Improved subseasonal prediction of South Asian monsoon rainfall using data-driven forecasts of oscillatory modes

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7 June 2024

California Institute of Technology

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Introduction

Motivation

There are oscillatory modes in the climate system important on subseasonal-to-seasonal timescales, such as the monsoon intraseasonal oscillation (MISO) and the Madden–Julian oscillation (MJO).

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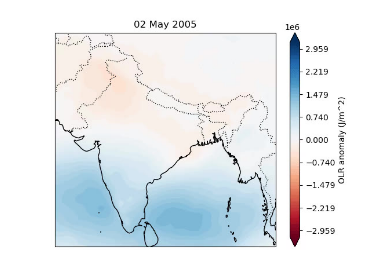
Often predictable from data beyond current dynamical models.

How to use data-driven forecasts of these modes to improve overall forecasts?

Oscillatory modes in Asian monsoon rainfall

The monsoon intraseasonal oscillation (MISO) is a northward-propagating rainfall mode of period $\sim$45 days.



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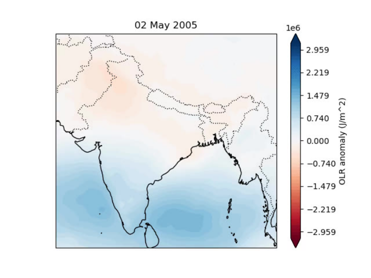

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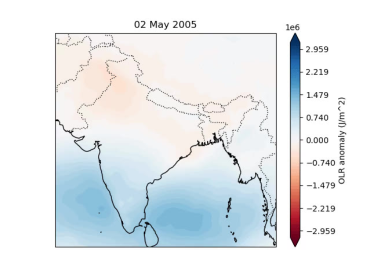

Controls active and break phases and regional distribution of monsoon rainfall.

Essential for subseasonal-to-seasonal prediction with relevance to agriculture, flooding, and water availability.

Combining ML forecasts of oscillatory modes with full-field physical forecasts

The full field admits a modal decomposition; i.e., through singular spectrum analysis (Ghil et al. 2002):

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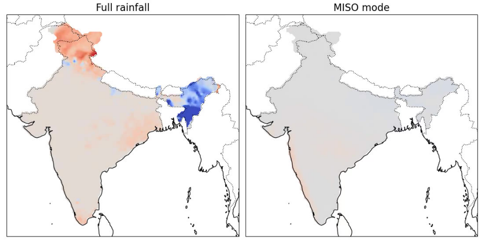
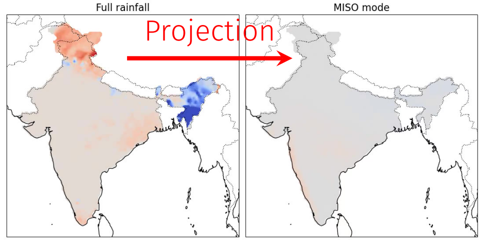
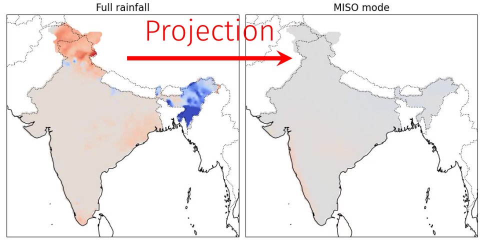
However, these predictions are not useful by themselves, since they only predict a *fraction of the total variance* of the full field.


Full rainfall
MISO mode



Mapping from full phase space to reduced subspace is *non-invertible*.

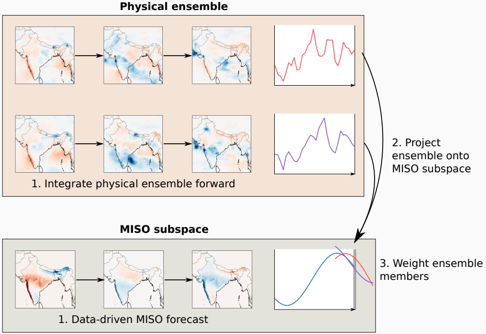


Mapping from full phase space to reduced subspace is *non-invertible.*

Tools from data assimilation can be used to inform the full phase space state from ML forecasts in the reduced subspace!

Methods and data

Ensemble Oscillation Correction



Idea (Bach et al. 2021): weight ensemble members of a physical model by their distance from an ML forecast in the corresponding subspace.

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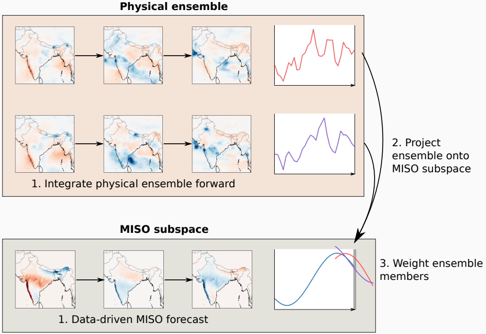

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Similar idea to importance sampling in particle filters: give more weight to ensemble members most likely to result in a predicted MISO pattern.

