



# NASA GMAO GEO5 S2S Prediction System Metrics, Post-processing and Products

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# GMAO's Near Real-Time Sub/Seasonal Prediction Suite

GMAO's GEOS S2S sub/seasonal forecasts are part of the National MultiModel Ensemble (NMME). We will also participate in an intercomparison of S2S systems with predicted aerosol.

Unlike weather prediction, sub/seasonal results are generally examined in terms of anomaly from some climatology, derived from a series of hindcasts.

GMAO's coupled Ocean Data Assimilation system runs in near real time and is used to initialize our seasonal forecasts

	Subseasonal	Seasonal
Length of Forecast	45 days	9-12 months
Frequency of forecasts	Every 5 days	Every 5 days
Number of Ensembles	4 per start date	Total of 10 per month
Frequency of submission	Once per week	Once per month
Initial Conditions from Hindcasts	GEOS S2S-2_1 ODA 1999-2016	GEOS S2S-2_1 ODA 1980-2016/7

# New Seasonal Prediction System - GEOS S2S-2\_1

## Model

- AGCM: Post MERRA-2 (current GMAO NWP) generation 0.5 degree, 72 hybrid sigma/pressure levels; GOCART interactive aerosol model, cloud indirect effect (2-moment cloud microphysics); MERRA-2 generation cryosphere; Catchment land model
- OGCM: MOM5, 0.5 degree, 40 levels;
- Sea Ice: CICE-4.0.

## Coupled Ocean Data Assimilation System

- atmosphere is “replayed” to “forward processing for instrument teams” (like MERRA-2);
- NCEP-like LETKF code/system, set here to behave as Ensemble OI;
- forecasts: initialized from ODA<sub>S</sub>, perturbations are produced from analysis differences;
- hindcasts: re-initialized from 5-day run of ODA<sub>S</sub>, perturbations from analysis differences;

## Observations

- nudging of SST and sea ice fraction from MERRA-2 boundary conditions;
- assimilation of satellite along-track ADT (Jason, Saral, ERS, GEOSAT, HY-2A, CryoSat-2);

- assimilation of *in situ* T<sub>Z</sub> and S<sub>Z</sub> including Argo, XBT, CTD, tropical moorings;



# Methods for Validation and Evaluation

## ➤ Forecast Mean Fields

- Model drift
- Forecast bias and correlation for atmosphere
- Cryosphere – Sea Ice Extent, Thickness
- Aerosol Optical Depth vs MERRA-2

## ➤ Probabilistic Evaluation

- Rank Histogram
- Potential Predictability
- Reliability
- Ensemble Spread/Error

## ➤ Atmospheric Variability

- Standard metrics: Pattern and time-series correlation for ENSO, MJO, PNA, NAO, GBI, etc... -- Ability to predict modes of variability
- “Forecasts of opportunity” – Prediction skill during high predictability events
- Specialized MJO metrics
- Stratospheric warmings and QBO
- Tropical Cyclones (Genesis Potential Index)

Examples and use during GEOS 5.2.2\_1 development

# Forecast Mean Fields: Seasonal Forecast Bias

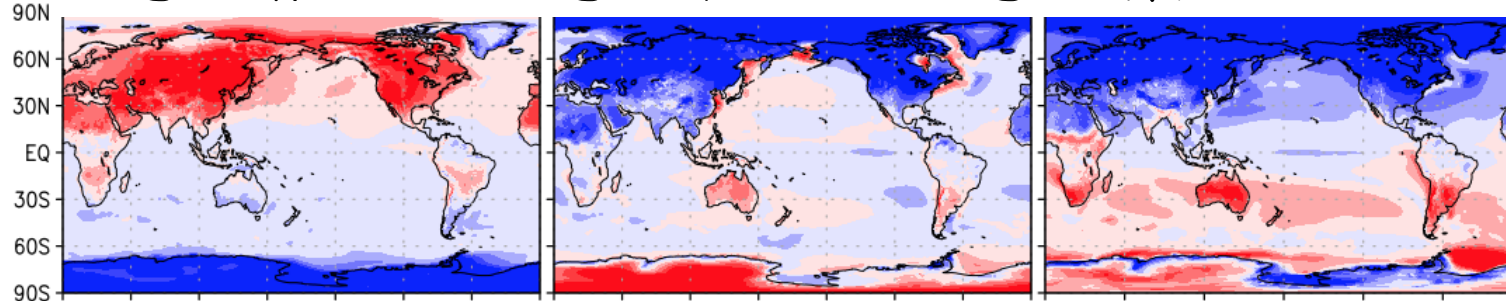
## 2-meter temperature difference from MERRA-2 – October I.C. Hindcasts

Lead 1 (Nov)

