Prospects of subseasonal climate prediction for lead times beyond two weeks

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A heightened focus on forecasts for Weeks 3-4 in the U.S.

OBAMA CALLS ON NOAA TO EXTEND OUTLOOKS 15–30 DAYS

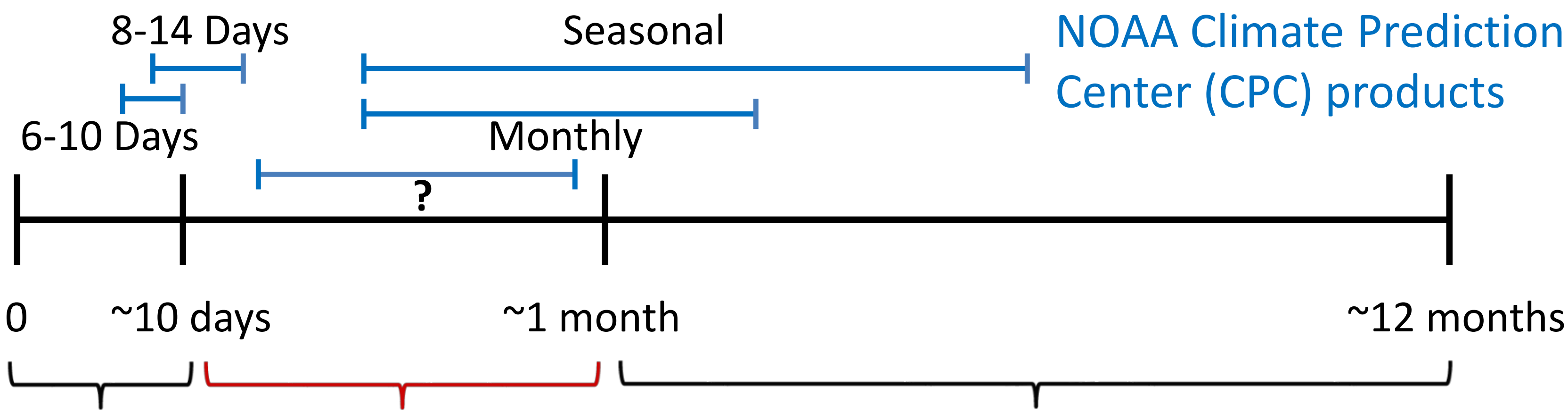
October 7, 2014 | At the United Nations Climate Summit in New York City on September 23, President Obama delivered a major speech with a focus on the impacts of climate change in the United States, progress the nation is making in mitigation, and the importance of building resilience and improving our weather and climate prediction capabilities.

According to a White House fact sheet on these commitments, the Administration intends to begin a coordinated U.S. effort, led by NOAA, to develop reliable extreme weather risk outlooks on time horizons beyond the current 14-day limit for large-scale weather features. This effort will initiate the development of such outlooks in the 15-to-30-day range and will explore potential new information products for the longer time scales on which climate change influences risk.

https://president.ucar.edu/government-relations/washington-update/376/obama-calls-noaa-extend-outlooks

Can we rise to the challenge?

Lead Time



- Based on **initial conditions**
- Rely on numerical weather prediction (NWP) model integrations

Forecast gap:

- Large growth of initial errors
- Boundary condition effects weak

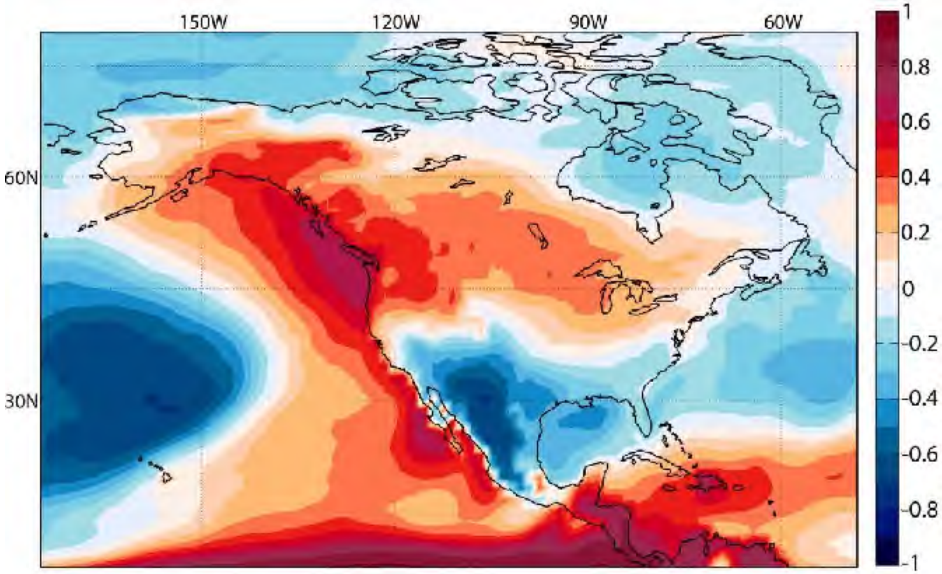
- Based on slowly varying **boundary conditions**
- Rely on coupled dynamical model integrations and statistical forecast methods

❖ **But there are some sources of predictability for Weeks 3-4**

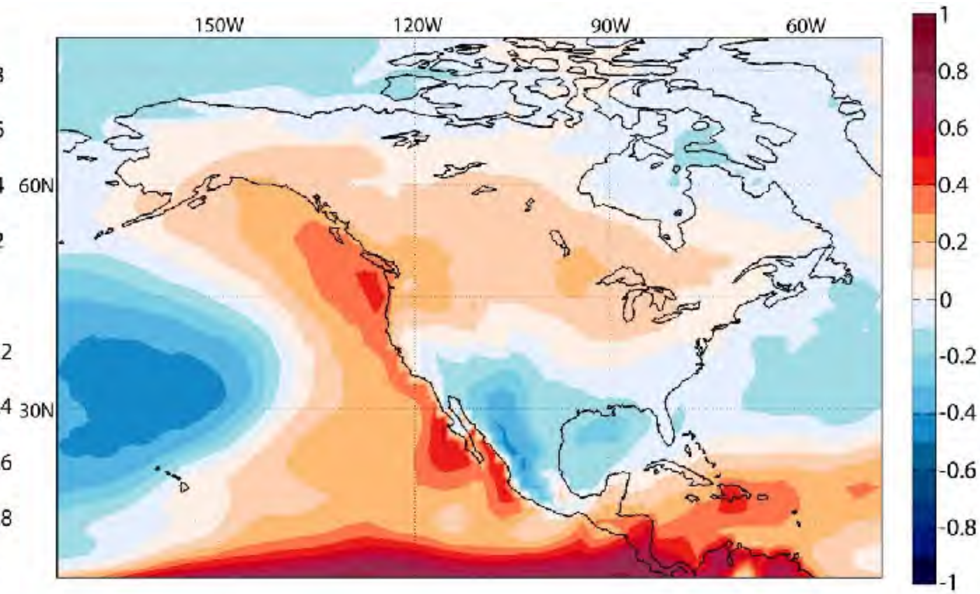
Sources of predictability for Weeks 3-4: The El Niño/Southern Oscillation (ENSO)

Correlation between Niño 3.4 SSTs and T2m (1980-2014)

