

# Leveraging oscillatory modes to improve forecasts of chaotic processes, with applications to the Indian monsoon

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Eviatar Bach

*University of Maryland, College Park*

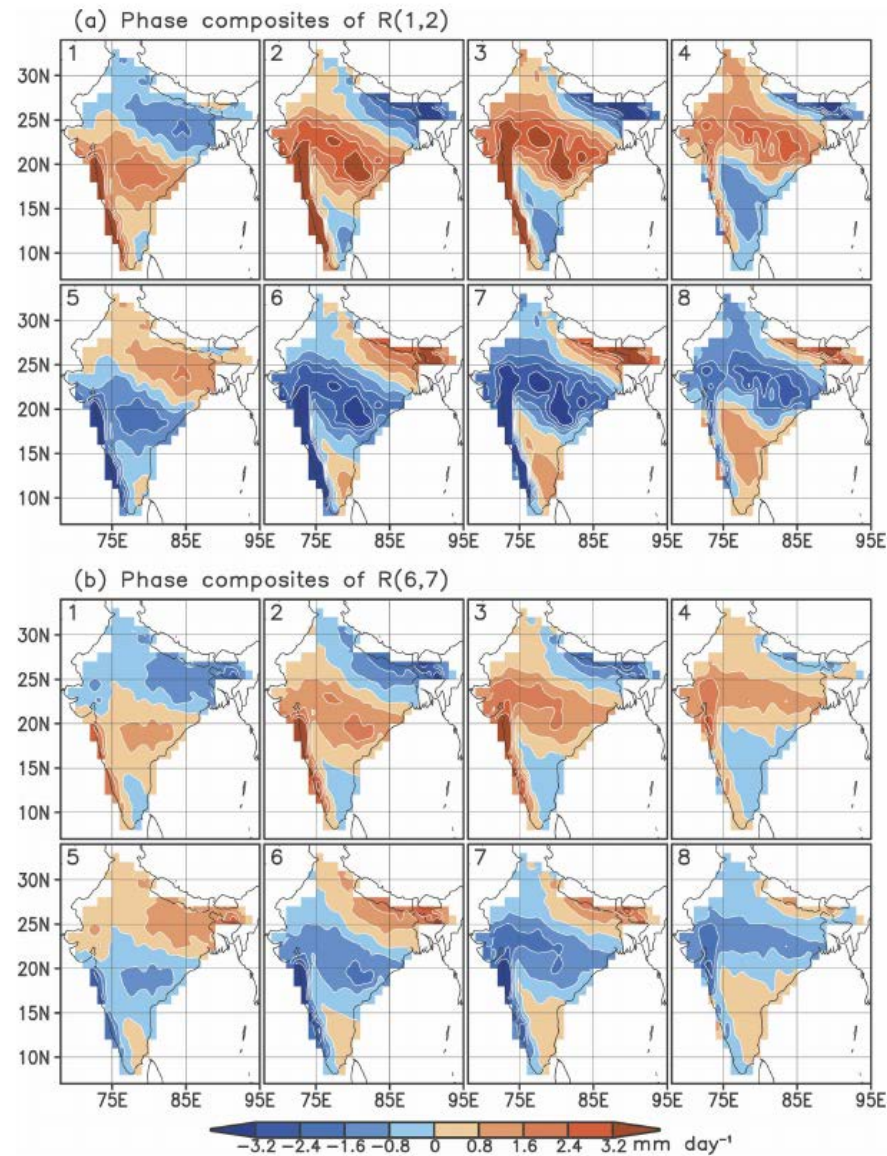
# Introduction

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# Monsoon intraseasonal oscillations

- According to various studies (Krishnamurthy and Shukla 2000, 2007), seasonal monsoon rainfall can be considered a superposition of seasonal mean due to boundary conditions and intraseasonal oscillations.
- There are two dominant intraseasonal oscillations, with periods of about 20 days and 45 days.
- The intraseasonal oscillations characterize the active and break phases of the monsoon, and regional rainfall patterns.