Methods

Extracted MISO from India Meteorological Department 0.25° gridded rainfall observations since 1901 using multi-channel singular spectrum analysis (M-SSA).

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Ensemble members weighted using EnOC.

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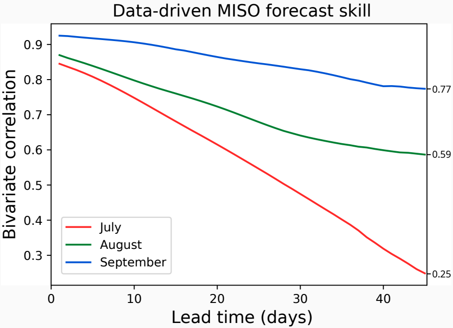
IFS has been shown to be state-of-the-art in subseasonal monsoon prediction. It has outperformed all other models to which it has been compared for this task (Jie et al. 2017; Vigaud et al. 2017).

Results

ML MISO forecasts are skillful for over a month



Correlation between ML MISO forecasts and MISO extracted from observations

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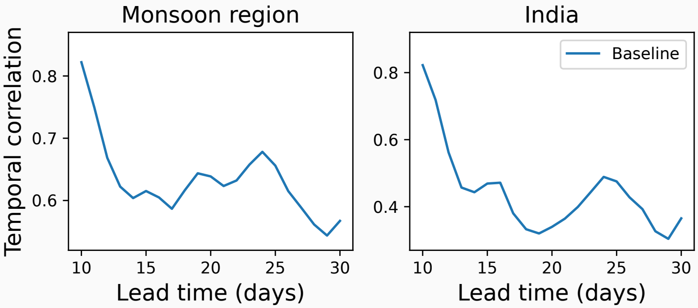

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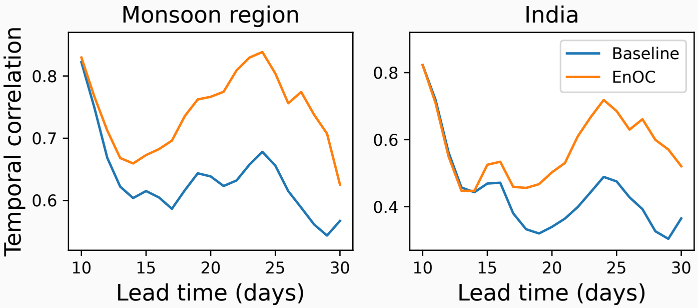

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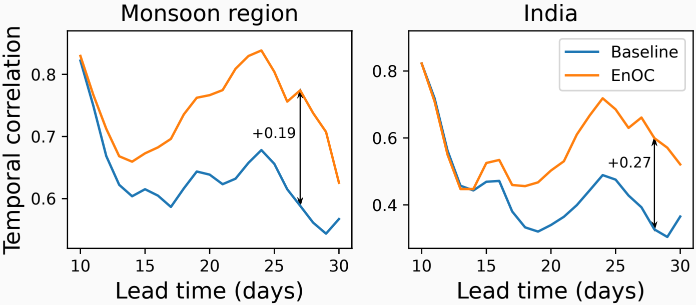

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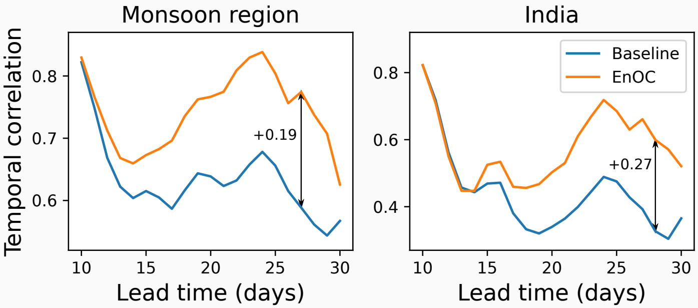

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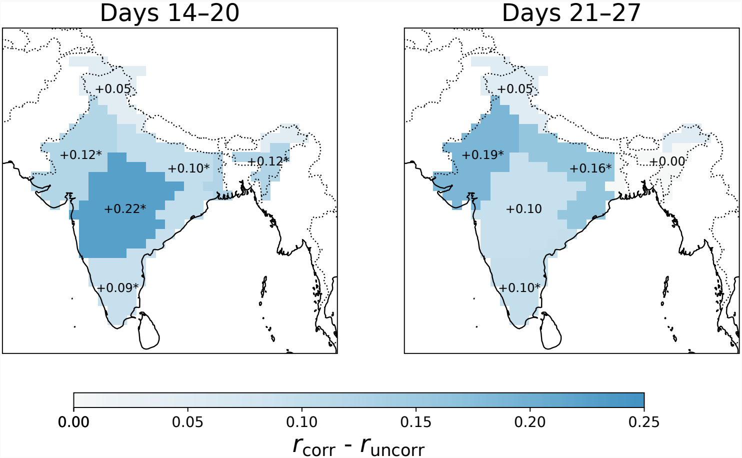
Regional improvements in skill



