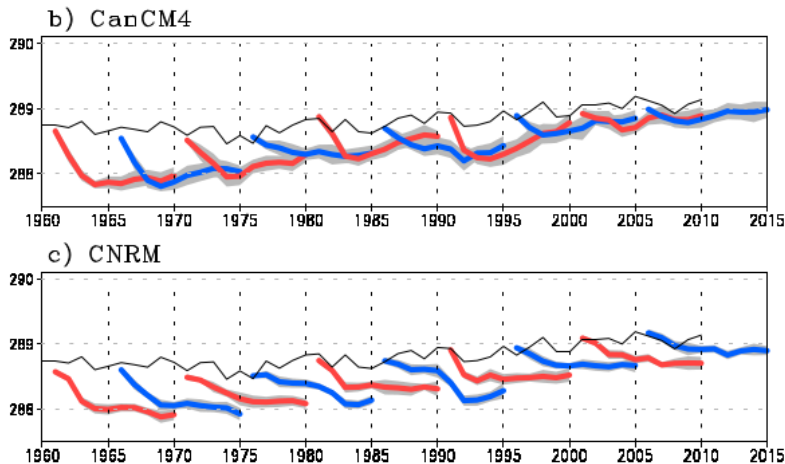
- Predictability studies are conducted in perfect model settings
- However all climate models are imperfect (have biases)
 - Extremely difficult to model the exact balance (small residual) of myriad (large) processes that lead to the mean state of the climate system and modes of variability
 - Small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



Initialized Predictions of Various Qols in Various Models

Display a Jump Behavior

Surface Temperature in CanCM4 and CNRM



(From Kim et al., 2012)

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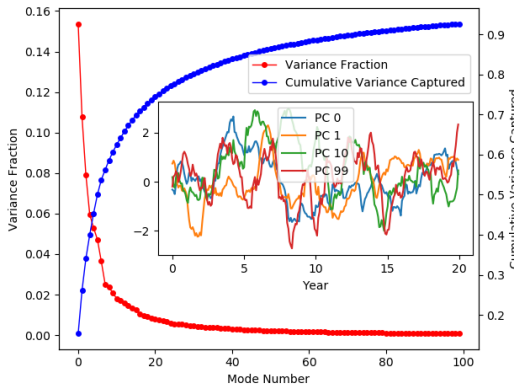
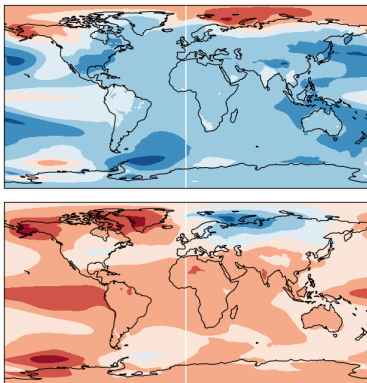
Summary and Future Work

What are the predictability characteristics of the spatiotemporal variability of surface temperature

- ▶ State of the art IPCC class model: NCAR CESM2
- ▶ Seasonal cycle removed
- ▶ Formulate problem with different forms/complexity, model order reduction, data augmentation, ...
- ▶ Develop learning based prediction system with different architectures
- ▶ Analyze predictability

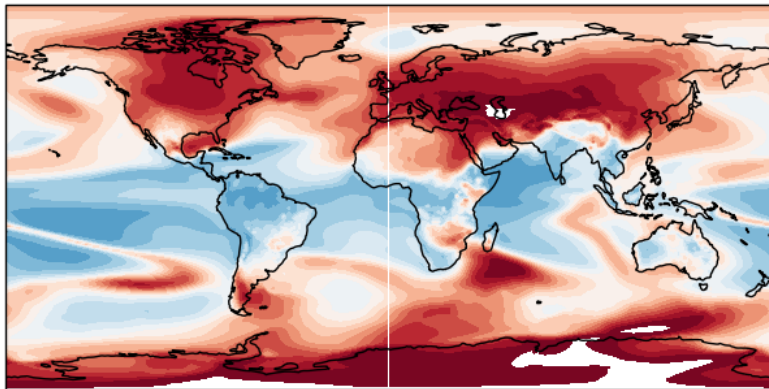
Modeling in Spatial Domain

PCA is used for model order reduction in some cases



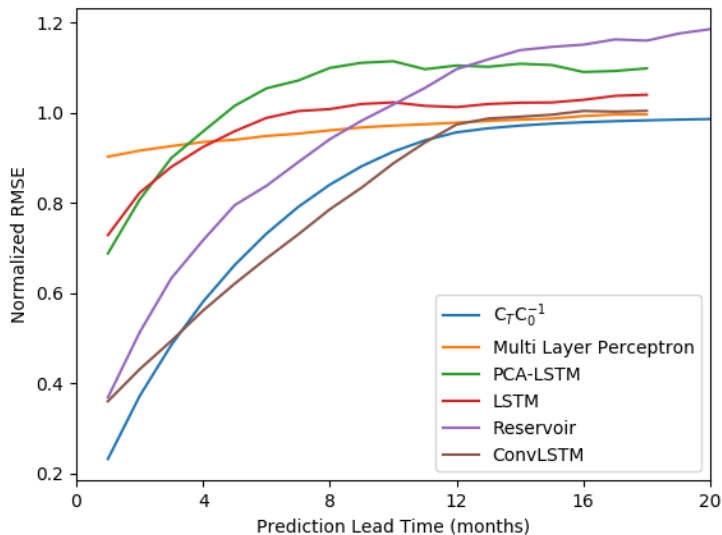
First two EOFs (left) of the interannual variability of global surface temperature. Variance fractions, cumulative variance explained, and evolution of the principal components over a short 20 year period are shown on the right