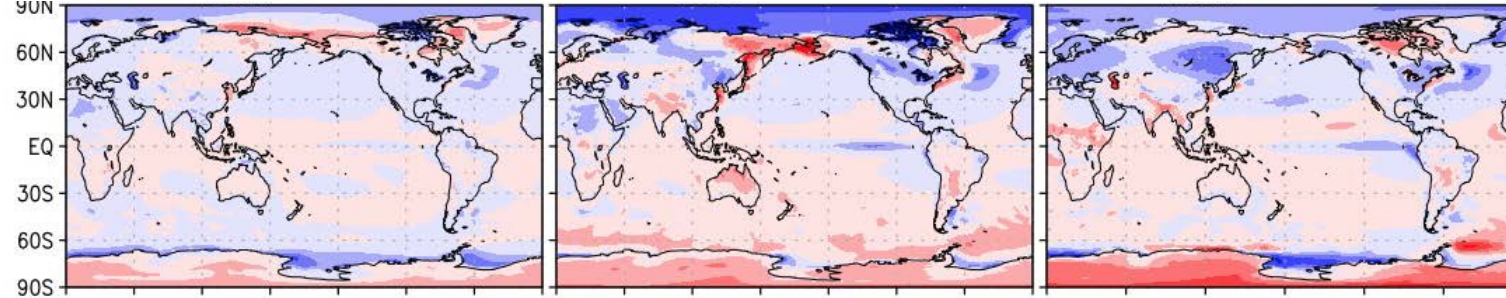
Lead 4 (Feb)

Lead 7 (May)

S2S-1\_0  
(previous)

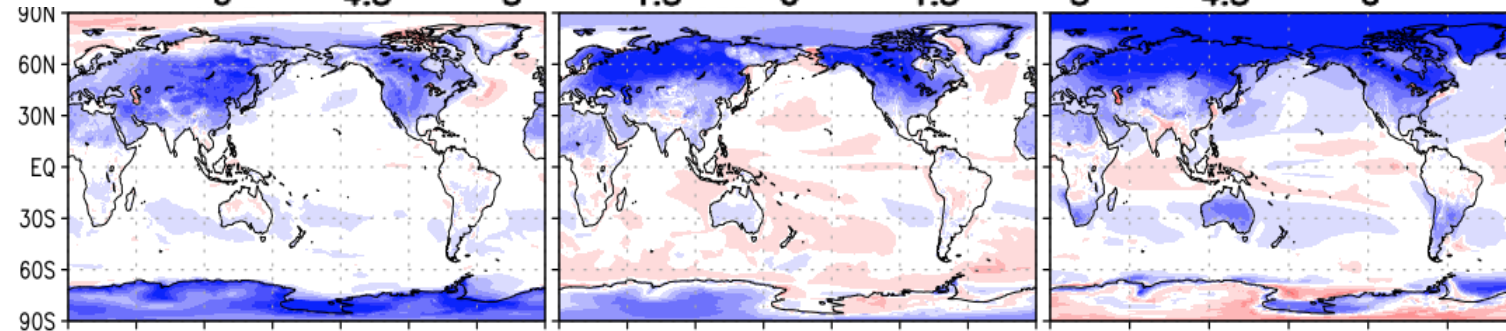
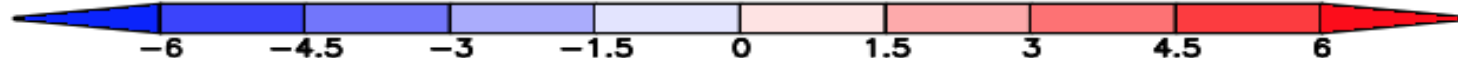


S2S-2\_1 (new)



