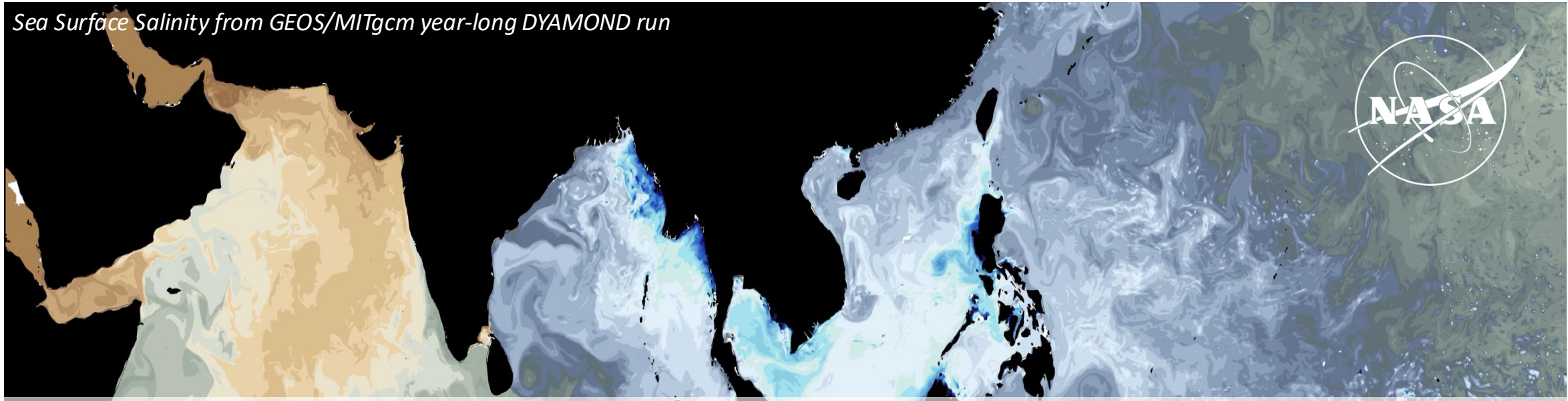

Seamless Prediction and Predictability across weather-subseasonal-seasonal timescales

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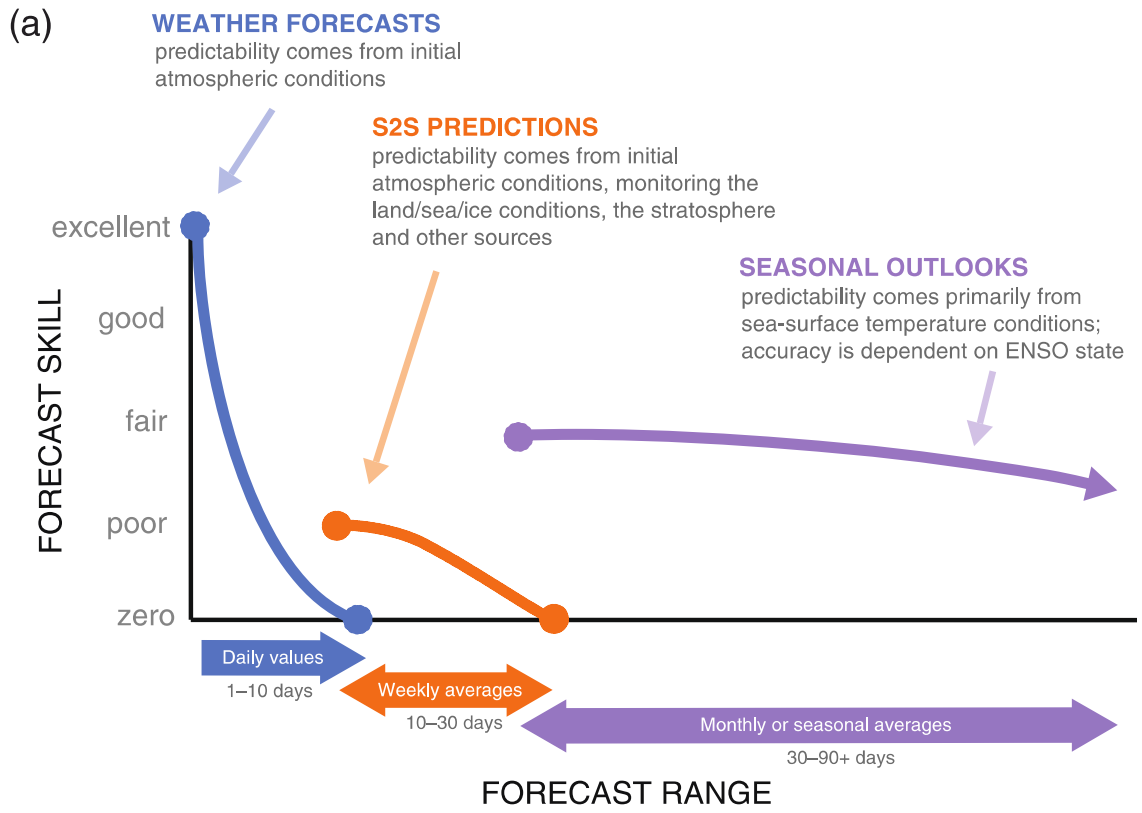
With: Timothy Delsole[3], Andrea Molod[1], Siegfried Schubert[1], Randal Koster[1]
(George Mason University[3])