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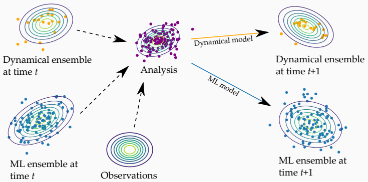
Future work: Application to other important modes of climate variability, in particular the Madden–Julian Oscillation and El Niño.

EnOC is a way of combining physical model forecasts with data-driven forecasts. Can be generalized using the Multi-Model Ensemble Kalman Filter (Bach and Ghil 2023).



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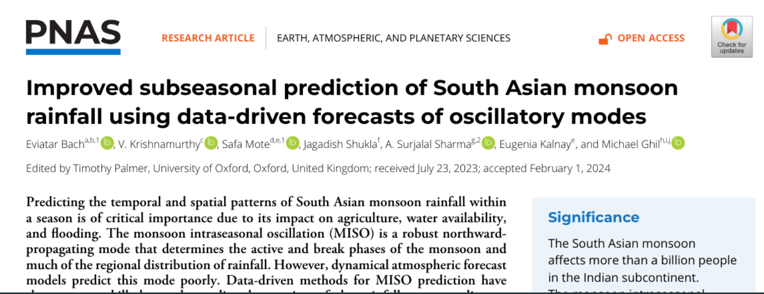
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Edited by Timothy Palmer, University of Oxford, Oxford, United Kingdom; received July 23, 2023; accepted February 1, 2024

Predicting the temporal and spatial patterns of South Asian monsoon rainfall within a season is of critical importance due to its impact on agriculture, water availability, and flooding. The monsoon intraseasonal oscillation (MISO) is a robust northward-propagating mode that determines the active and break phases of the monsoon and much of the regional distribution of rainfall. However, dynamical atmospheric forecast models predict this mode poorly. Data-driven methods for MISO prediction have

Significance

The South Asian monsoon affects more than a billion people in the Indian subcontinent.

My email: eviatarbach@protonmail.com

My website: eviatarbach.com

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Predictability of MISO

Various studies have demonstrated predictability of MISO using data-driven methods (Krishnamurthy and Sharma 2017; Alexander et al. 2017).

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The data-driven methods generally predict MISO better than models.

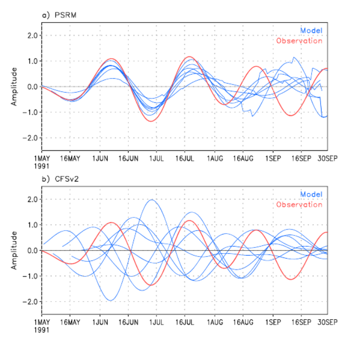

Figure 1: From Krishnamurthy and Sharma 2017

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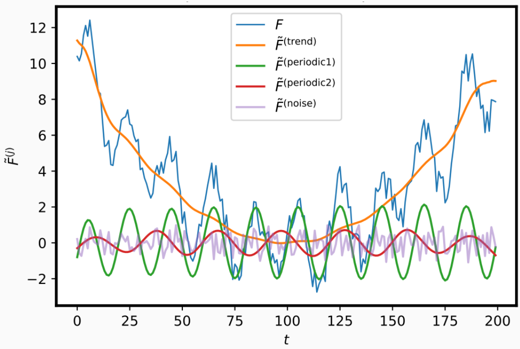
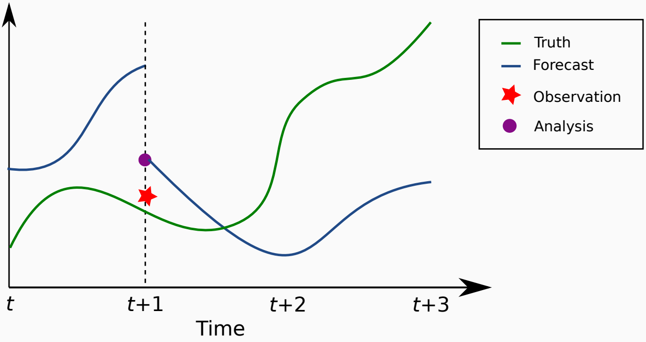


By Jordan D'Arcy

When the physical model is *perfect*, its forecast from the last analysis is the best we can do.