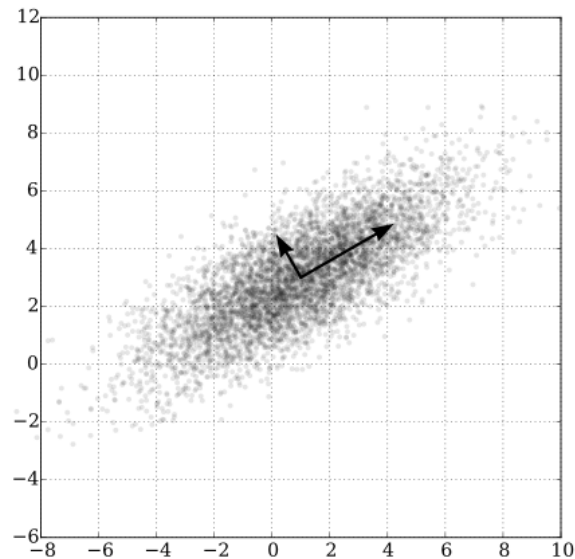
# Monsoon intraseasonal oscillations



The two dominant MISOs, from  
Krishnamurthy and Shukla (2007)

# Singular spectrum analysis

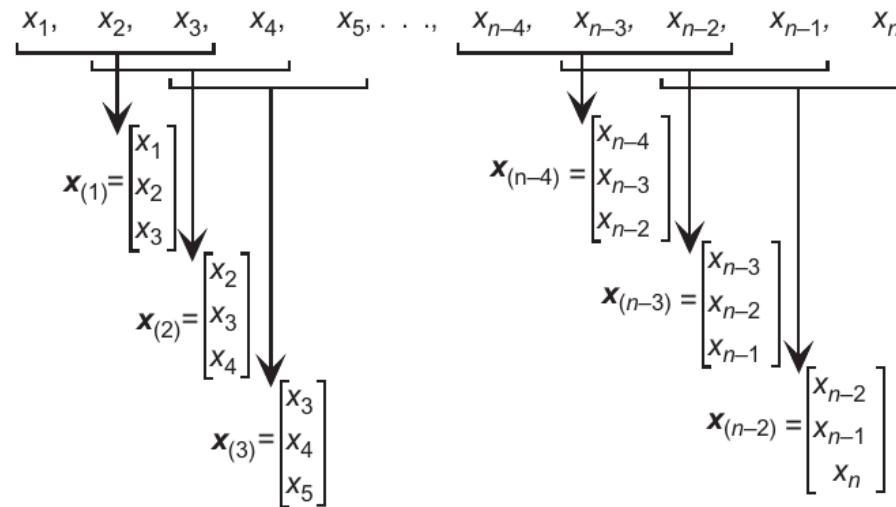
- Given some data, principal component analysis (**PCA**) finds a set of orthogonal vectors which explain the most variance.



- Singular spectrum analysis** (SSA, Ghil et al., 2002) is PCA applied to time-series data.
- The multivariate version is called multi-channel SSA (M-SSA), same as extended empirical orthogonal functions.