WGNE39-WGSIP25, November 6th 2024

Forecast skill estimate: Relative skill is based on differing forecast averaging period.



Source: White et al. 2017, DOI: 10.1002/met.1654

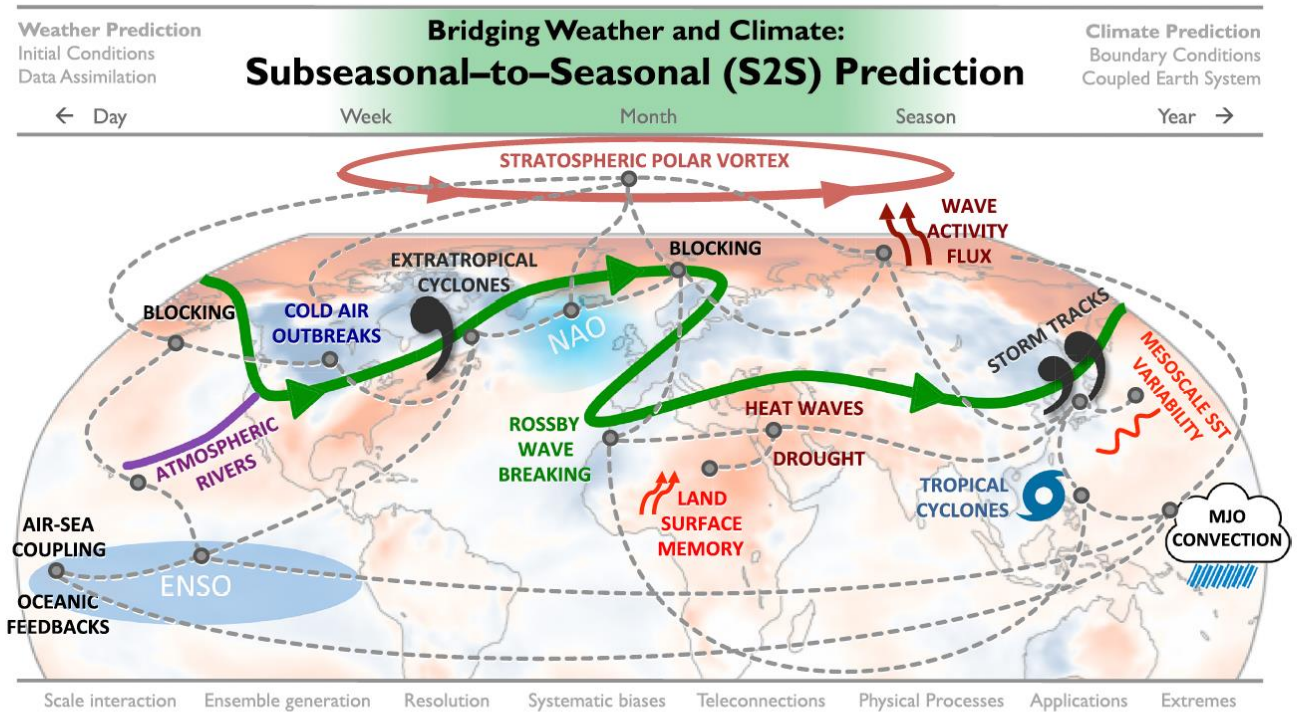