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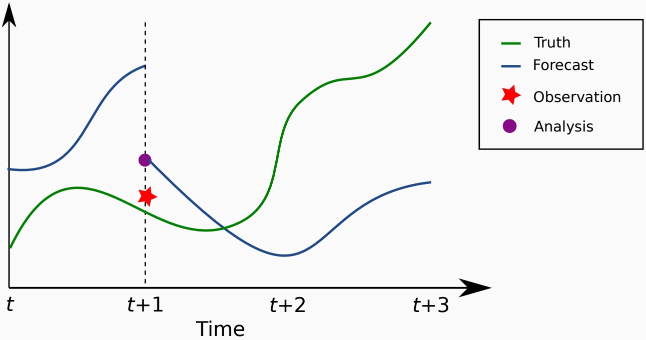

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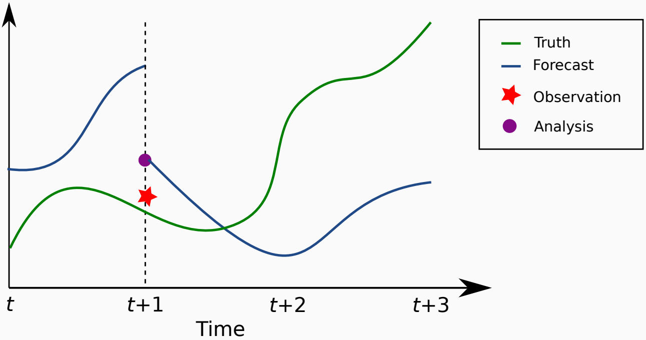

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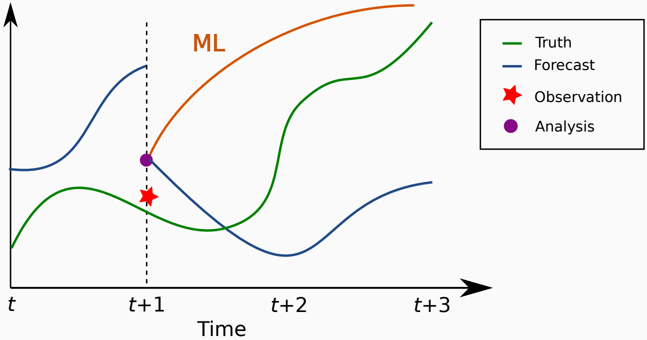

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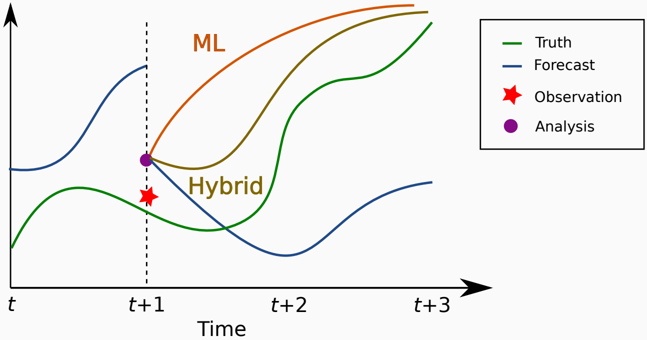

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- More sophisticated weighting: EnOC with data assimilation (EnOC-DA)

Big picture

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The MM-EnKF is a framework and methodology to combine all three.

Multi-model data assimilation

- The multi-model Kalman filter assimilation step is

$$\mathbf{x}^{\mathrm{a}} = \mathbf{P}^{\mathrm{a}} \left(\sum_{m=1}^{M} \mathbf{G}_m^T \left(\mathbf{P}_m^{\mathrm{f}} \right)^{-1} \mathbf{x}_m^{\mathrm{f}} + \mathbf{H}^T \mathbf{R}^{-1} \mathbf{y} \right), \tag{3}$$

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- Now, the weights for each model m are inversely proportional to $\mathbf{P}_m^{\mathrm{f}}$. If we set $M = 1$, we recover the regular Kalman filter equations.

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  - This vorticity anomaly leads to low-level moisture convergence, and a northward shift of convection.

Monsoon intraseasonal oscillations

- One theory for the northward propagation involves a vertical shear mechanism (Jiang, Li, and Wang 2004):
  - Convection + easterly vertical shear induces a barotropic vorticity anomaly north of convection.
  - This vorticity anomaly leads to low-level moisture convergence, and a northward shift of convection.

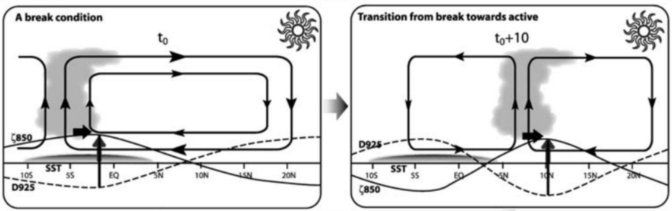

Figure 2: From Goswami 2012