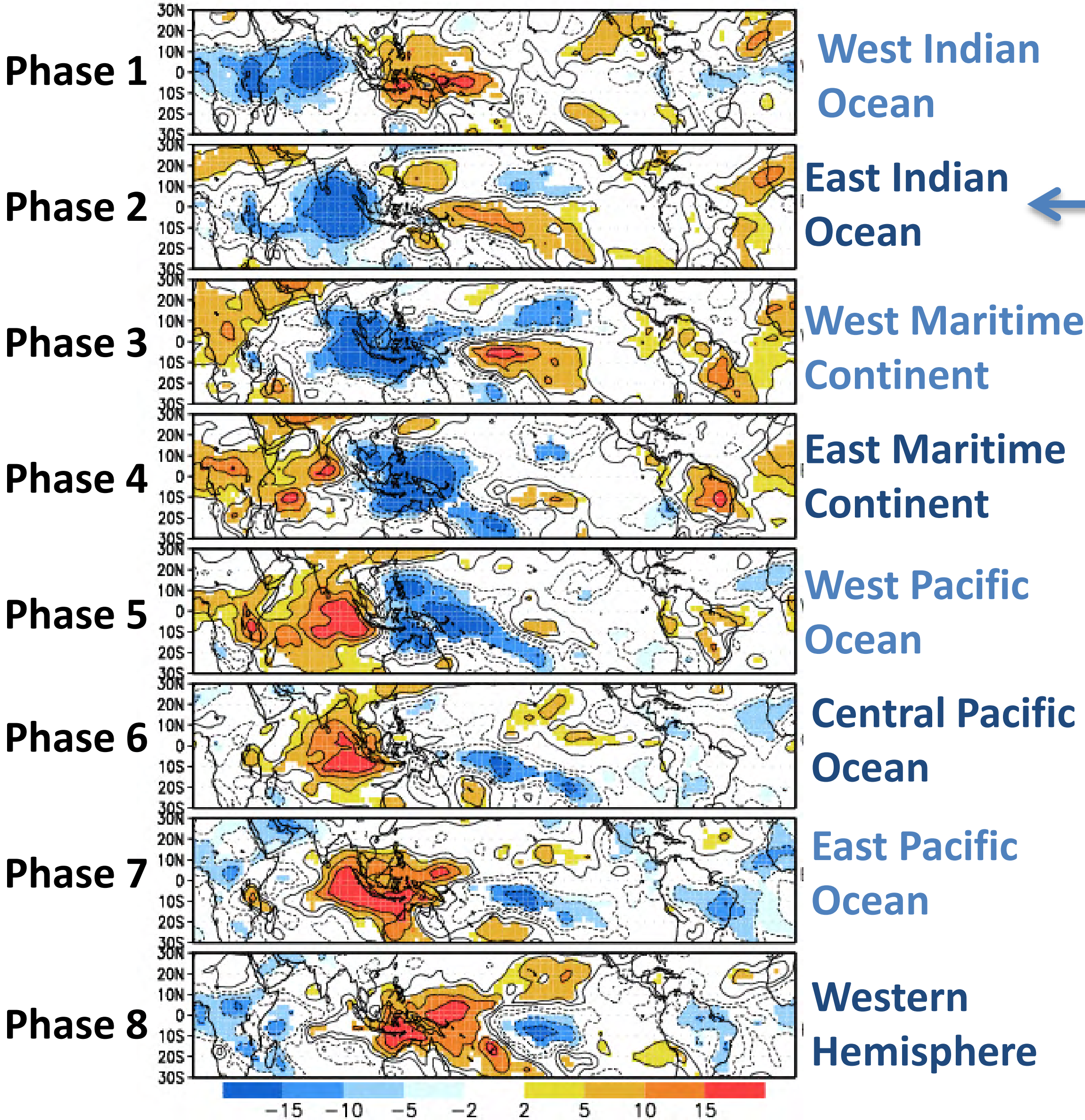
Seasonal mean:
DJFM T2m and Niño 3.4



Weeks 3-4:
14-day mean T2m and lag -14d Niño 3.4

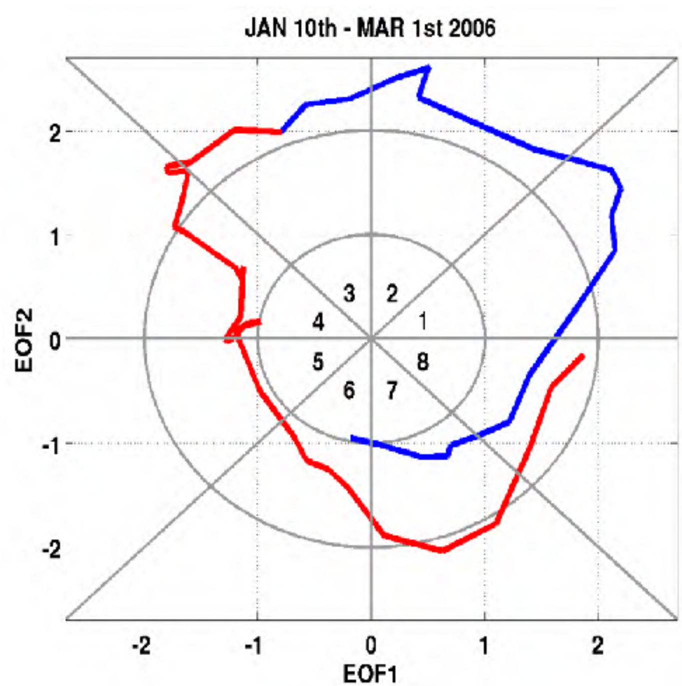


Sources of predictability for Weeks 3-4:
The Madden-Julian Oscillation (MJO)



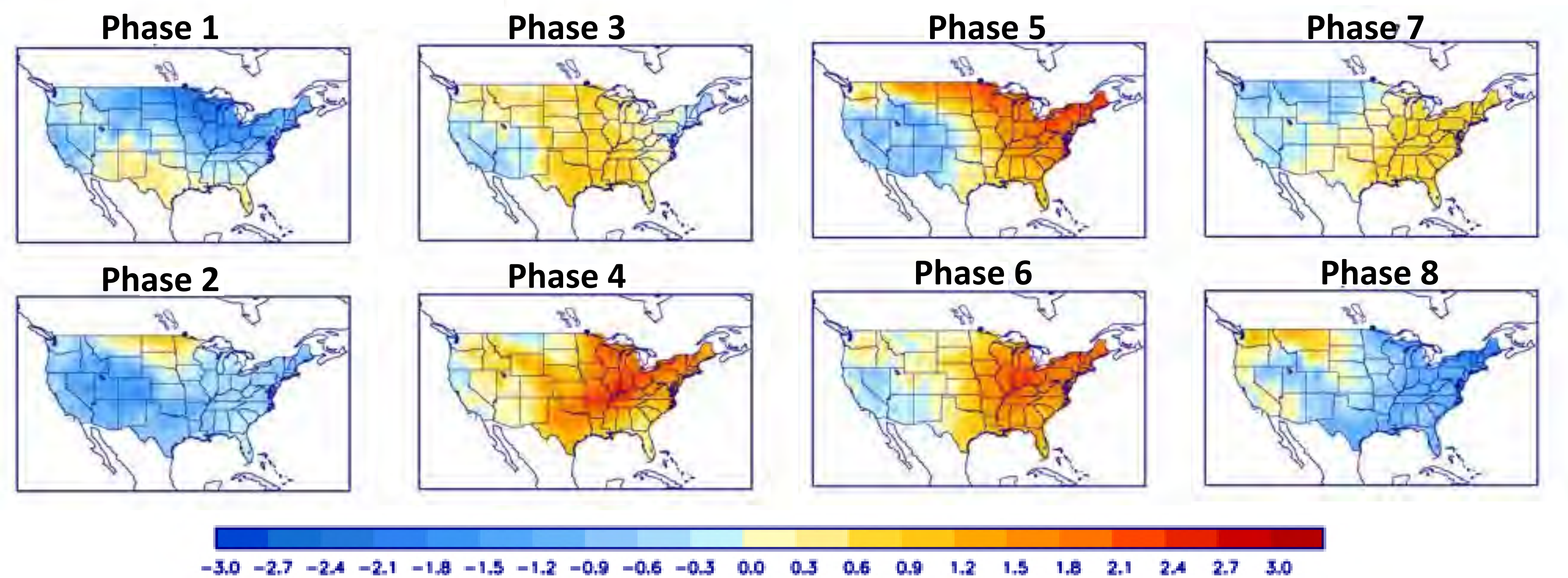
The Wheeler-Hendon Index

OLR anomalies associated with MJO propagation from phase 1 – phase 8 (**blue** = enhanced convection)



Impact of the Madden-Julian Oscillation:
The Wheeler-Hendon Index and US temperatures

Simultaneous surface air temperature composite anomalies (°C, DJF)



NOAA CPC MJO composites page

http://www.cpc.ncep.noaa.gov/products/precip/CWlink/MJO/Composites/Temperature/

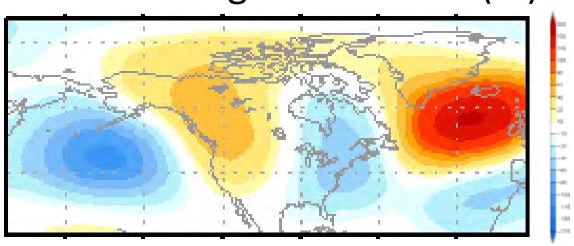
Zhou, L'Heureux, Weaver, and Kumar (2014)

The MJO strongly influences North American wintertime circulation for lead times of up to four weeks.

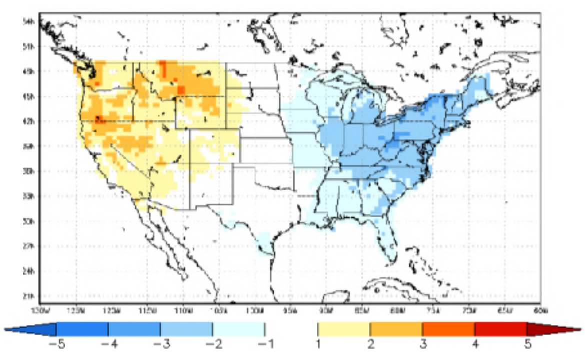
One of the dominant winter atmospheric patterns (top left) strongly affects U.S. temperatures (bottom left).

A weekly cluster pattern

500-hPa height anomalies (m)



Temperature anomalies (°C)

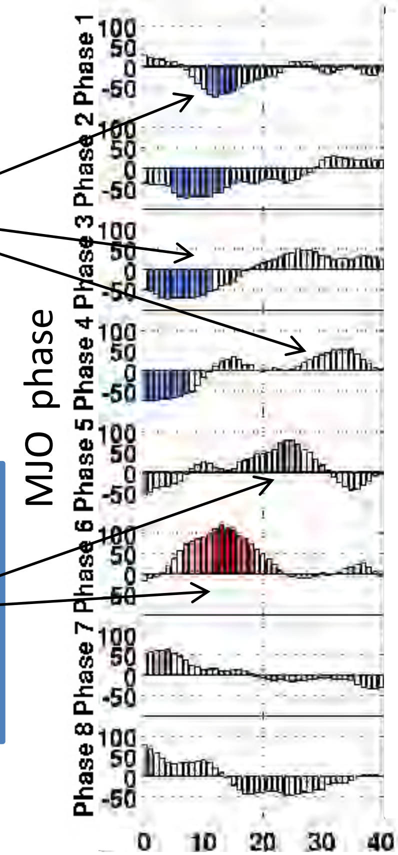


Riddle, Stoner, Johnson, L'Heureux, Collins, and Feldstein (2013, *Climate Dynamics*)

MJO influence on cluster pattern

Anomalous frequency of cluster pattern (top left) occurrence (%)

The MJO gives information on pattern occurrence 10-25 days in advance

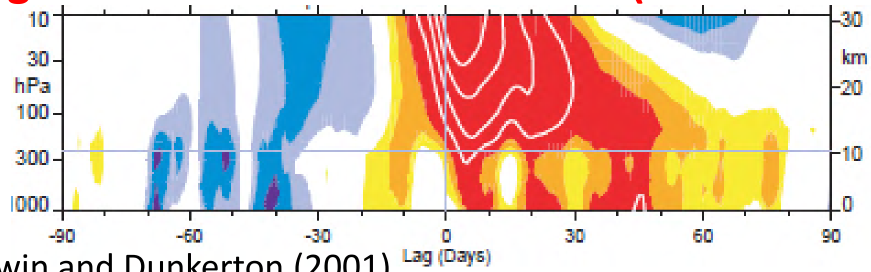


Days that MJO precedes pattern

Other potential sources of predictability for Weeks 3-4:

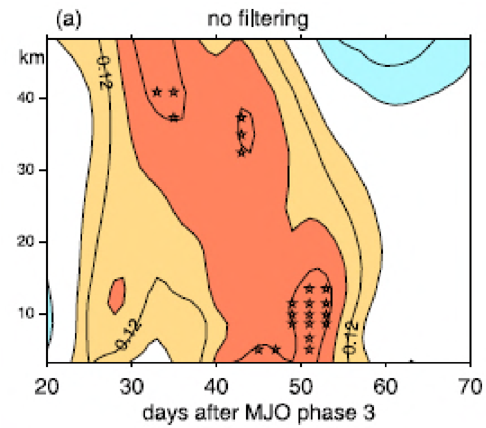
- **Stratosphere-troposphere coupling**

Negative Northern Annular Mode (warm colors)