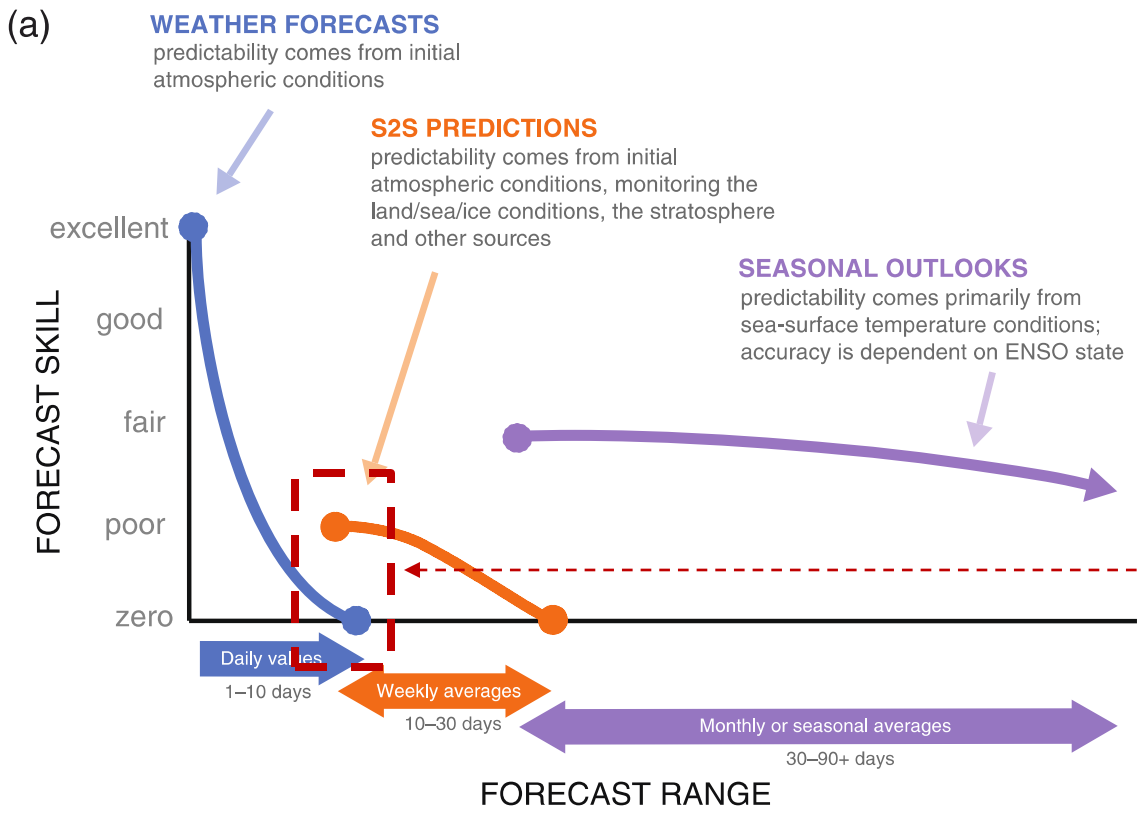


Figure 1. A schematic representation of many of the atmospheric phenomena and numerical modeling considerations needed to make accurate forecasts in the subseasonal-to-seasonal time scale.