# Singular spectrum analysis

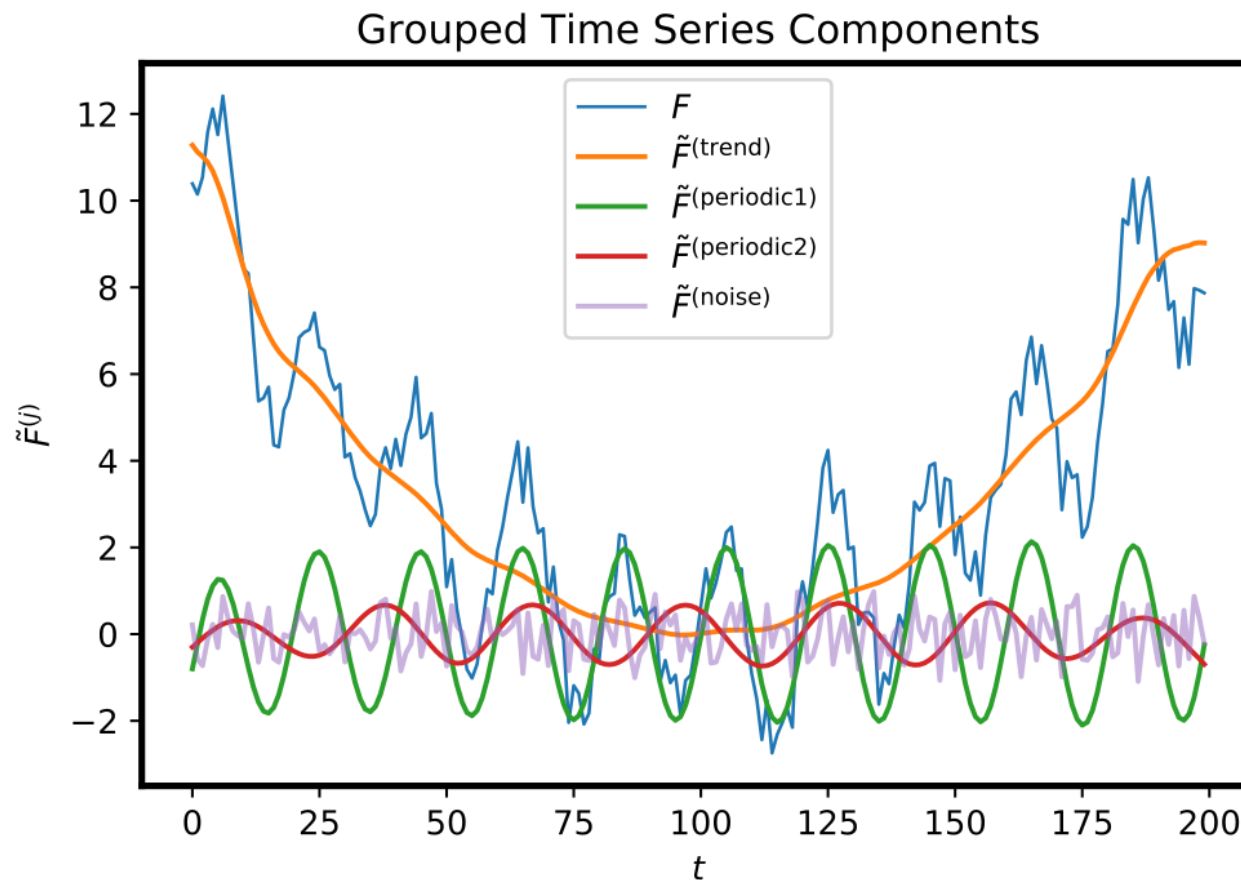
- We form sliding windows of length  $M$  (embedding dimension) of a time-series and apply PCA to them.



- This gives a set of modes that explain the most variance in the time-series.
- Trend, oscillatory, and noise modes can be identified.

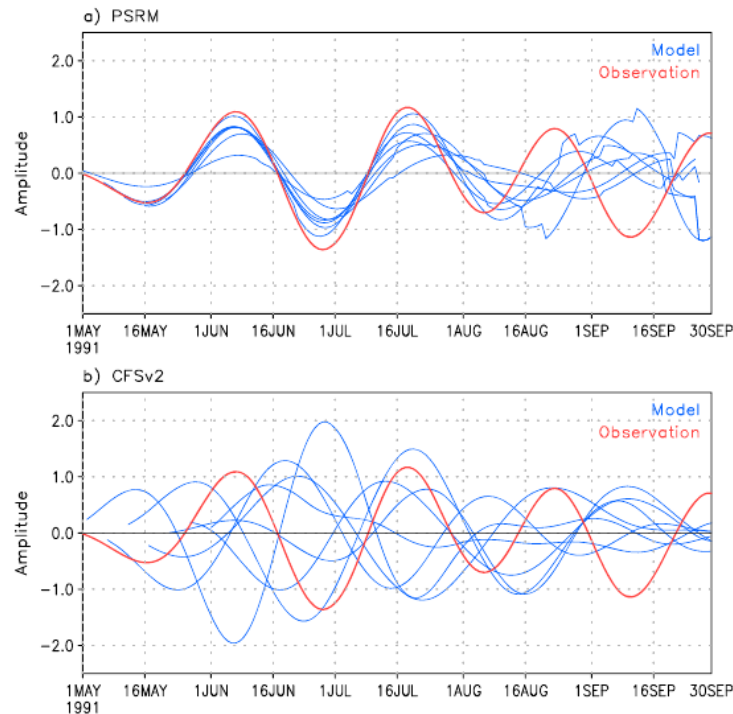
# Singular spectrum analysis

- By projecting original time-series onto the eigenvectors for each mode, the **reconstructed components (RCs)** corresponding to each mode can be recovered.
- Example:



# Predictability of MISO

- Krishnamurthy and Sharma (2017) have demonstrated predictability of MISO using a data-driven forecast:
- This data-driven method predicts MISO much better than the Climate Forecasting System (CFS):



Data-driven MISO forecasts (top), and MISO predicted by CFS (bottom). From Krishnamurthy and Sharma (2017).