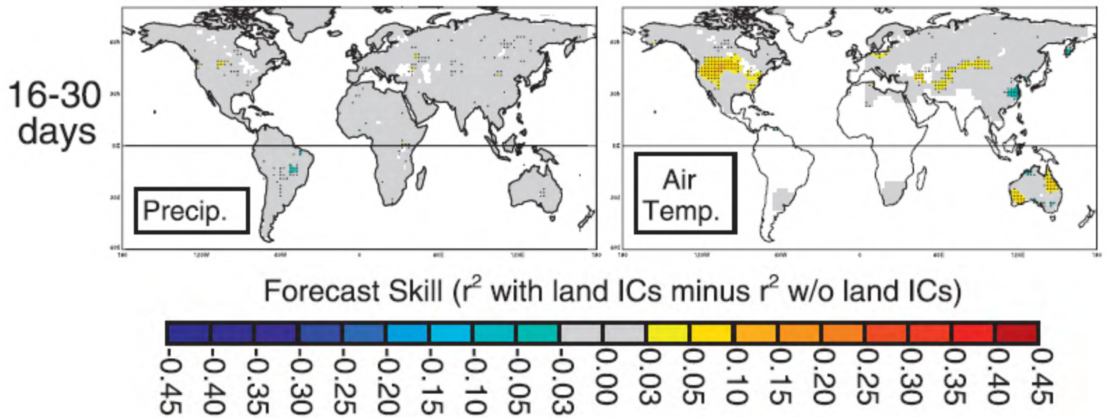
Baldwin and Dunkerton (2001)

Normalized polar cap height



Garfinkel, Feldstein, Waugh, Yoo, and Lee (2012)

- **The land surface (e.g., snow cover and soil moisture) and its role in land-atmosphere interactions**



JJA

Koster et al. (2011)

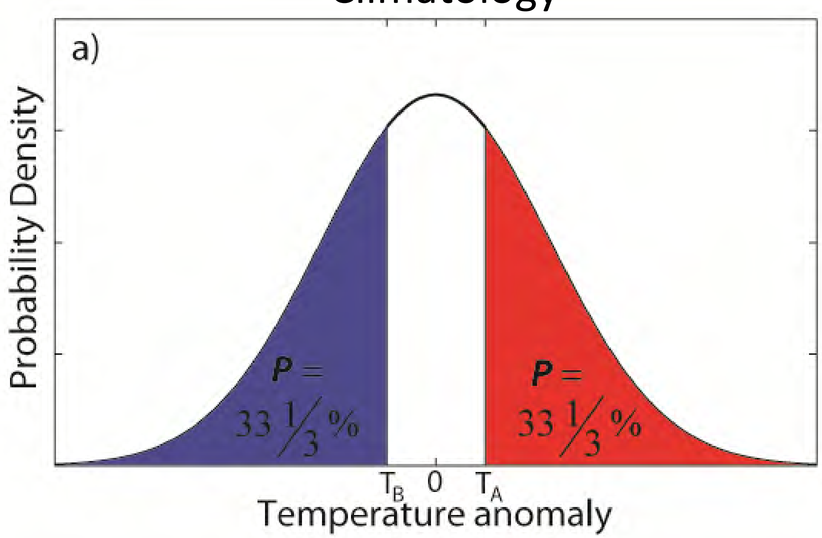
- **The long-term trend**

Statistical temperature forecast guidance based on the initial state of the MJO and ENSO

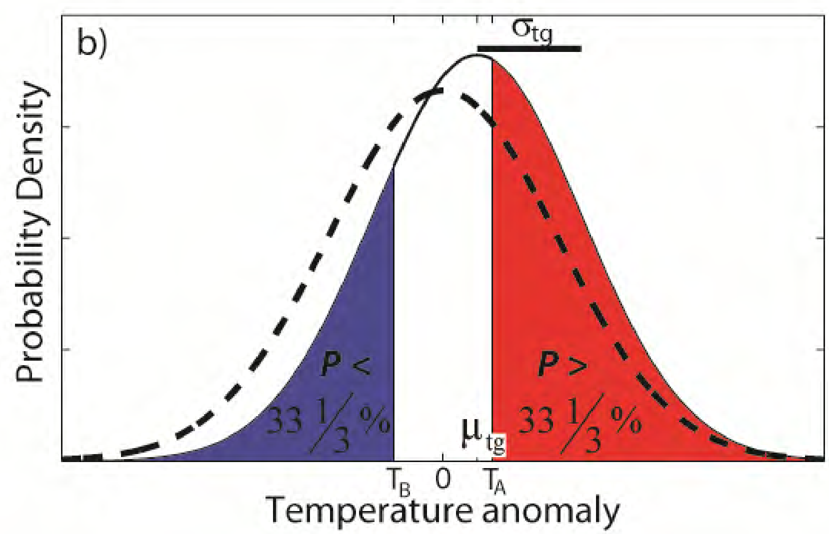
- ERA-Interim 2-m temperature (T2m) data, December – March 1980-2010, North America domain, 7-day running mean anomalies

- Main forecast steps:
  1) Calculate mean and variance of T2m anomaly corresponding to MJO and ENSO state; add the two means and variances for each grid point and forecast lag
  2) With the assumption of a Gaussian T2m anomaly distribution and with a linear trend term added, calculate the probability of T2m in the upper and lower tercile for each lead time

Climatology

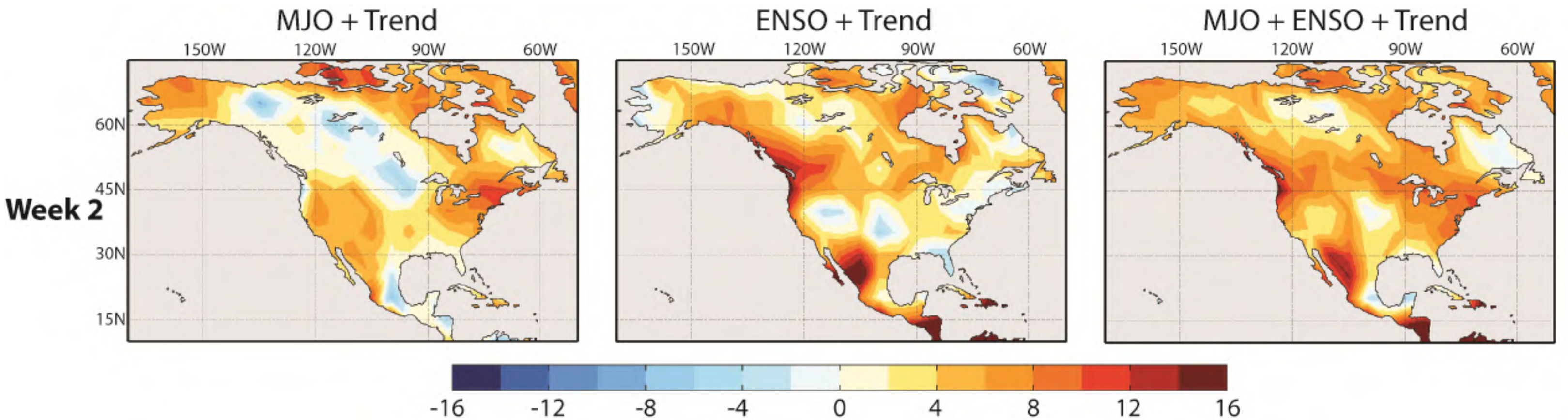


MJO+ENSO+trend forecast

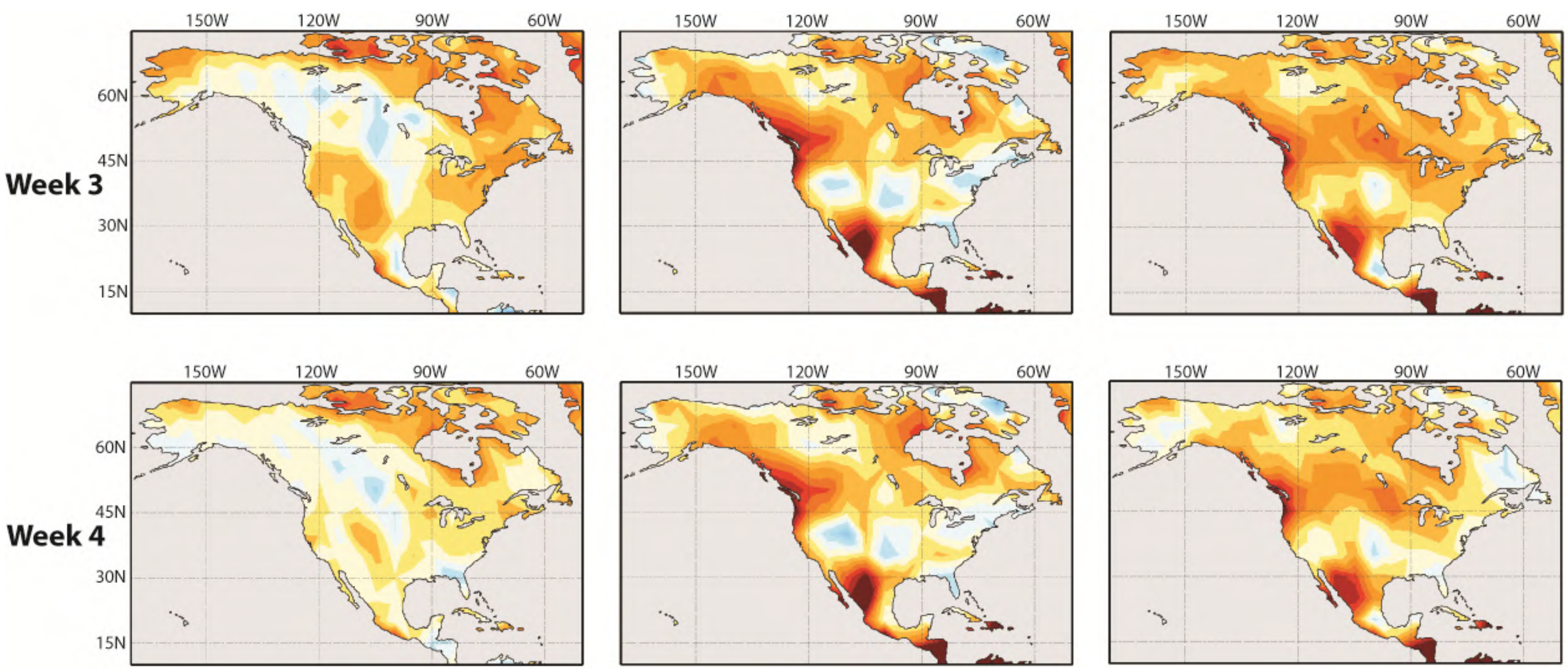


The MJO and ENSO primarily impact different regions of North America.