Lang et al., 2020



Time averaging increases the signal to noise ratio enough to obtain reliable forecasts.

Switch from daily to weekly averages. Source of predictability changes to slowly varying modes.

↑ Persistent signal, ↓ weather noise

In order to beat down the noise, what kind of averaging is needed is decided a priori.

Goals:

1. Study the smooth transition of predictability from weather to subseasonal lead times and that from subseasonal to seasonal lead times using **GEOS-S2S-2** retrospective forecasts

2. Determine how the predictability may vary with state or regime using appropriate metrics.

3. Develop a metric that can utilize windows of opportunity.

Predictable Component Analysis

Predictable Component Analysis

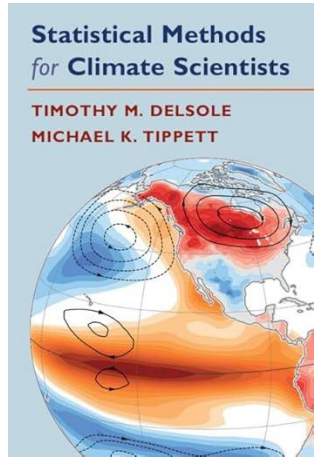
$$Forecast\ F' = Signal + Noise$$

(space x time (t))

Decompose total predictability into components that optimize predictability.

Predictable Component Analysis (PrCA) finds linear combinations of variables that **maximizes predictability (signal-to-noise ratio)** of ensemble forecasts.

- Distinguish the signal in the forecasts.
- Determine the evolution of signal (measured by the F-value).
- **Signal (S)** = variance of ensemble means.
- **Noise (N)** = variance *about* the ensemble means.



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Predictable Component Analysis

PrCA identifies patterns and coefficients (variates) with maximum signal-to-noise (S/N) ratio.

$$F = E\frac{\hat{\sigma}_S^2}{\hat{\sigma}_N^2}$$

Optimization -> Generalized Eigenvalue Problem:

$$\tilde{\boldsymbol{\Sigma}}_S \ \tilde{\boldsymbol{q}} = \lambda \ \tilde{\boldsymbol{\Sigma}}_N \ \tilde{\boldsymbol{q}} \qquad \text{(where, } \lambda = \text{S/N)}$$

signal covariance | S/N ratio | noise covariance

- Eigenvalues λ gives maximized F values (S/N ratios).
- Eigenvalues are ordered in descending order as $F_1 \geq F_2 \geq \ldots\ldots\ldots \geq F_M$
- 1st maximizes S/N, 2nd maximizes S/N subject to being uncorrelated with the 1st, and so on.

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Application of Predictable Component Analysis to GEOS S2S-2 reforecasts

PrCA applied to GEOS S2S-2 reforecasts

- 1999 – 2024 : 25 winters (December January February)
- Variable : 2m Temperature anomalies (lead-time dependent)
- Forecasts were initialized 5 day apart: 18 start dates
- Number of ensembles: 4
- Total number of conditions: 25 years * 18 start dates = 450
- Region: Contiguous U.S

  (Missing data: 2017)