Absolute Difference

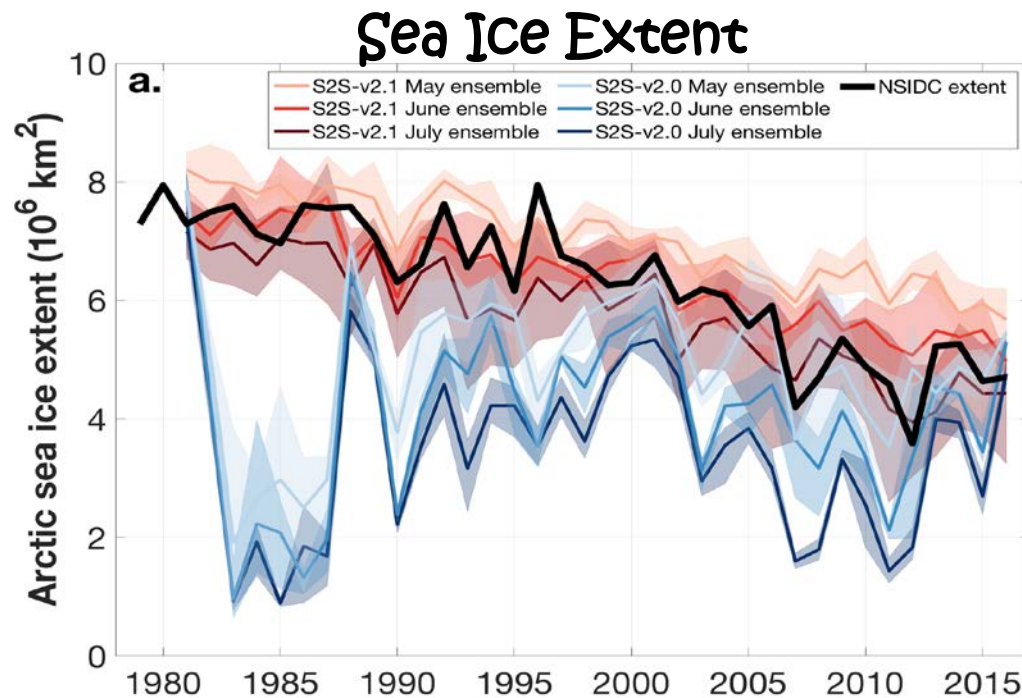
(blue → new system has less bias)





# Forecast Mean Fields: Cryosphere

- Patterns of sea ice concentration are not particularly useful.
- Hemispheric ice extent is a widely used metric - area encompassed by 15% concentration contour. Must account for different land/sea masks. Can be used to examine re-freeze day and ice-free day metrics.
- Ice thickness satellite products are available but remain challenging to use.



- The **S2S-v2.1** hindcast system can explain up to 80% of September sea ice extent variance over the hindcast period.
- In large part, sea ice forecast skill arises from appropriately representing its long-term decline.
- Removing the long-term trend (following Bushuk et al., 2017) decreases skill

# Forecast Mean Fields: Ice Thickness

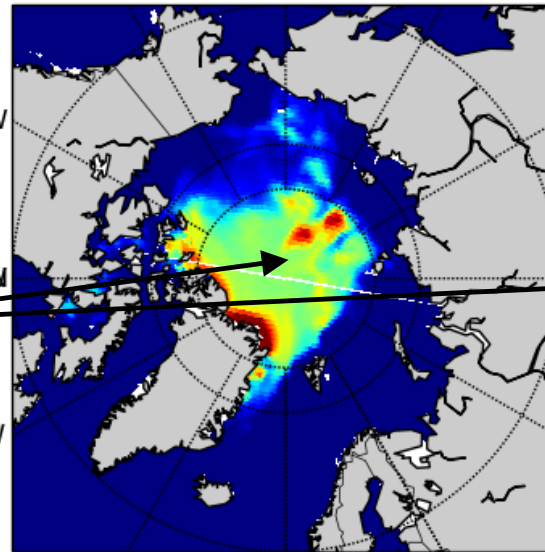
Sea ice fraction assimilation methodology created initial conditions that resulted in anomalous “blobs” of sea ice, not present in Validation data

Re-distribution of sea ice fraction among the ice thickness categories in CICE resulted in improved initial states and forecasts

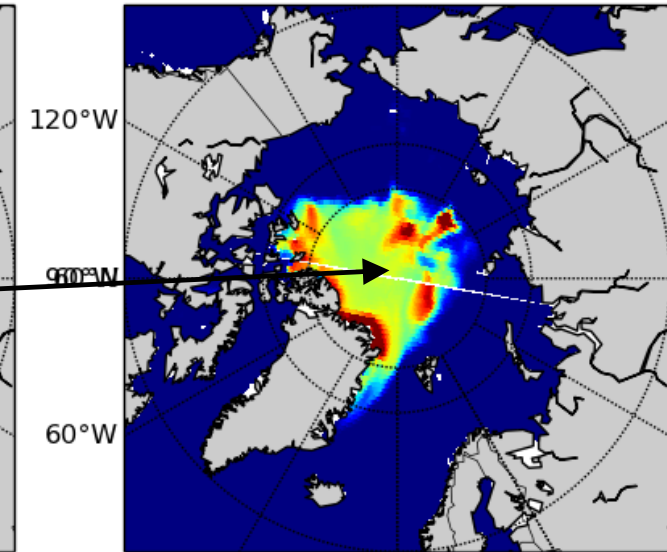
New algorithm to assimilate sea ice fraction is being evaluated for GEOS S2S-3\_0 using the ensemble spread to inform the distribution among thickness categories.