Mean Heidke Skill Scores (HSS)



The MJO influence decays between weeks 2 and 4, whereas the ENSO influence remains nearly constant at these timescales.

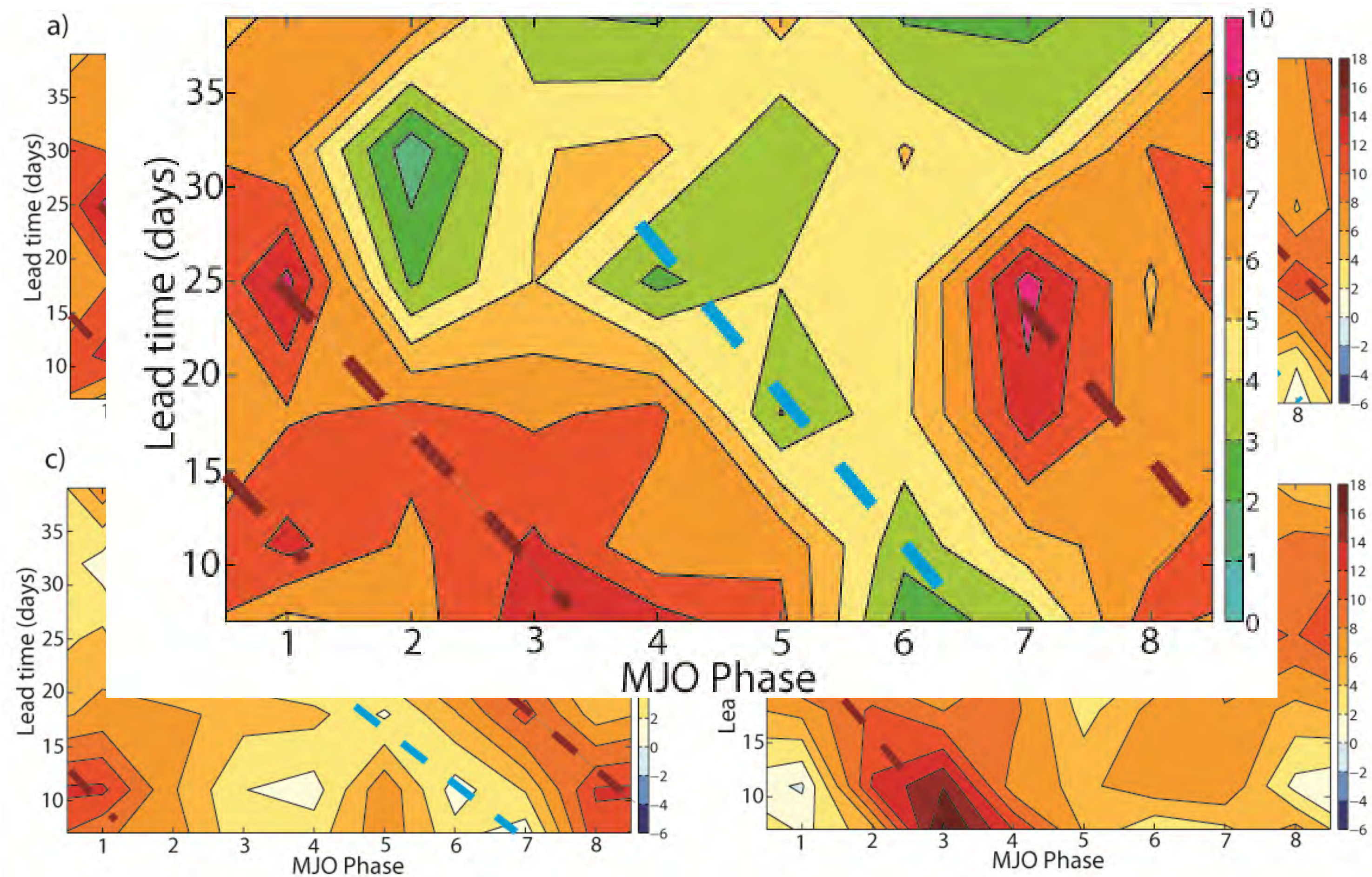


Johnson, Collins, Feldstein, L'Heureux, and Riddle (2014)

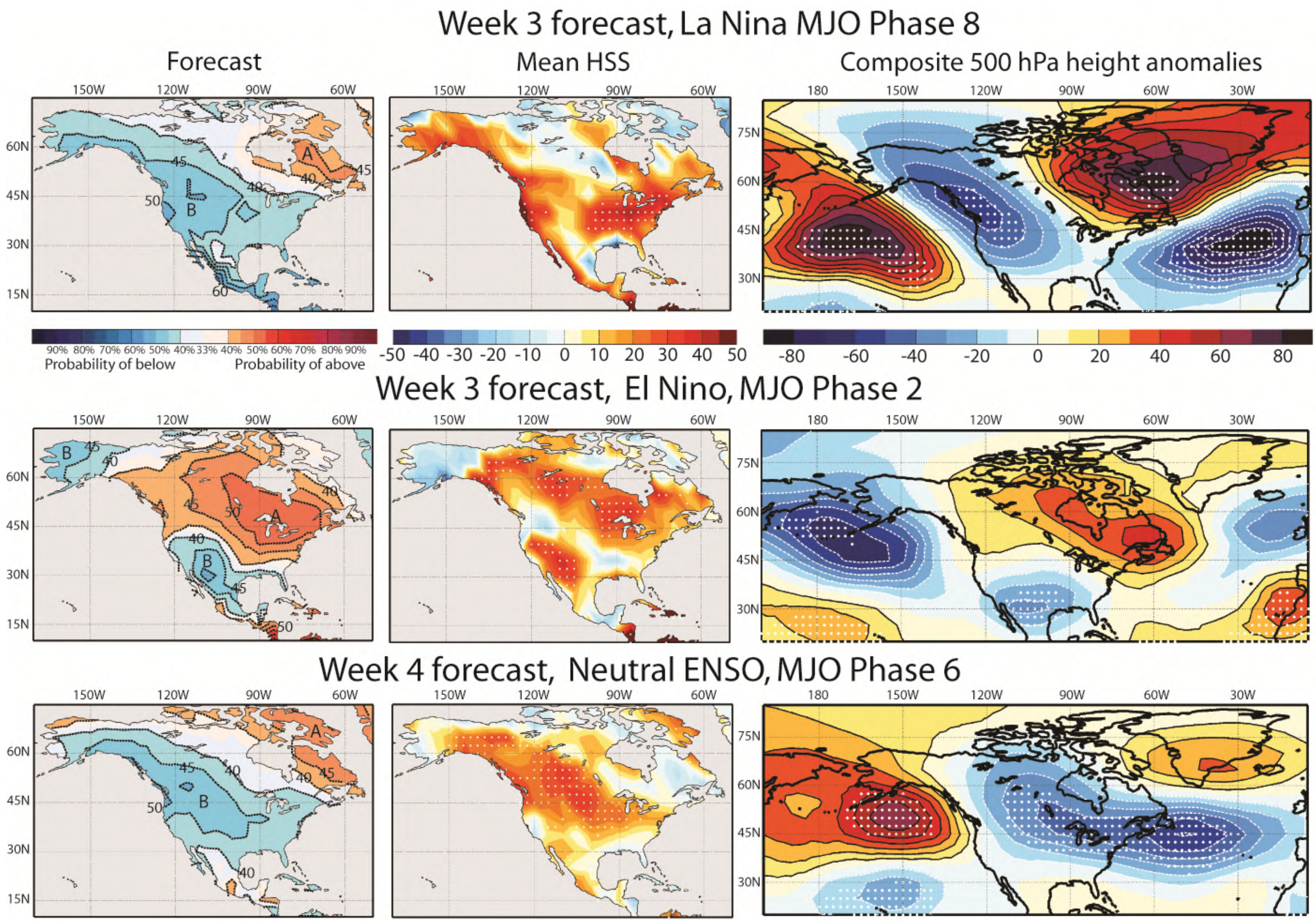
Particular MJO phases have stronger impacts on North American temperatures.

- Lin et al. (2010): response of oppositely signed tropical convective heating anomalies near 80°E and 160°E reinforce each other
- Such an east-west dipole of convective heating corresponds with MJO phases 3 and 7

Spatial mean HSS

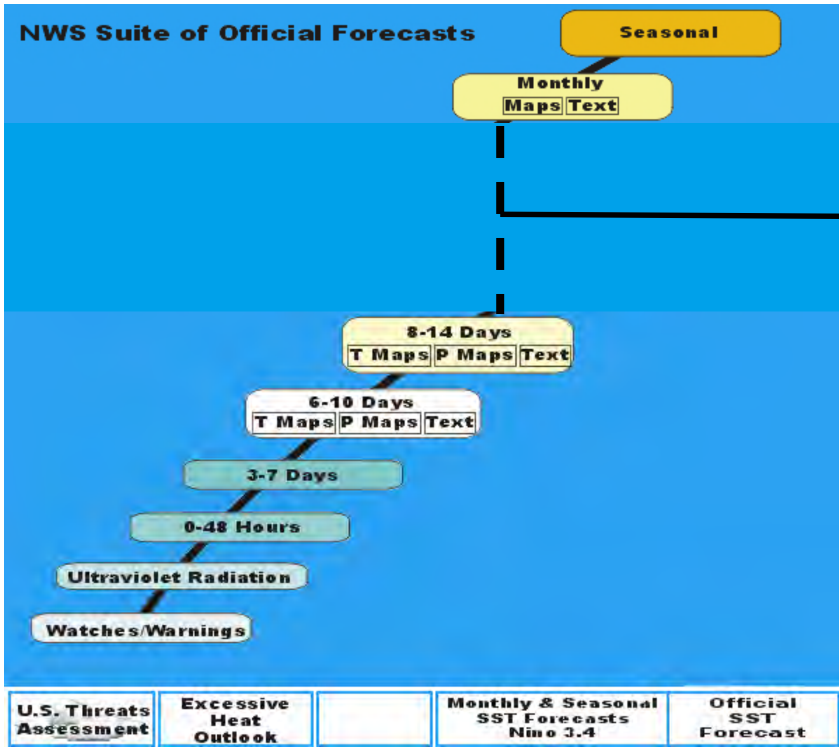


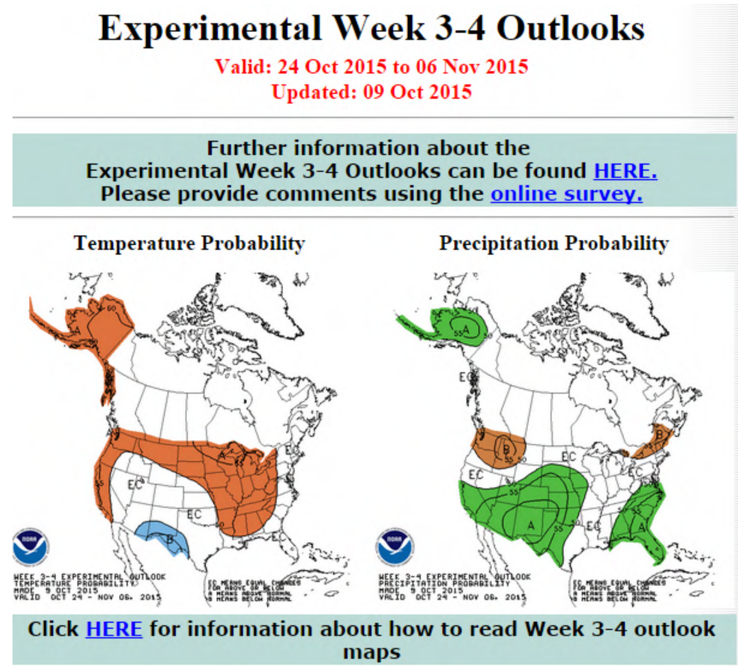
For some initial states of the MJO and ENSO, the skill scores of the weeks 3-4 T2m forecasts from the empirical model are substantially higher than the typical skill scores of dynamical models.