# Ensemble oscillation correction

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# Motivation

- The oscillatory modes are much more predictable than the overall time-series.
- Forecasting methods have been developed for individual modes.
- However, there is no way to go backwards, from the Reconstructed Components (unless we forecast all the modes) to the original time-series.
- How do we use forecasts of the RCs to improve prediction of the full time-series?

# Motivation

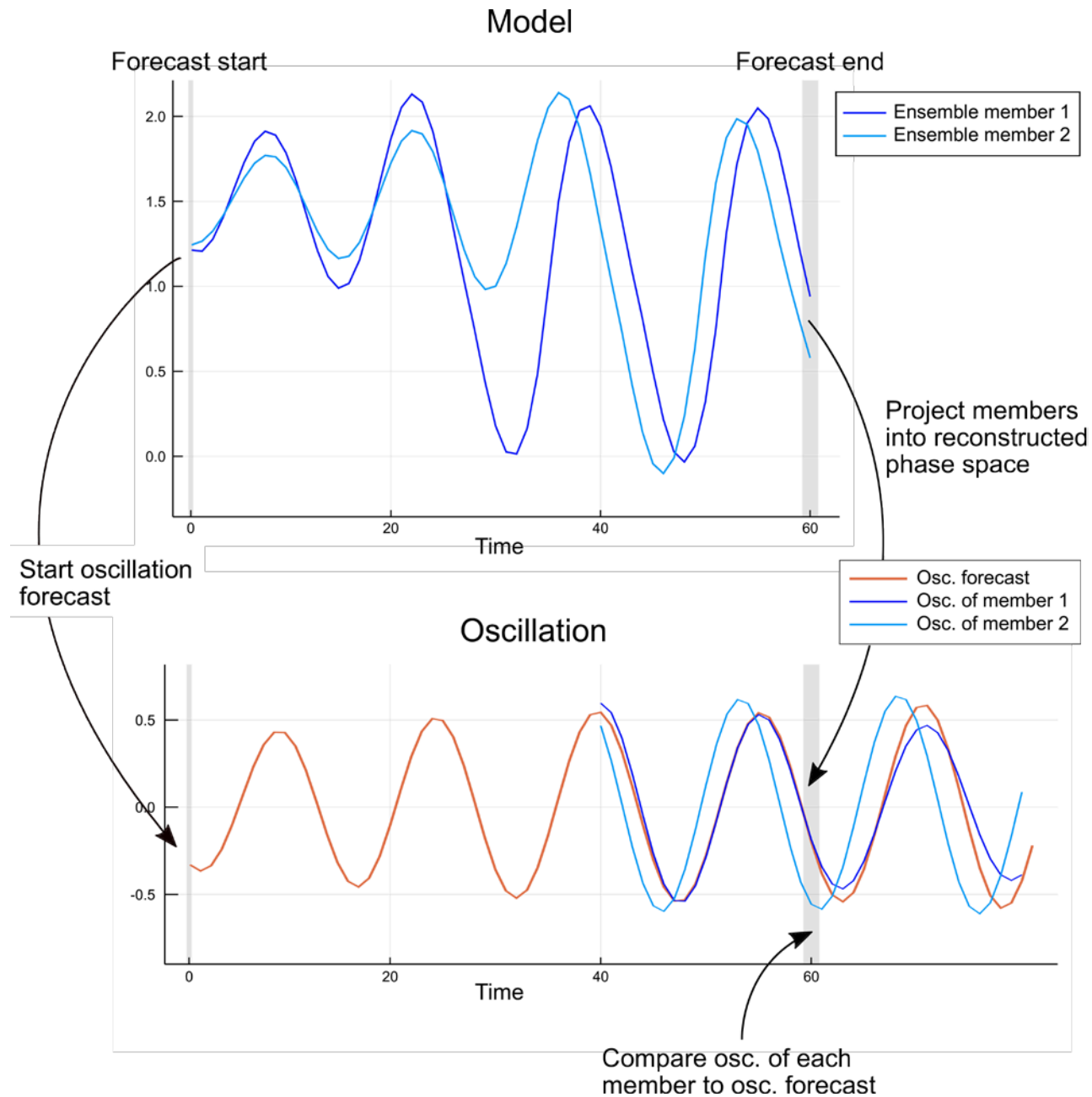
- Generally, in ensemble forecasting, it is better to use as many ensemble members as possible.
- However, what if we have some reason to believe some ensemble members are better than others?
- We can forecast oscillatory Reconstructed Components accurately purely from data.
- **Idea: for the ensemble mean, use only the ensemble members whose oscillation is close to that of a data-driven oscillation forecast.**