Experiments with assimilation of Cryosat ice thickness show improved sea ice thickness forecasts

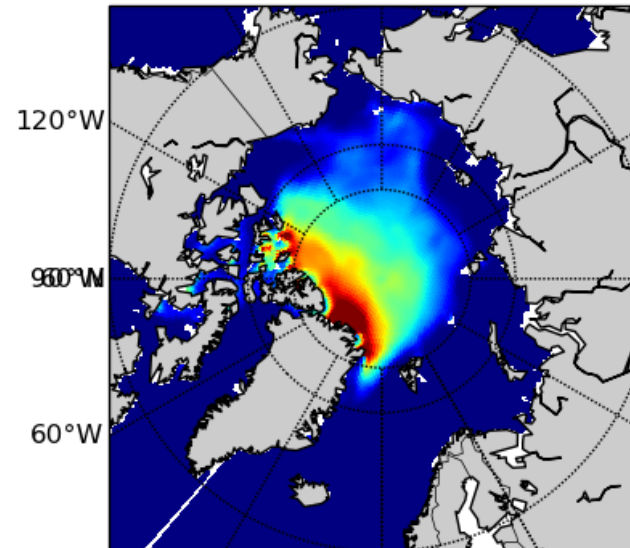
Control 08/2012



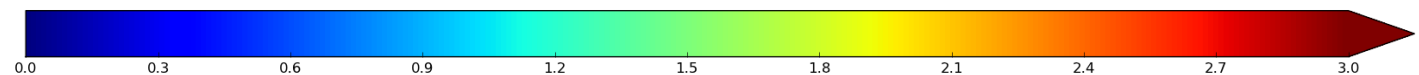
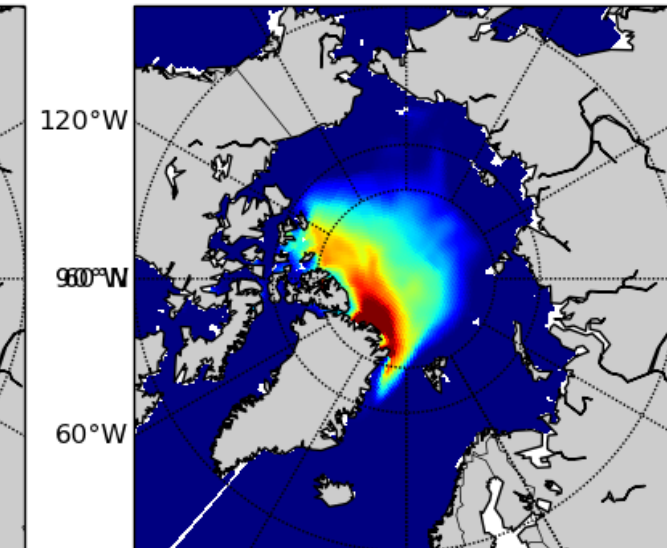
Control 09/2012



GIOMAS 08/2012



GIOMAS 09/2012



# Forecast Mean Fields: Ice Thickness

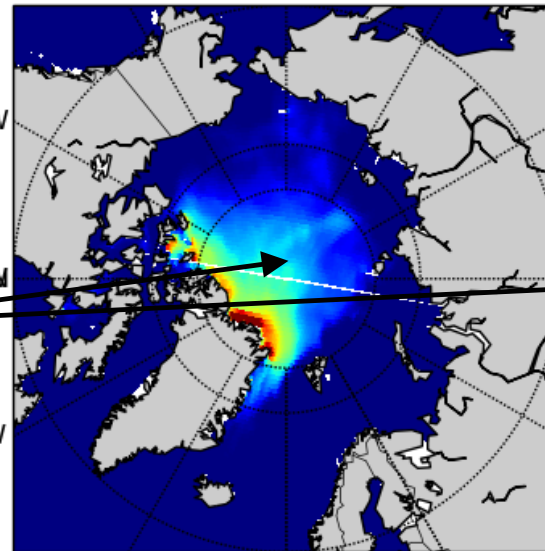
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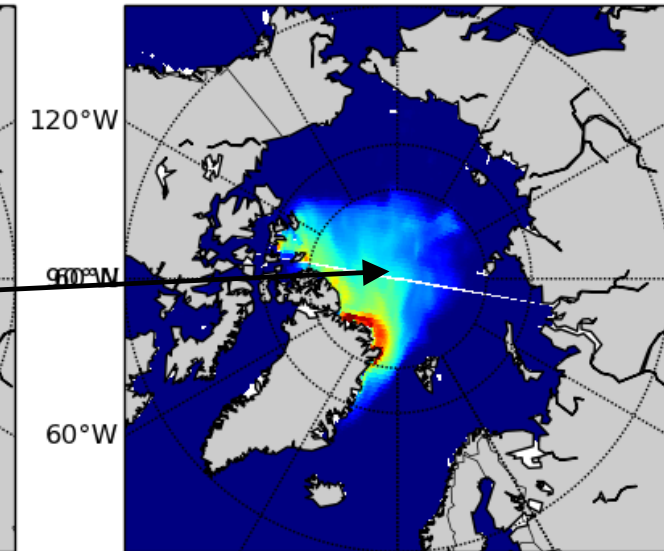
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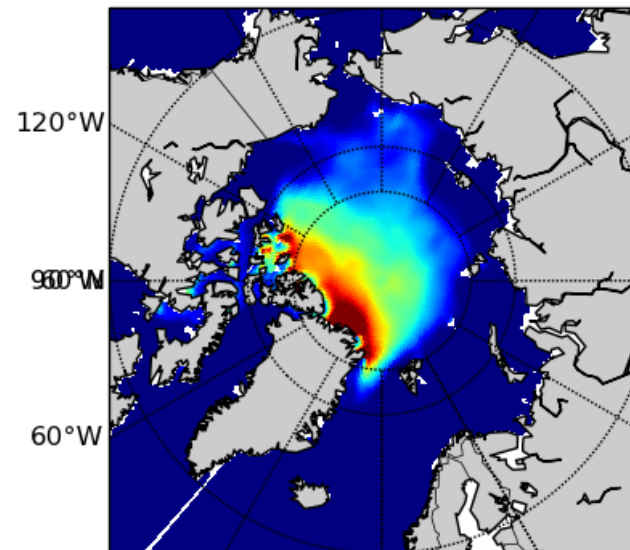
S2S-2\_1 08/2012