NOAA CPC Experimental Week 3-4 Outlooks

- ❖In September 2015 NOAA Climate Prediction Center (CPC) began issuing Experimental Week 3-4 Outlooks

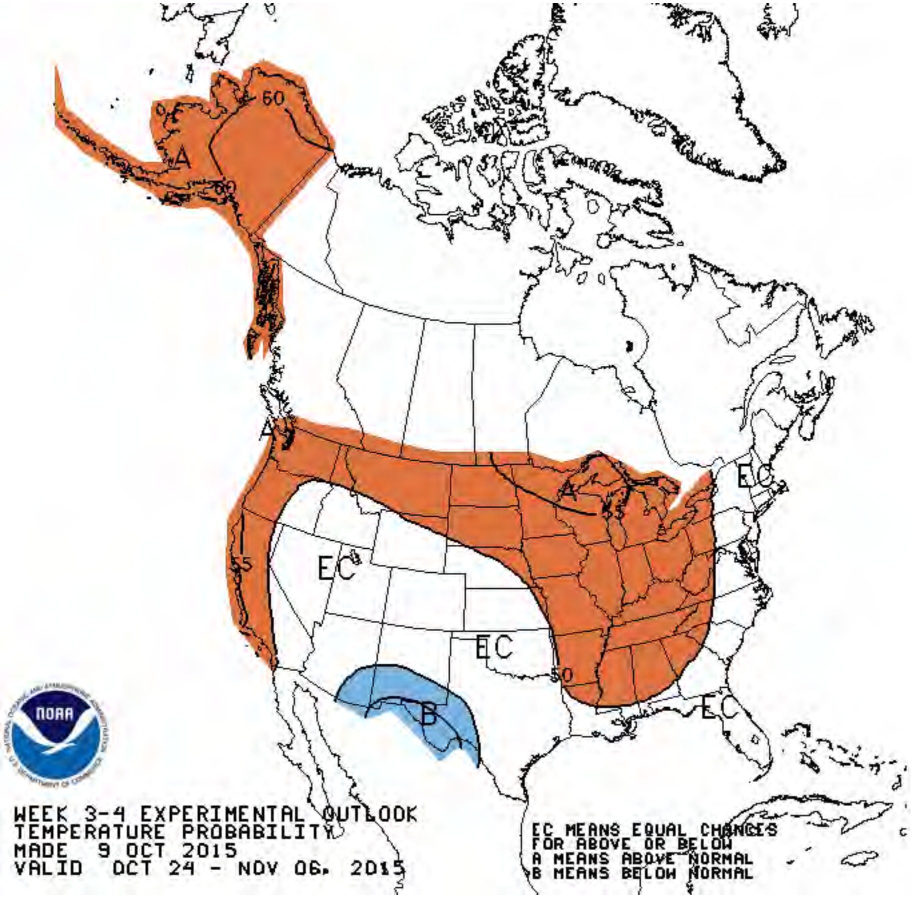


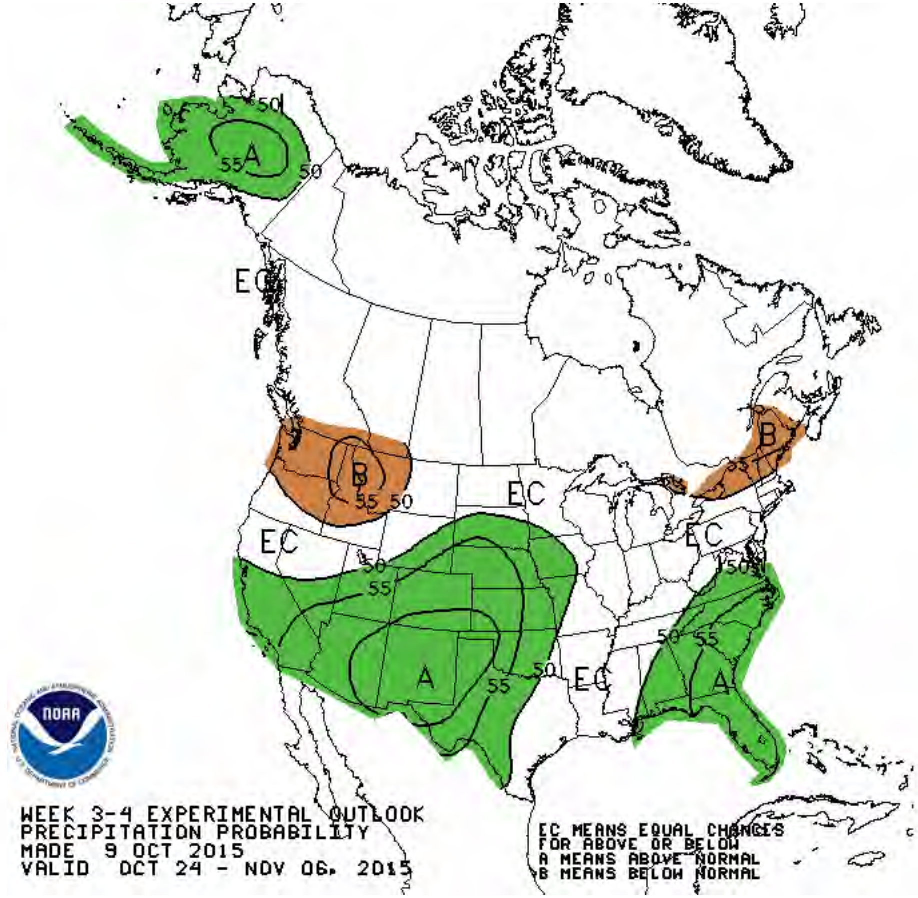


http://www.cpc.ncep.noaa.gov/products/predictions/WK34/

- ❖MJO/ENSO statistical guidance (extended to precipitation and all seasons) regularly used by forecasters
- ❖Dynamical guidance: CFSv2, ECMWF, and JMA

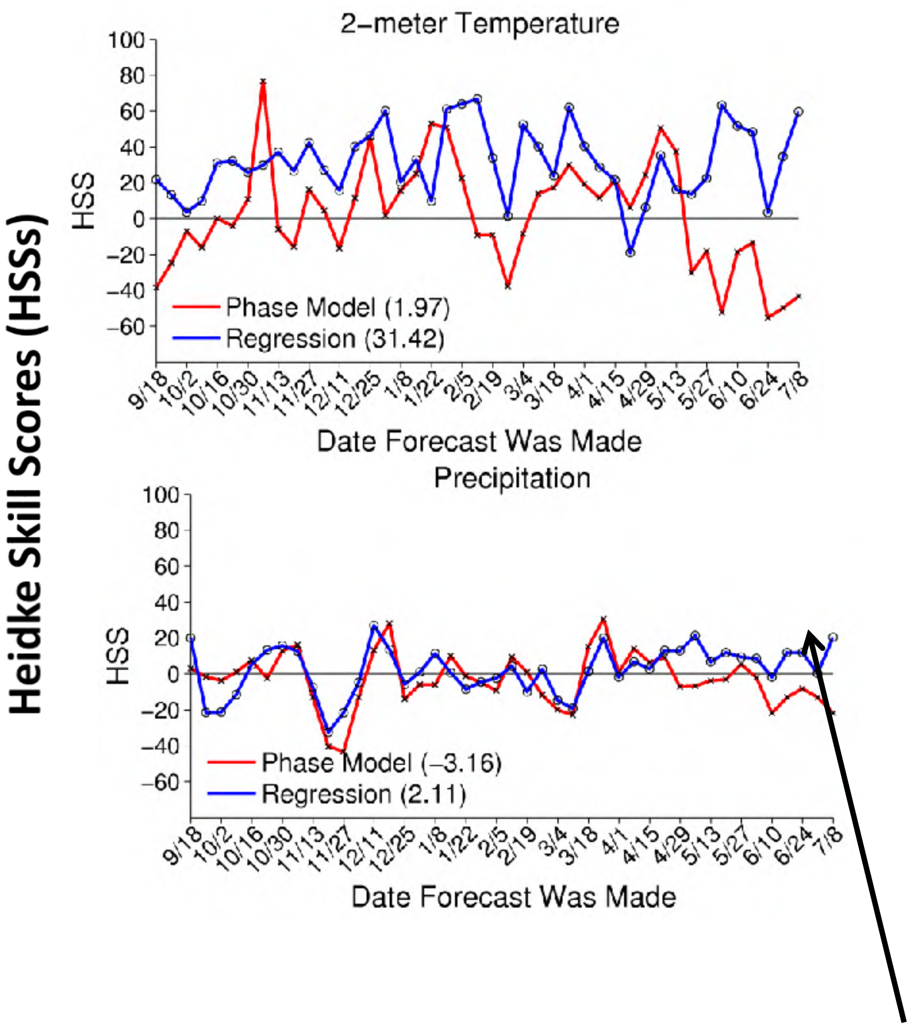
Example Experimental Week 3-4 Outlook.





Statistical guidance emphasizing the subseasonal ENSO footprint was strongly utilized. This guidance, along with the dynamical consensus leads to a more confident precipitation outlook relative to temperature. Above-median precipitation is favored

The statistical forecast guidance has been successful over CONUS but **success greater for temperature than for precipitation**.