# Ensemble oscillation correction

## **Ensemble oscillation correction** algorithm:

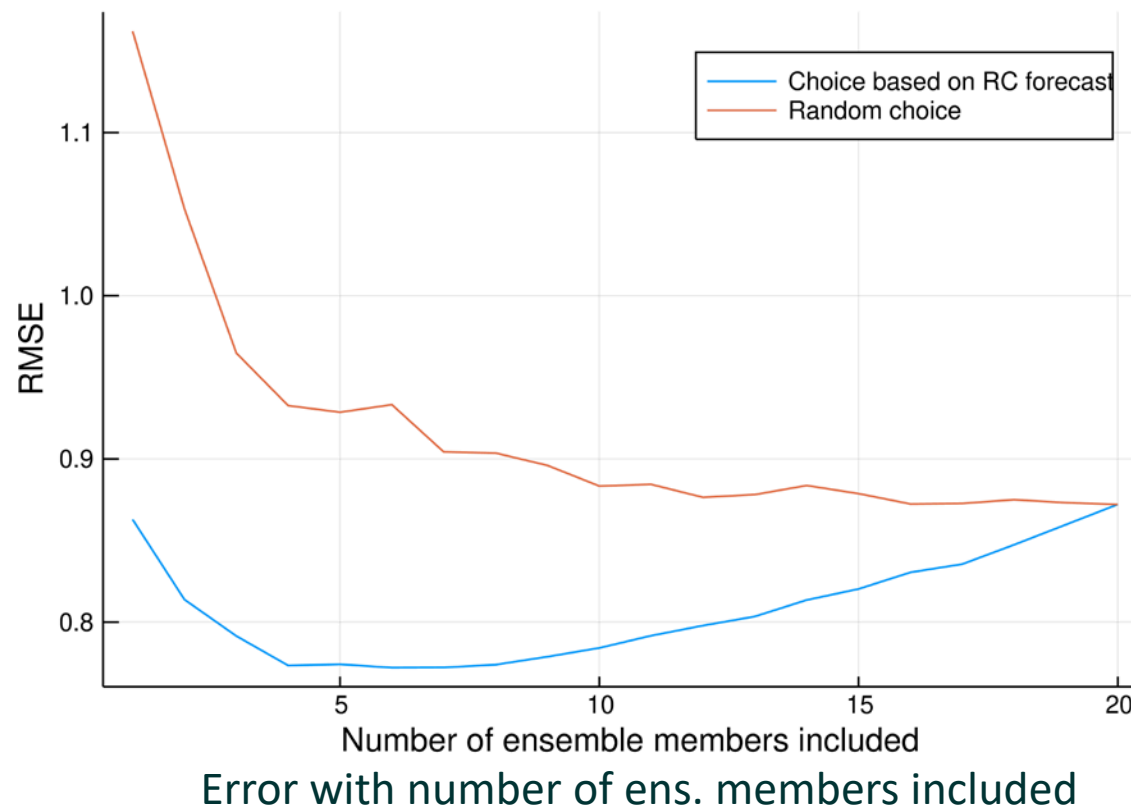
- Using best estimate of the system state, map into oscillatory RC space and forecast the oscillation a window  $h$  into the future.
- Integrate ensemble members window  $h$  into the future.
- Map each ensemble member into oscillation space, and compare to oscillation forecast.
- Compute the ensemble mean using the best ensemble members, as determined by their discrepancy from the oscillation forecast.

# Ensemble oscillation correction



# Choosing optimal number of ensemble members to average over

- If we care only about error in ensemble mean, we can easily find the optimal number of ensemble members to average over using a historical ensemble + estimate of true state.
- Trade-off between benefits of large ensemble, detriment of including inaccurate members.