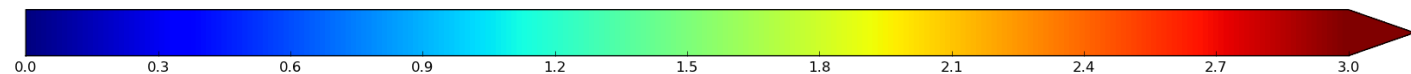
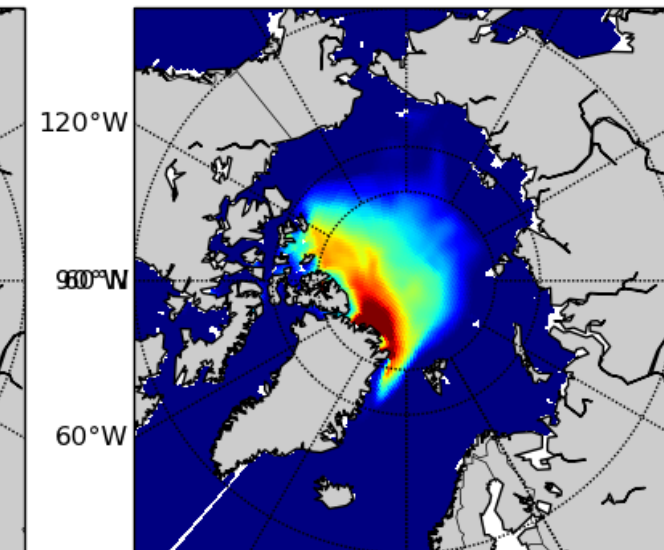
S2S-2\_1 09/2012