JGR Atmospheres

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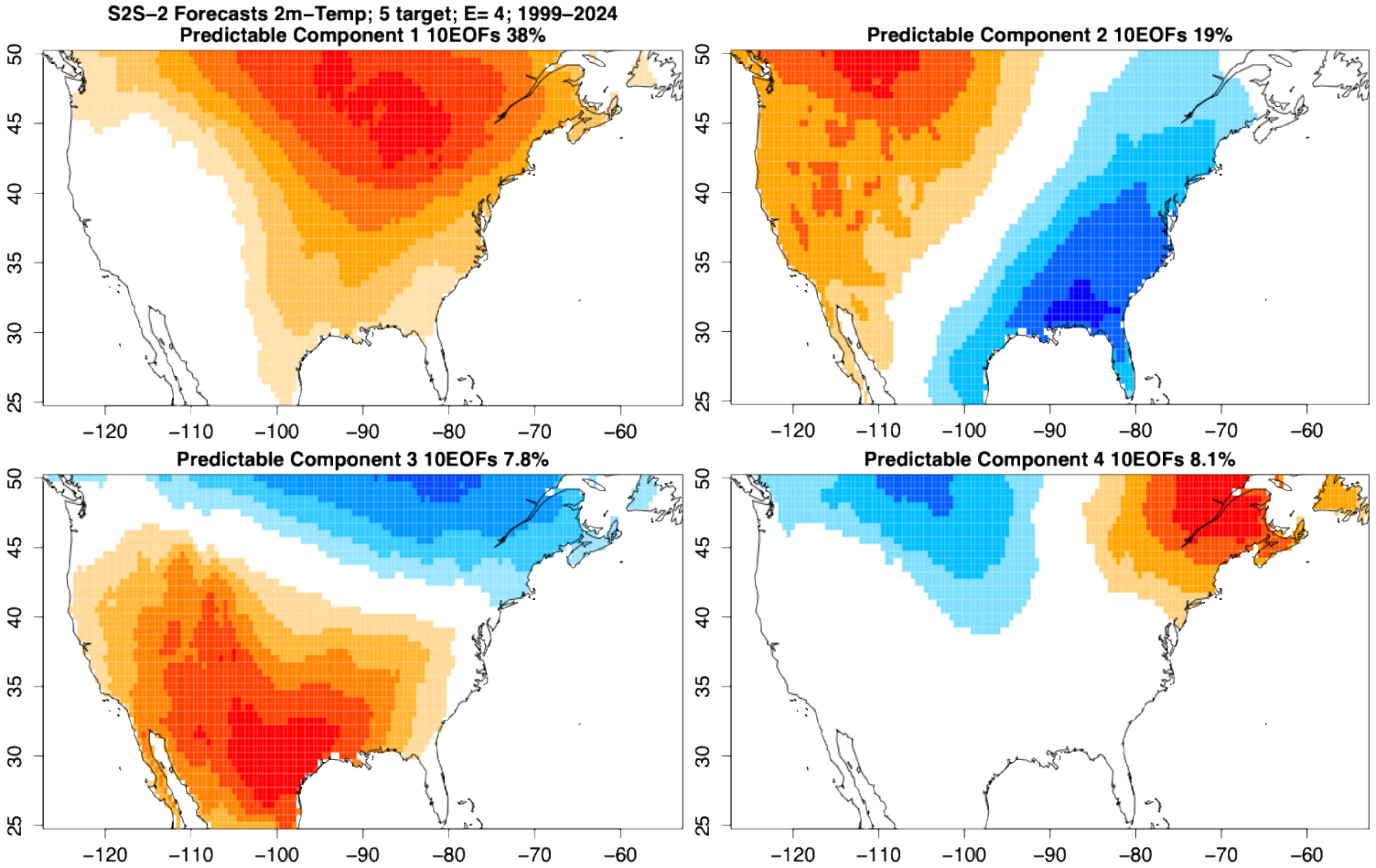