# Experiments

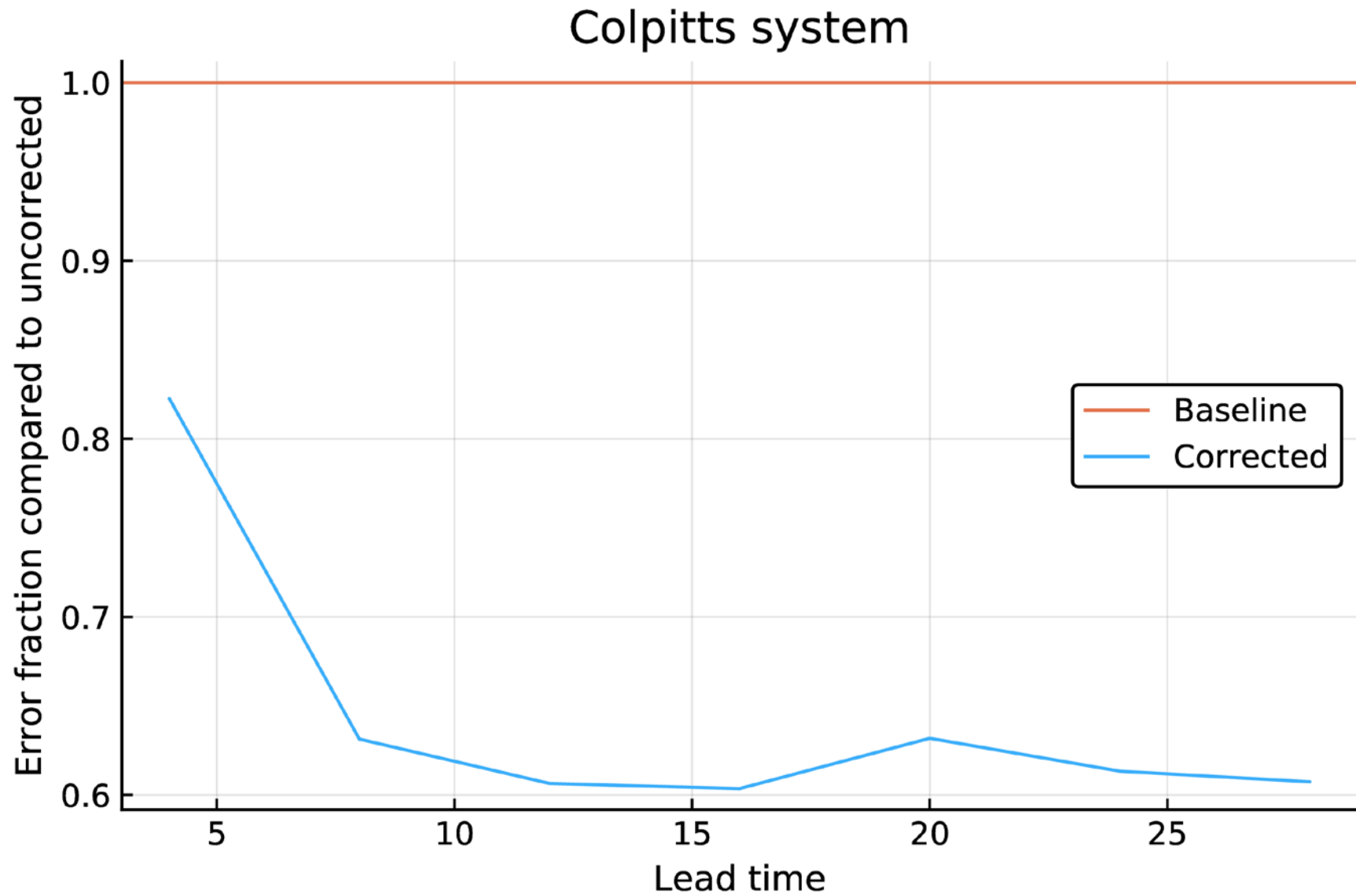
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# Experiments

- We show results of the method applied to toy chaotic oscillators with parametric model error.
- This is meant to emulate the case of MISO, where the oscillatory mode is badly predicted by the model.
- In general, error reduction depends on:
  - Portion of variance from oscillations (e.g., MISO represents ~14% of the variance)
  - Window at which regular ensemble loses skill
  - Window for which Reconstructed Components forecast is skillful
  - Model error
  - Ensemble spread