GIOMAS 08/2012



GIOMAS 09/2012





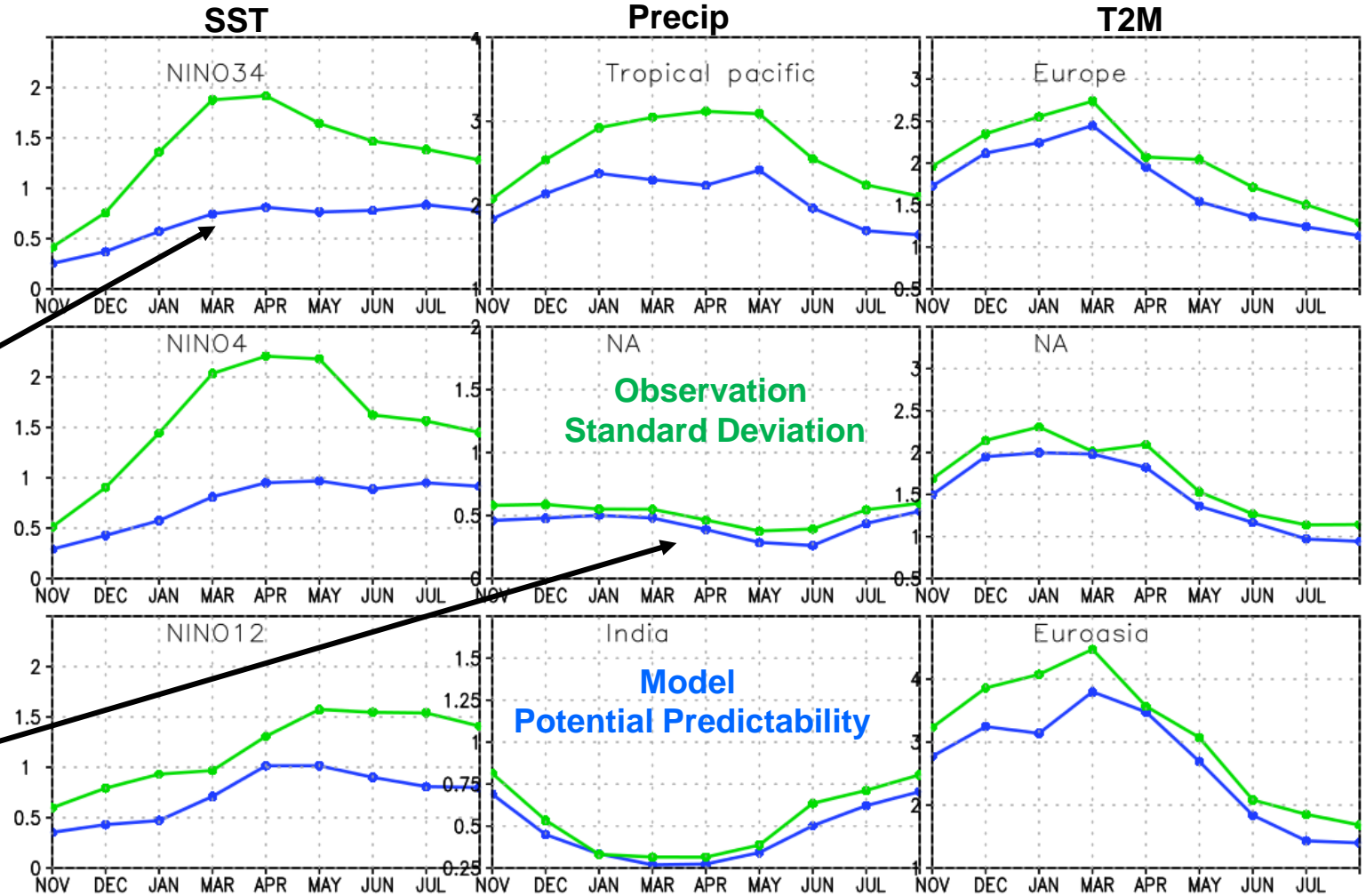
# Probabilistic Evaluation: Potential Predictability

## Potential predictability

- Measure of ensemble spread
- Average distance among ensemble members
- Observational variance is shown for reference