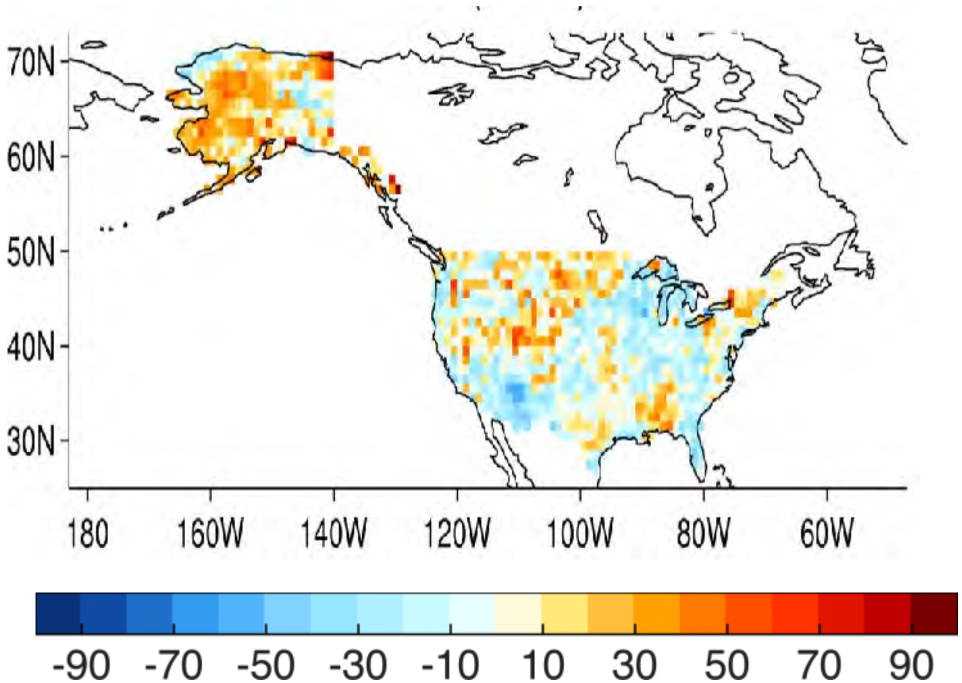
Mean HSS

- HSS > 0: skill relative to a random forecast
- Blue and red lines: two different versions of the statistical model
- Precipitation regression model has outperformed the ECMWF (mean HSS = -0.1) but not the JMA (3.3) or CFSv2 (7.6) dynamical forecast models

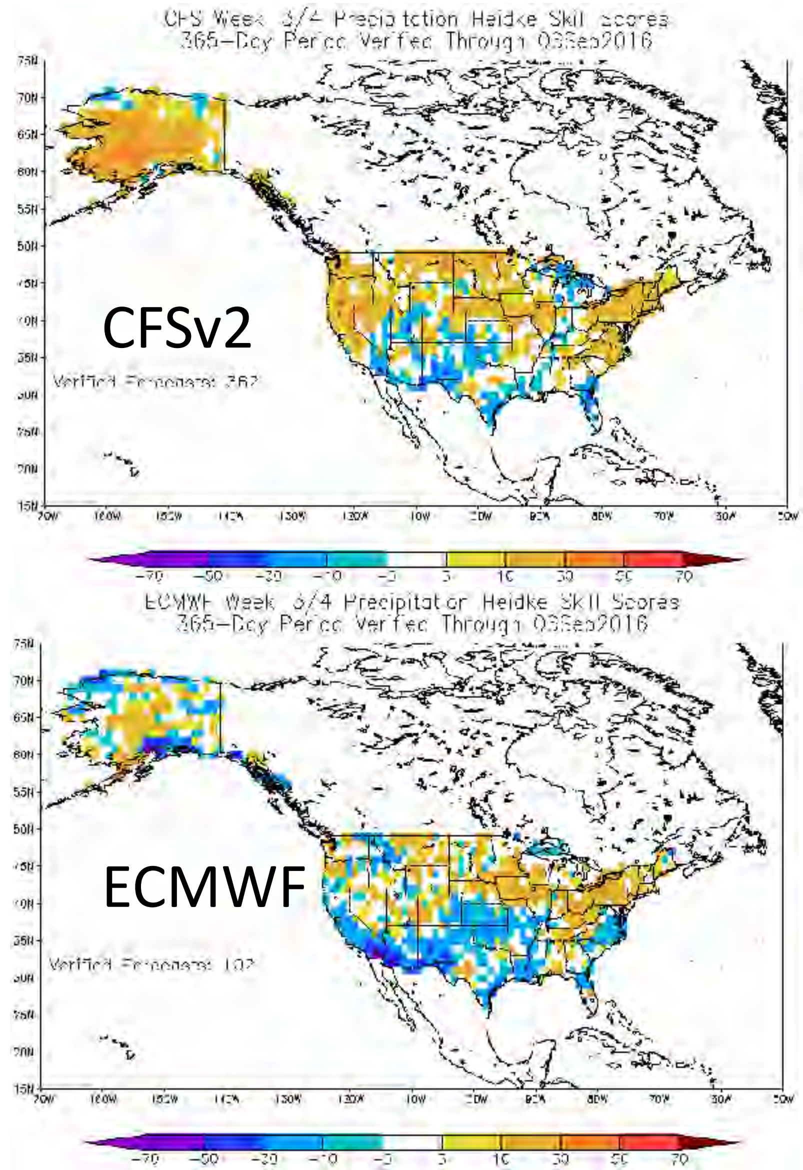
However, both statistical and dynamical forecast models have performed poorly in the southwestern U.S.

<u>Statistical guidance</u>

Mean Weeks 3-4 HSS for precipitation phase model in fall through mid summer 2016



<u>Dynamical guidance</u>



Can similar forms of statistical guidance provide skill over East Asia?

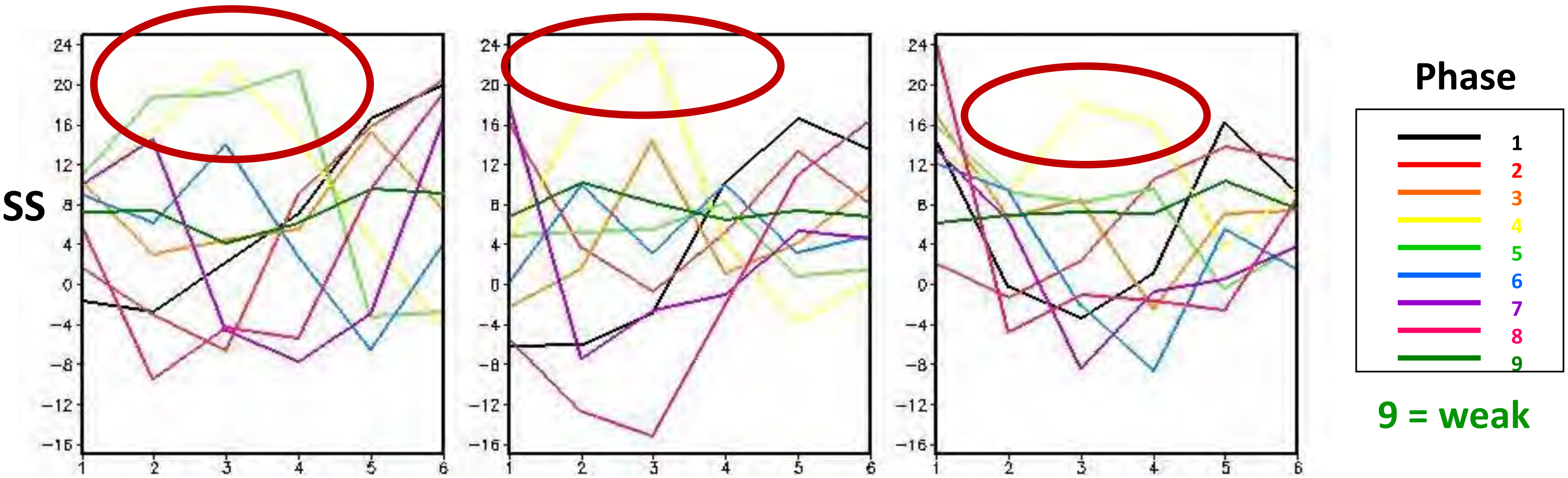
Preliminary analysis with Shing Chang and Changhyun Yoo

- Probabilistic **temperature** forecasts for **MJJASO** with three predictors: time, Niño 3.4 SST, and one of three ISO indices: BSISO (Lee et al. 2012), BSISO (Kikuchi et al. 2012), and MJO (Wheeler and Hendon 2004)

- Probabilistic **temperature** forecasts for **DJF** with three predictors: time, Niño 3.4 SST, and MJO

Preliminary results: MJJASO HSSs for Taipei

HSS



Indices:

Lead time (weeks)

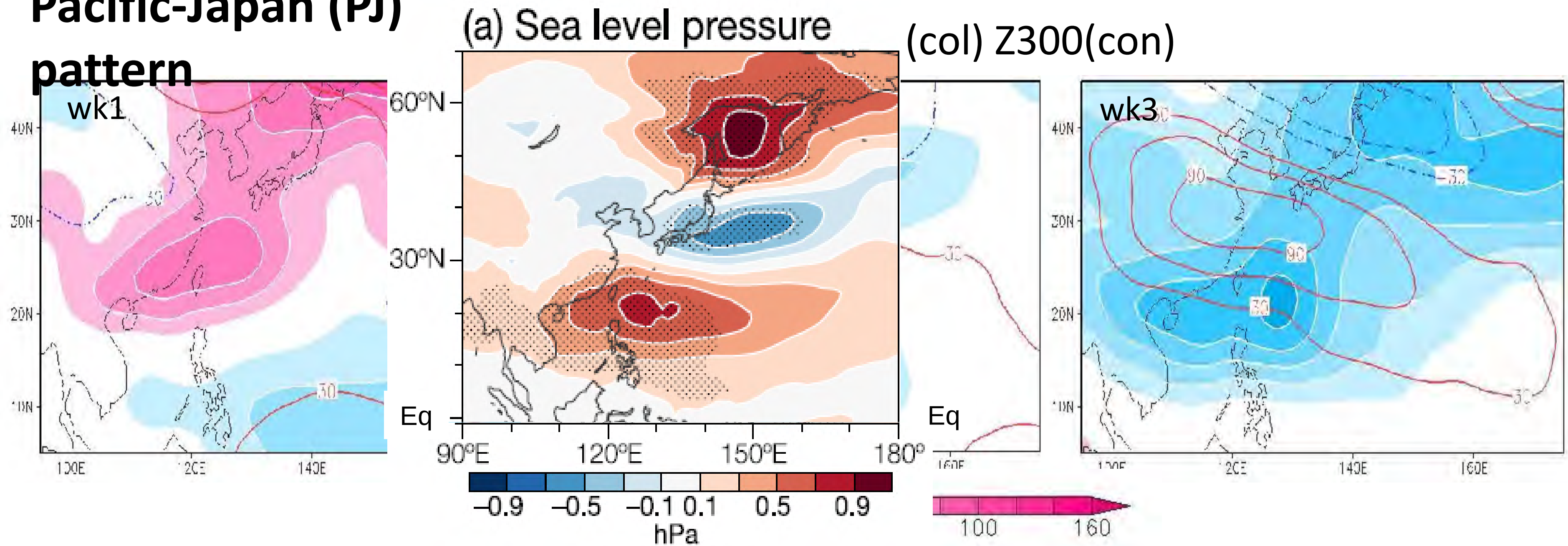
Kikuchi et al. (2012) Wheeler and Hendon (2004) Lee et al. (2012)