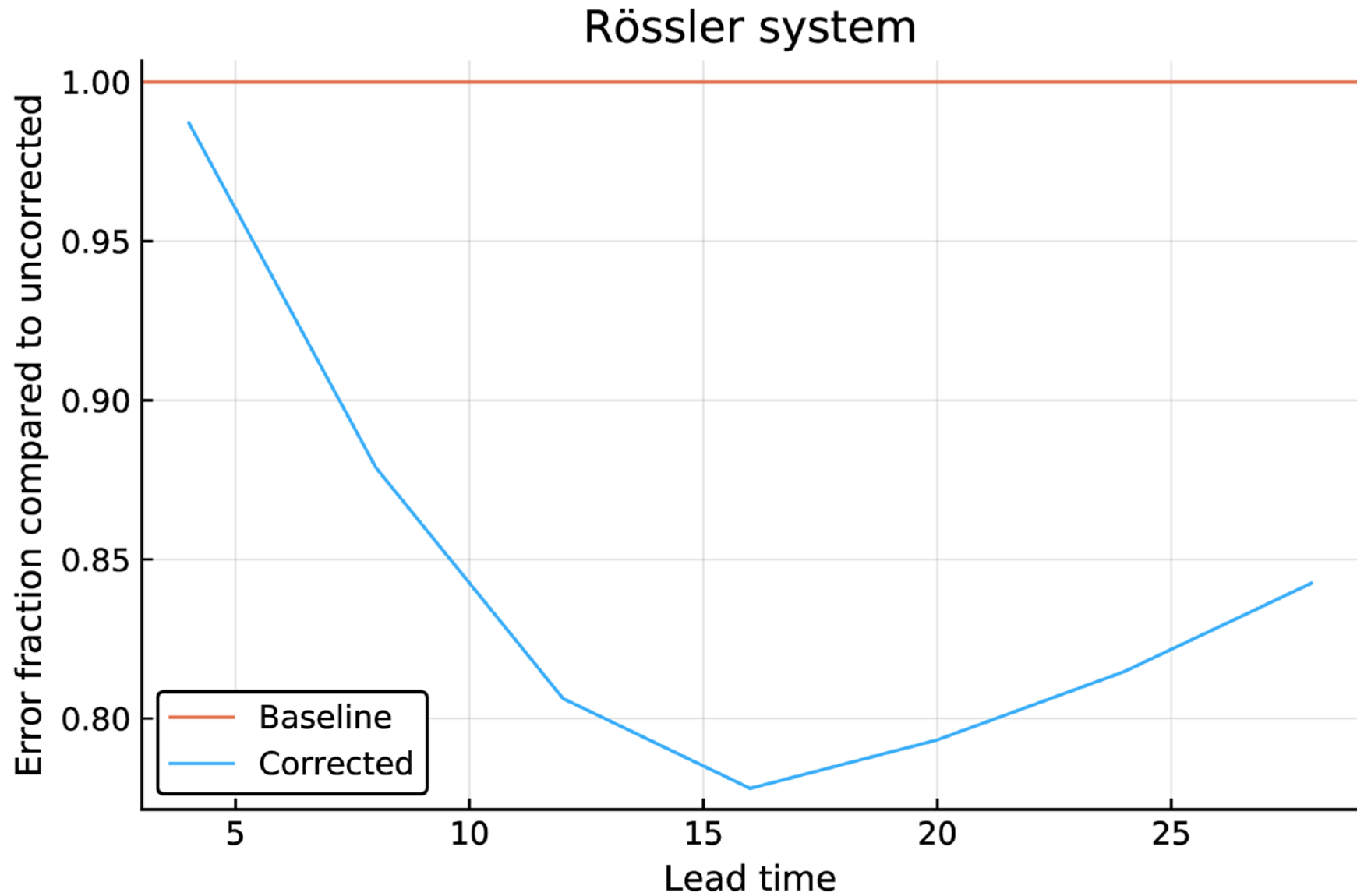


# Colpitts oscillator



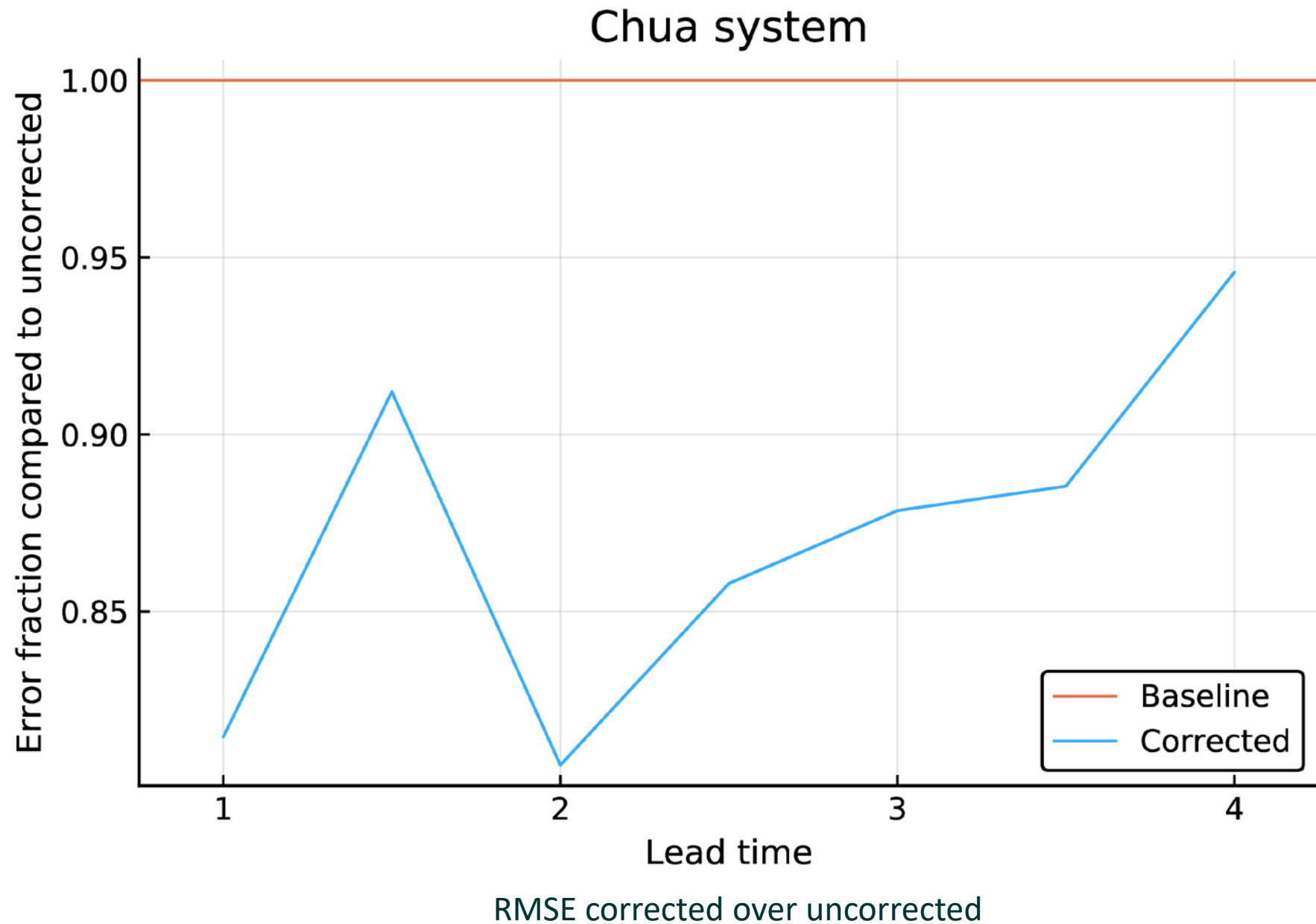
RMSE corrected over uncorrected

# Rössler oscillator



RMSE corrected over uncorrected

# Chua oscillator



# Error analysis

- Under some assumptions, we can derive an estimate of the RMSE reduction of this method:

$$\frac{\text{RMSE}_{\text{corrected}}}{\text{RMSE}_{\text{uncorrected}}} \approx \sqrt{1 - \left( \begin{array}{c} \% \text{ of variance of} \\ \text{osc. modes} \end{array} \right)}$$

- Numerical experiments show that this is a reasonable estimate when the method works well.

## Future plans

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# Future plans

- Paper on the method and tests with toy models soon to be submitted to *Journal of Climate*.
- Test ensemble oscillation correction method with Indian monsoon and MISO:
  - Use India Meteorological Department (IMD) gridded rainfall data to run SSA and predictions of MISOs.
  - Using an ensemble of CFS runs, implement ensemble oscillation correction at different lead times.
- The MISOs make up ~14% of daily variance, from which we could estimate an error reduction of about 7%, higher or lower depending on the region.
- Could improve other variables too, due to correction of the potential vorticity field (Lien et al., 2013)

# Future plans

- Following the implementation of ensemble oscillation correction, we plan on developing a new hybrid of data assimilation, machine learning, and a physical model.
- Machine learning is generally inadequate for predicting high-dimensional geophysical systems, but previous work has shown hybrids of machine learning and a model are better than either separately.
- Idea: use data assimilation formalism to optimally combine forecasts of model and machine learning.
- Potential to improve monsoon rainfall forecasts.

# References

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