Spread too low over the ocean

Spread is good over the land

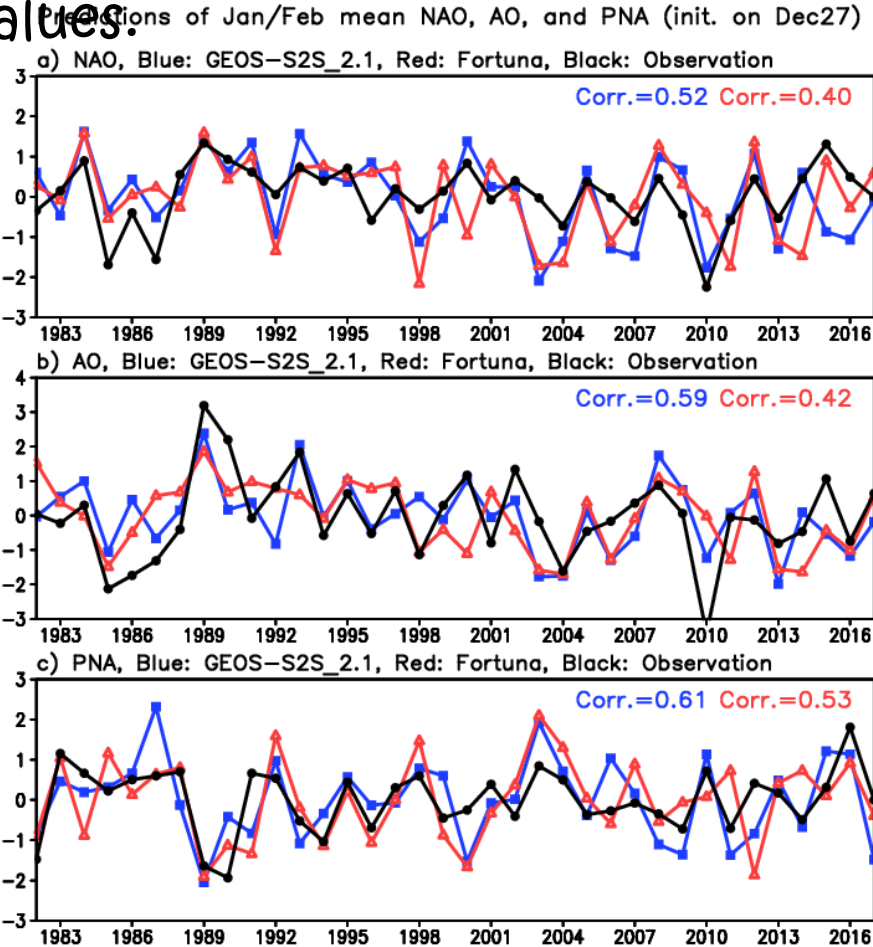


# Atmospheric Variability: NAO, AO, PNA, MJO, GBI

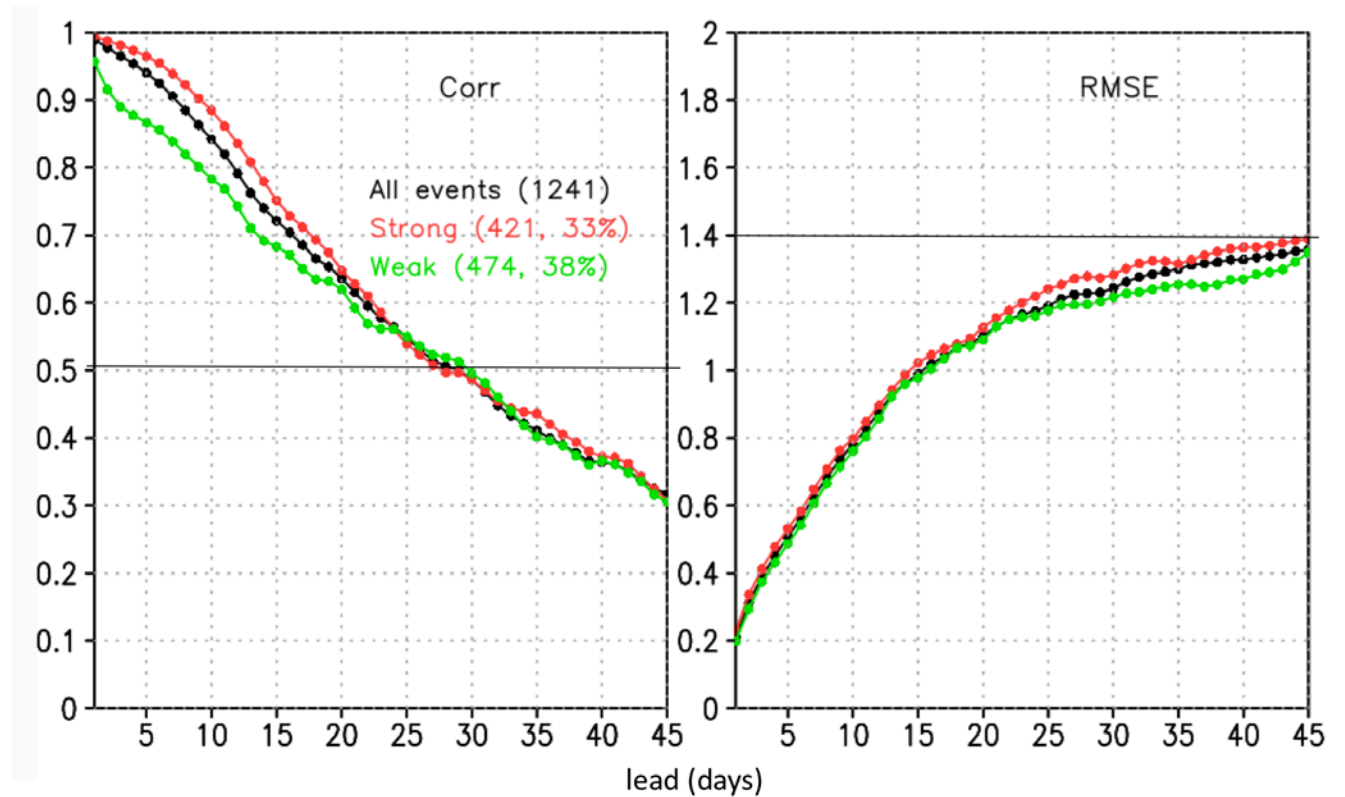
Prediction skill of these modes is evaluated with pattern correlations of the eigenvectors and time series correlations of the eigenvalues.