Week 3 skill enhancement after MJO phase 4

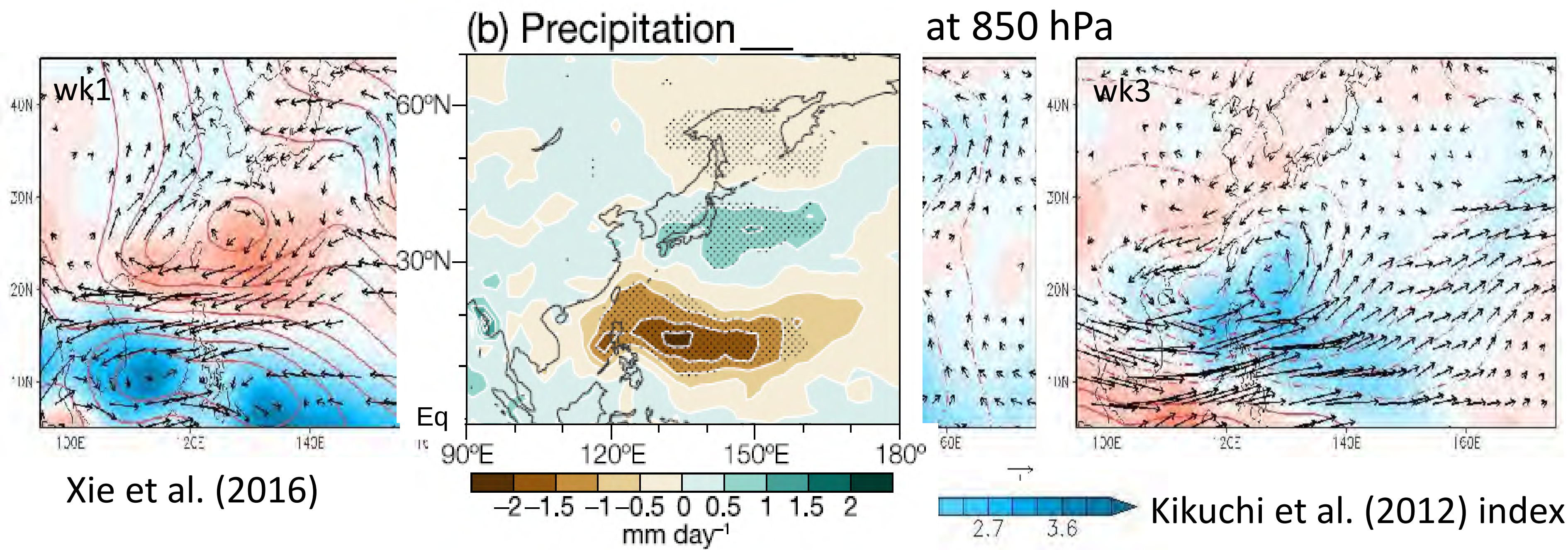
Composite evolution: BSISO phase 4

Pacific-Japan (PJ) pattern

(col) Z300(con)



at 850 hPa

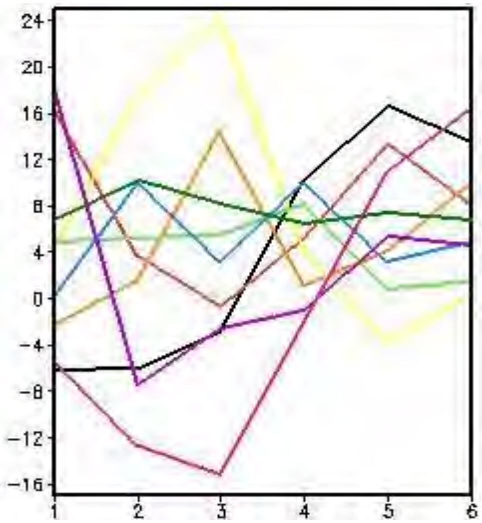


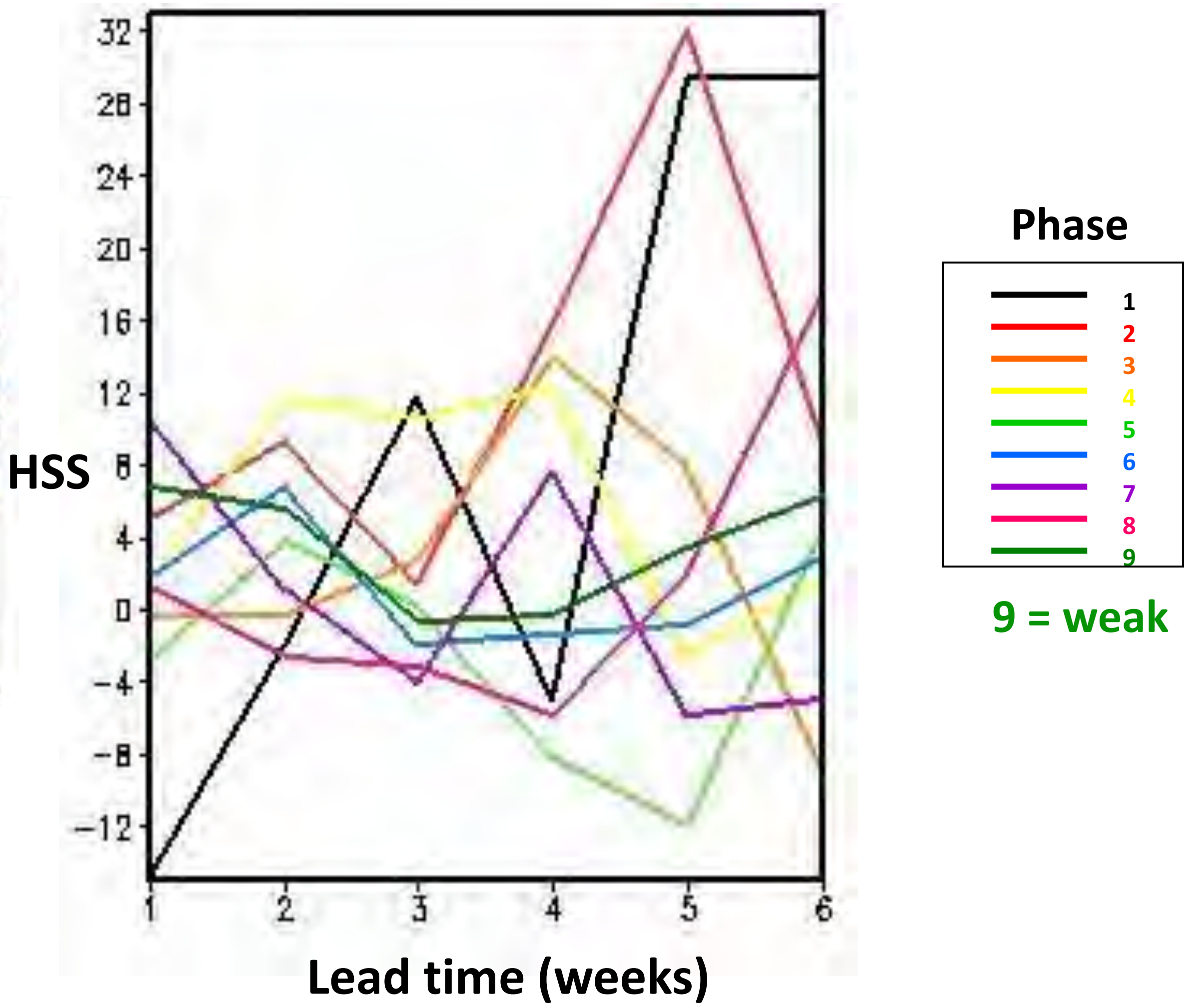
Xie et al. (2016)

Kikuchi et al. (2012) index

Preliminary results: DJF HSSs for Taipei

MJJASO

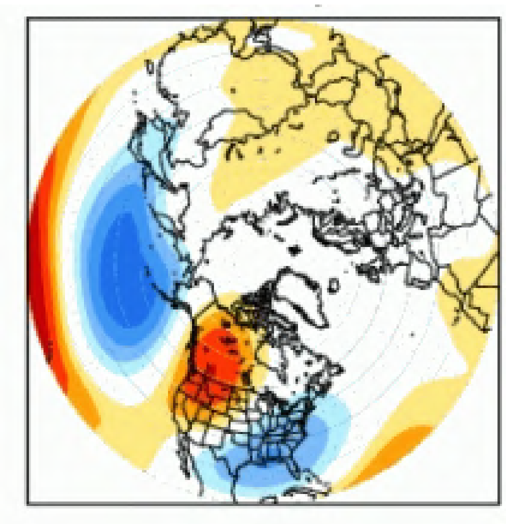




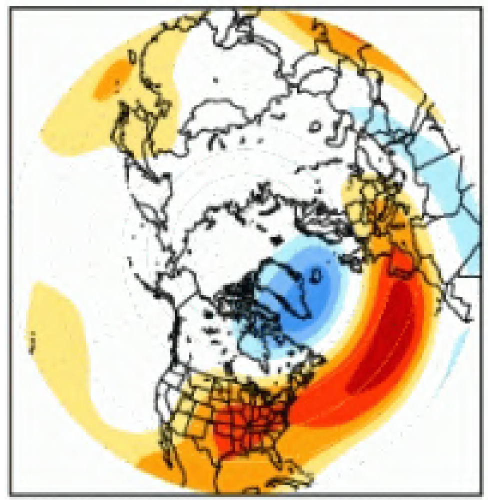
Wheeler and Hendon (2004) index

Going beyond MJO, BSISO, ENSO, and trend:
Statistical forecasts of teleconnection pattern indices