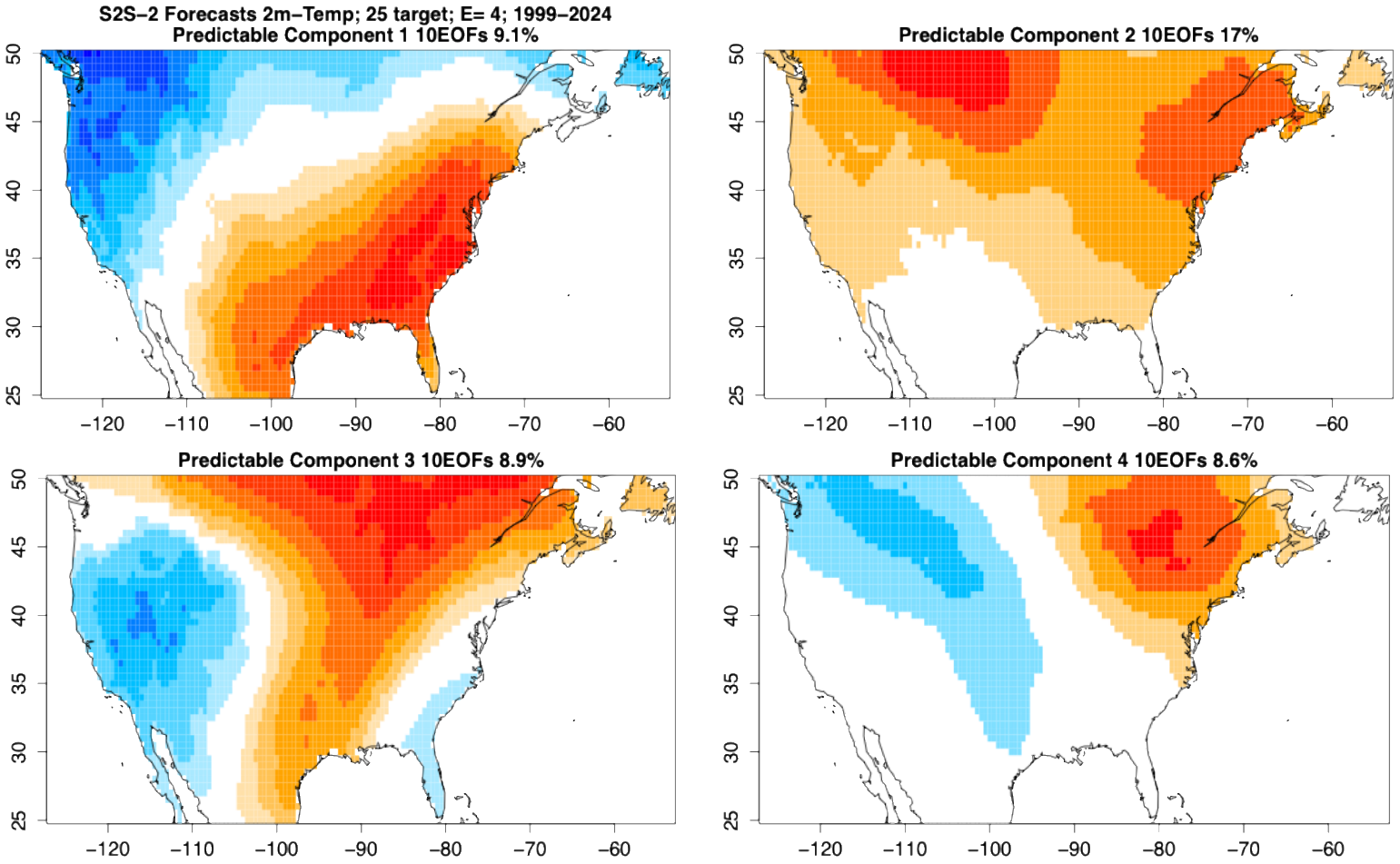
GEOS-S2S Version 2: The GMAO High-Resolution Coupled Model and Assimilation System for Seasonal Prediction