Teleconnection patterns create “forecasts of opportunity” – forecasts during extrema of the indices are evaluated separately

Temporal Correlation



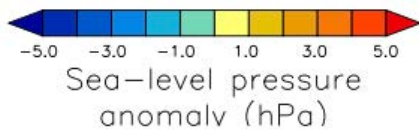
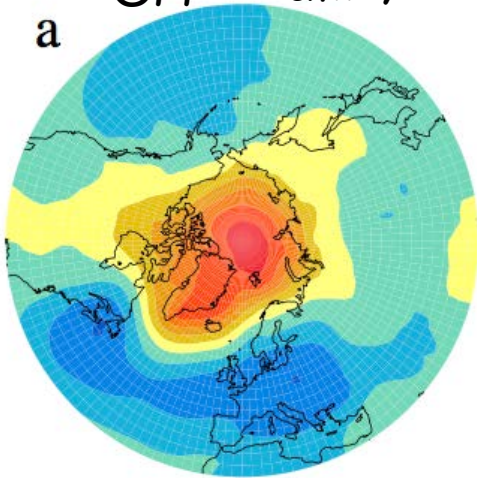
## MJO forecast skill in SubX hindcasts



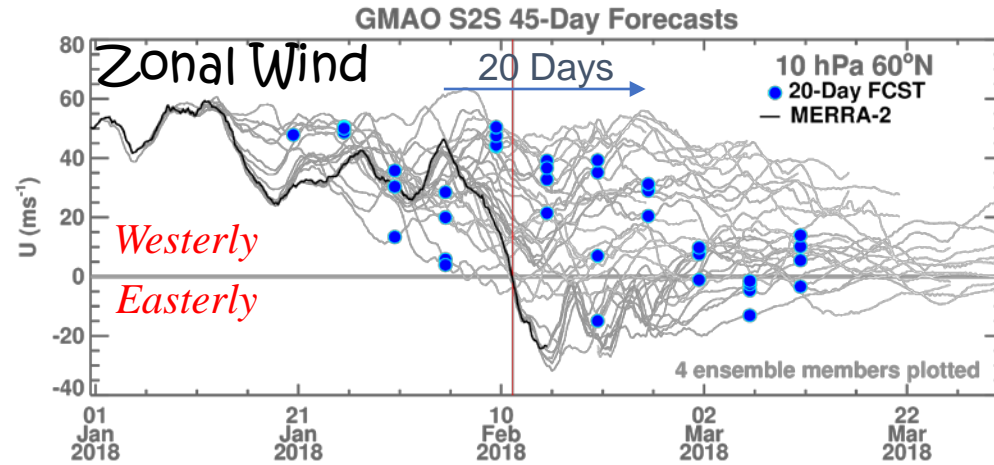
# Atmospheric Variability: Sudden Stratospheric Warming

Average SLP anomaly in the month following an SSW – “Forecast of Opportunity”

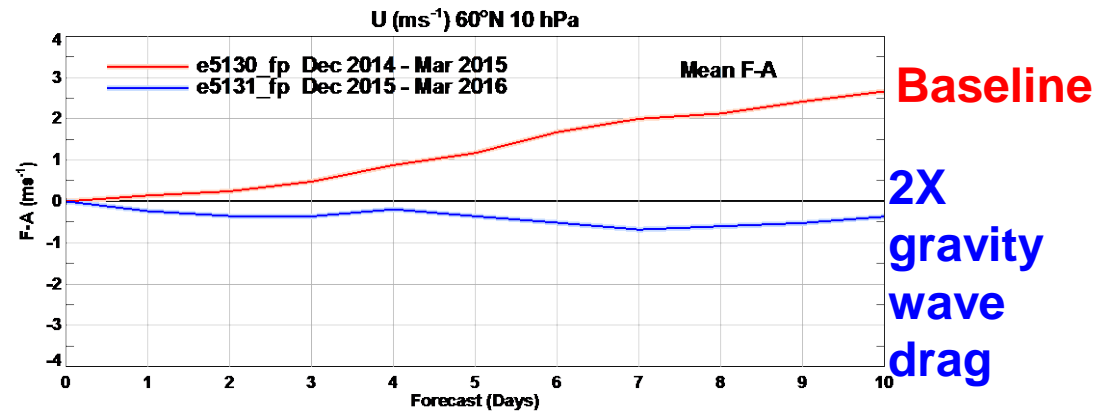
a



[Kidston et al. 2015]



- Poor seasonal prediction skill of SSW events
- Tuning gravity wave drag to reduce forecast bias can improve prediction skill



Analysis and slide courtesy of Joan Alexander and Lawrence Coy



# **NASA GMAO GEOS S2S Prediction System Metrics, Post-processing and Products**

- **Evaluation of a suite of standard S2S metrics related to forecast mean and variability, along with metrics related to reliability**
- **Evaluation of “NASA-specific” metrics related to the particulars of GMAO and NASA goals and mission, such as aerosol optical depth, stratospheric circulation and sea ice thickness**
- **Metrics used during system development – eg., S2S-3\_0 development includes algorithm to improve ensemble spread**
- **GMAO also performs “targeted forecasts” designed to evaluate particular processes (eg., sensitivity to Pinatubo emissions)**
- **S2S forecast output includes fields targeted to particular users in addition to NMME, such as the developers of a predictive biomass burning scheme using Fire Weather Index. The flexibility is there to accommodate additional requests**