Prediction Error Map



Errors greater at mid and high latitudes
Errors greater over land

Comparison of Predictive Skill Across DNN Architectures and Other Statistical/Dyn. Models (No Climate Models)



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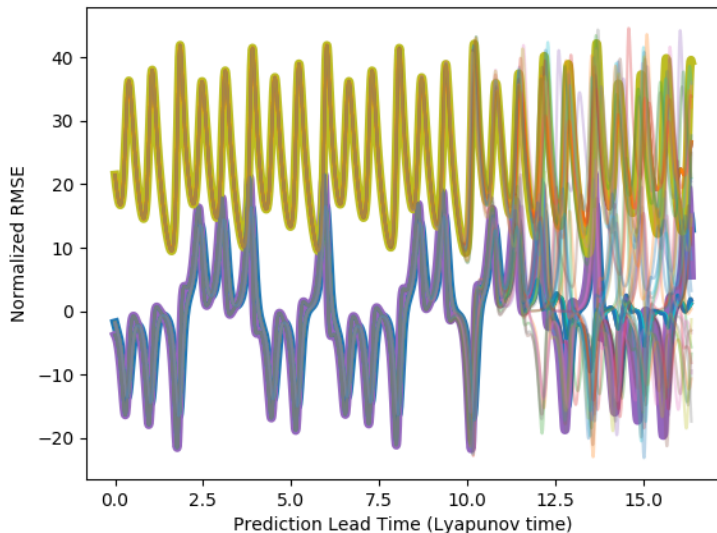
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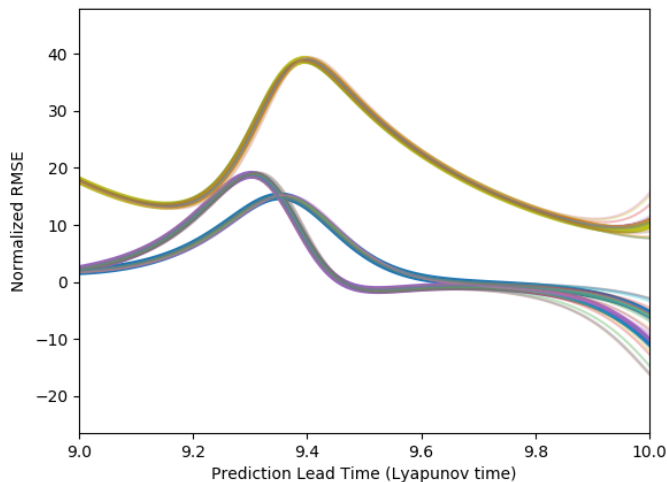
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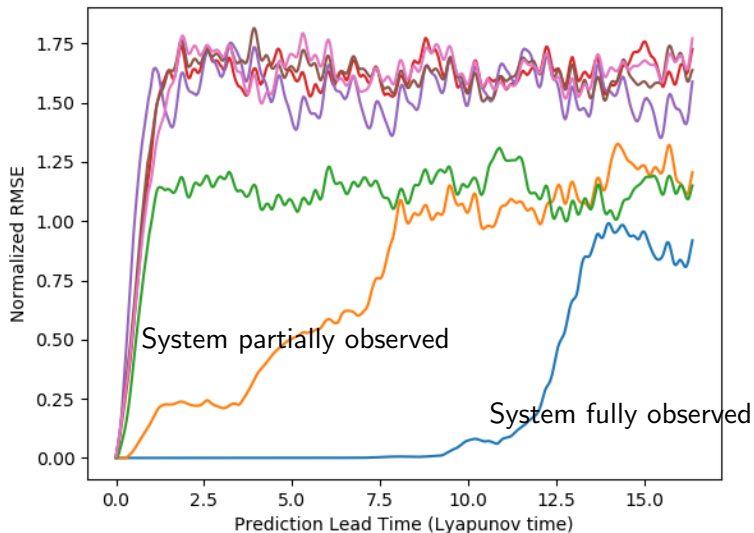
When presented with the full system, the neural network can learn the Lorenz '63 attractor



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However, not so when the system is only partially observed



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(Ongoing work)

- ▶ Predictability studies conducted in perfect model settings suggest that predictability extends to the decadal timescale
- ▶ In reality, however predictive skill vanishes much much faster. Model bias is one reason
- ▶ What do data driven methods have to offer in this setting?
- ▶ Learning based prediction system developed for an Earth System Model
- ▶ The system and the predictions need to be analyzed to identify predictable patterns and establish predictability
- ▶ Transfer methodology to observations