Andrea Molod, Eric Hackert, Yury Vikhliaev, Bin Zhao, Donifan Barahona, Guillaume Vernieres, Anna Borovikov, Robin M. Kovach, Jelena Marshak ... See all authors

Most Predictable Component
Lead time 5-day

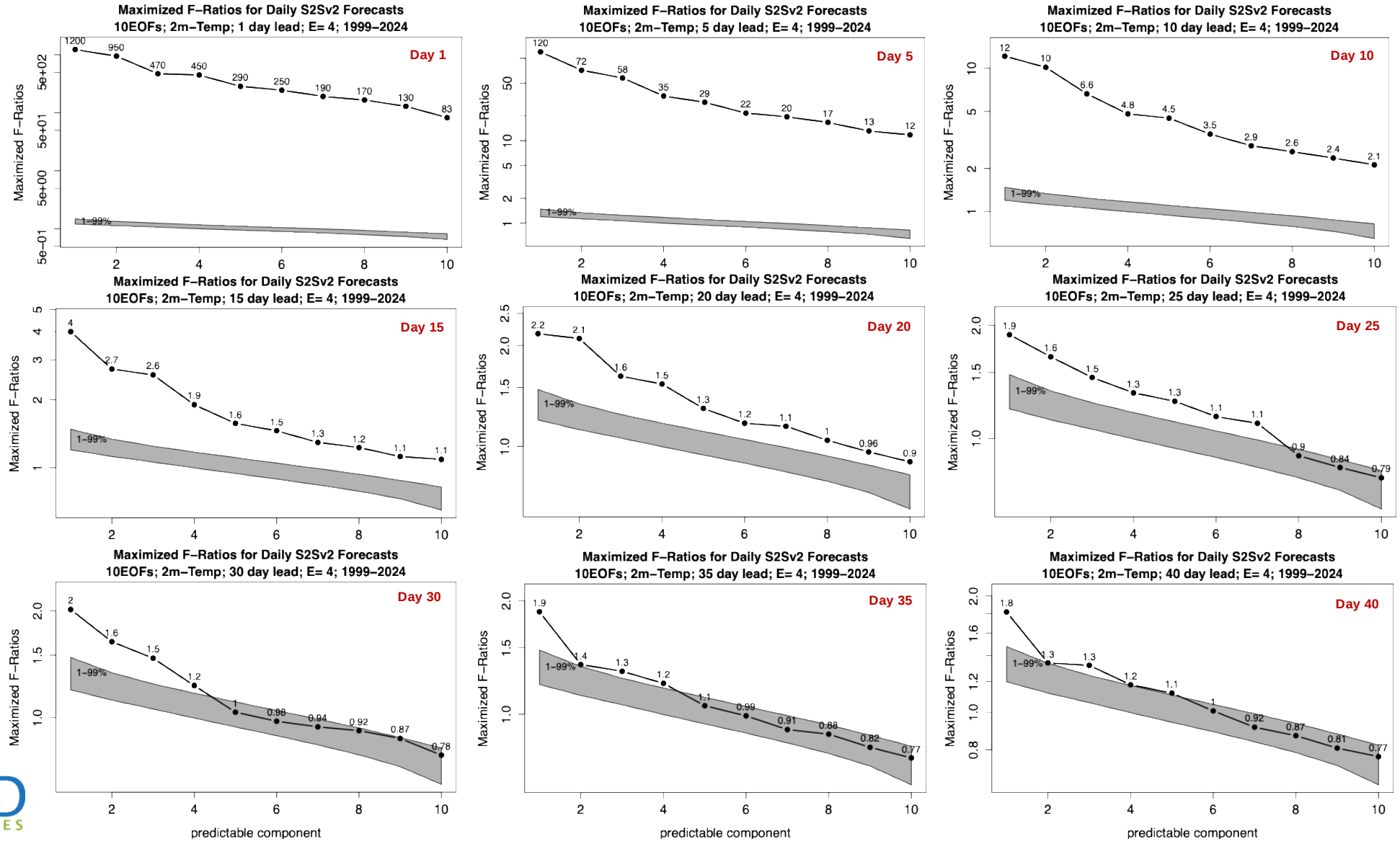


Most Predictable Component
Lead time 25-day



Higher variance may not necessarily lead to higher S/N

Maximized Signal-to-Noise Ratios at various forecast lead times



Summary

- S/N ratio is detected at every grid point.
- The developed framework will be applied to GEOS-S2S-3 forecast dataset.
- PrCA can be applied to forecasts to detect predictable modes in forecasts.
- PrCA will be applied to different regions (e.g. Tropics, Europe, etc.).
- PrCA can be applied on decadal timescales as well.

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