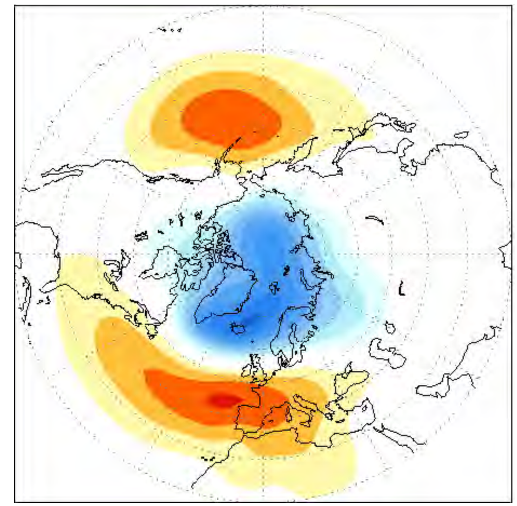
Pacific/North American Pattern (**PNA**)



North Atlantic Oscillation (**NAO**)



Arctic Oscillation (**AO**)



- Forecasts of two-week mean indices in DJF (1980-2013)
- **Partial least squares regression (PLSR)** is used
- Predictors: tropical outgoing longwave radiation (**OLR**), 300 hPa geopotential height (**z300**), and 50 hPa geopotential height (**z50**)

What is PLS regression?

- A fairly new method (Wold 1966) with limited applications in atmospheric science (e.g., McIntosh et al. 2005, *J. Climate*; Smoliak et al. 2010, *GRL*; Wallace et al. 2012, *PNAS*)

- Sort of a cross between principal component analysis (PCA) and multiple linear regression

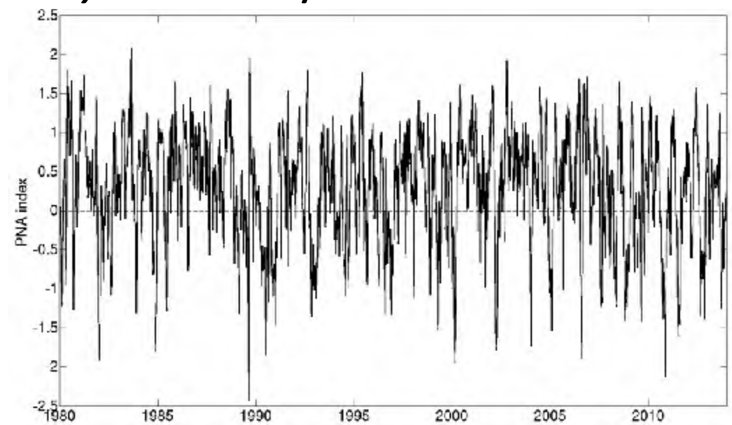
- Essentially a multiple linear regression decomposed into steps, where the steps determine “optimal” indices that are used as the predictors in the multiple regression

- These optimal indices are projections onto new variables that are a linear combination of the original predictor variables (*latent vectors* or *PLS components*), and each successive PLS component explains less predictand variance than the previous component

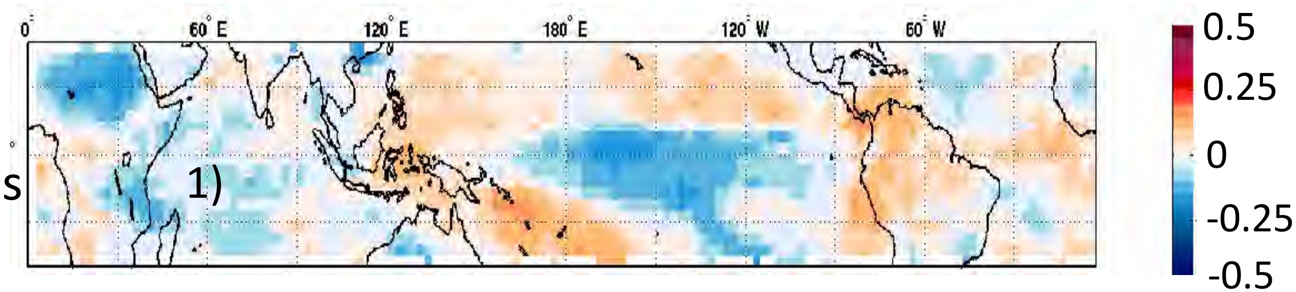
How does it work?

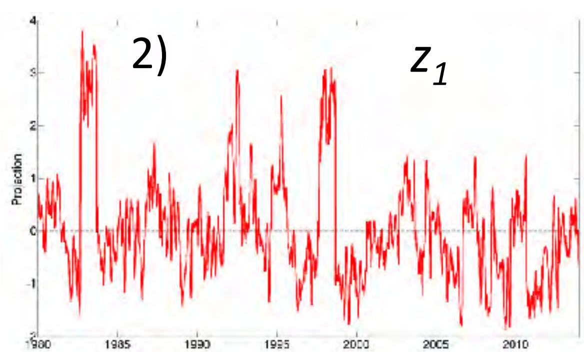
1) Calculate correlation coefficients between predictand y and each gridded predictor time series.
2) Project all predictor maps onto the correlation map to obtain a new predictor time series z_1.
3) Regress y on z_1.
4) Linearly remove z_1 from y and all gridded predictor time series, and repeat steps 1-3.

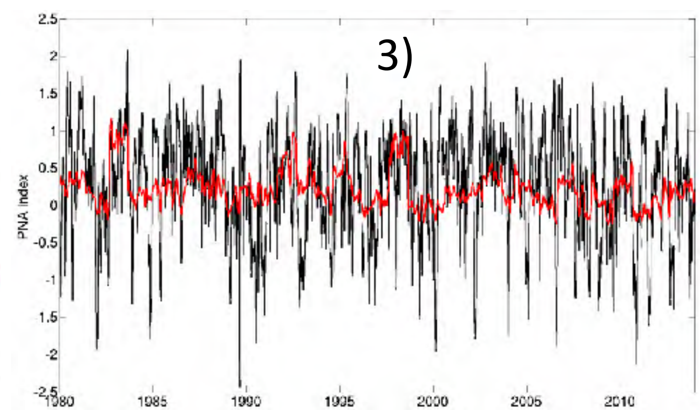
y: DJF daily PNA time series



Corr between y and lagged OLR



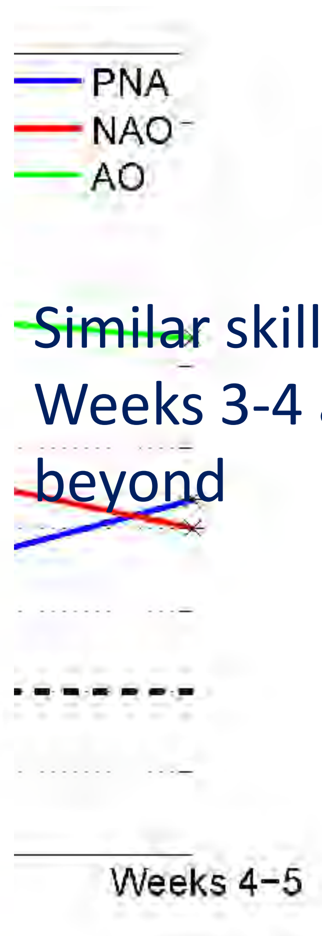




PLSR forecasts of DJF teleconnection pattern indices

Correlation between forecast and verification

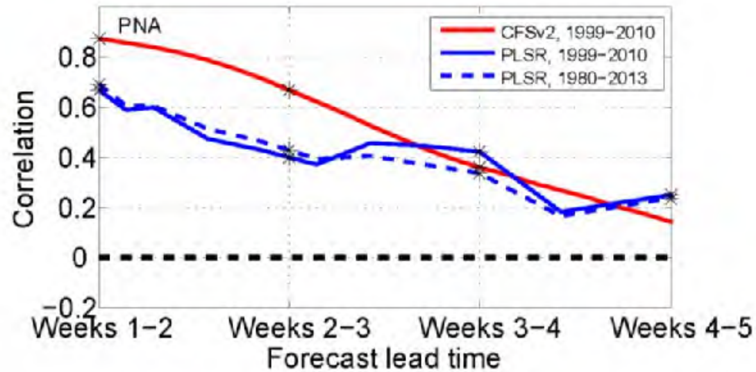
Comparison with a dynamical forecast model (CFSv2)

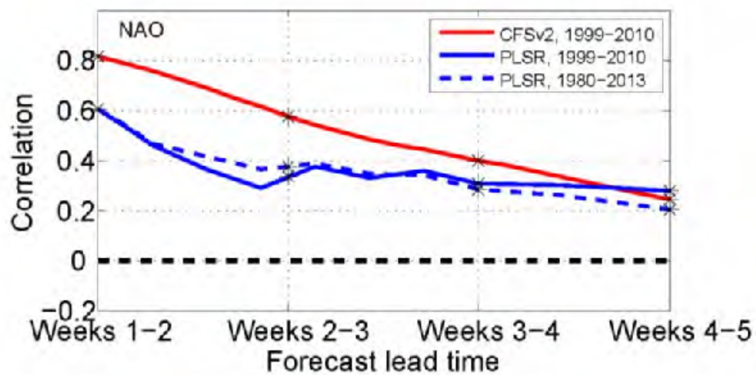


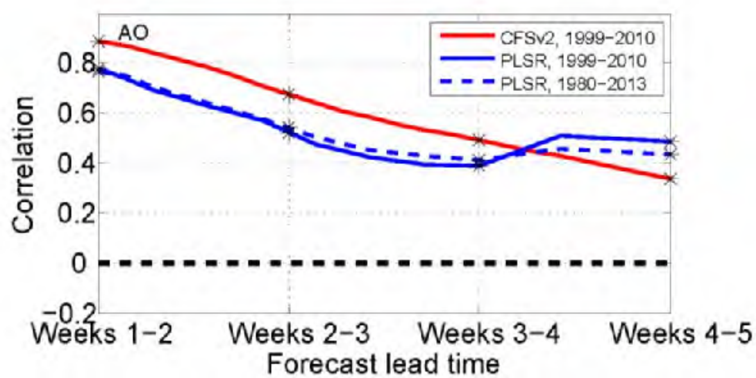
PNA

NAO

AO



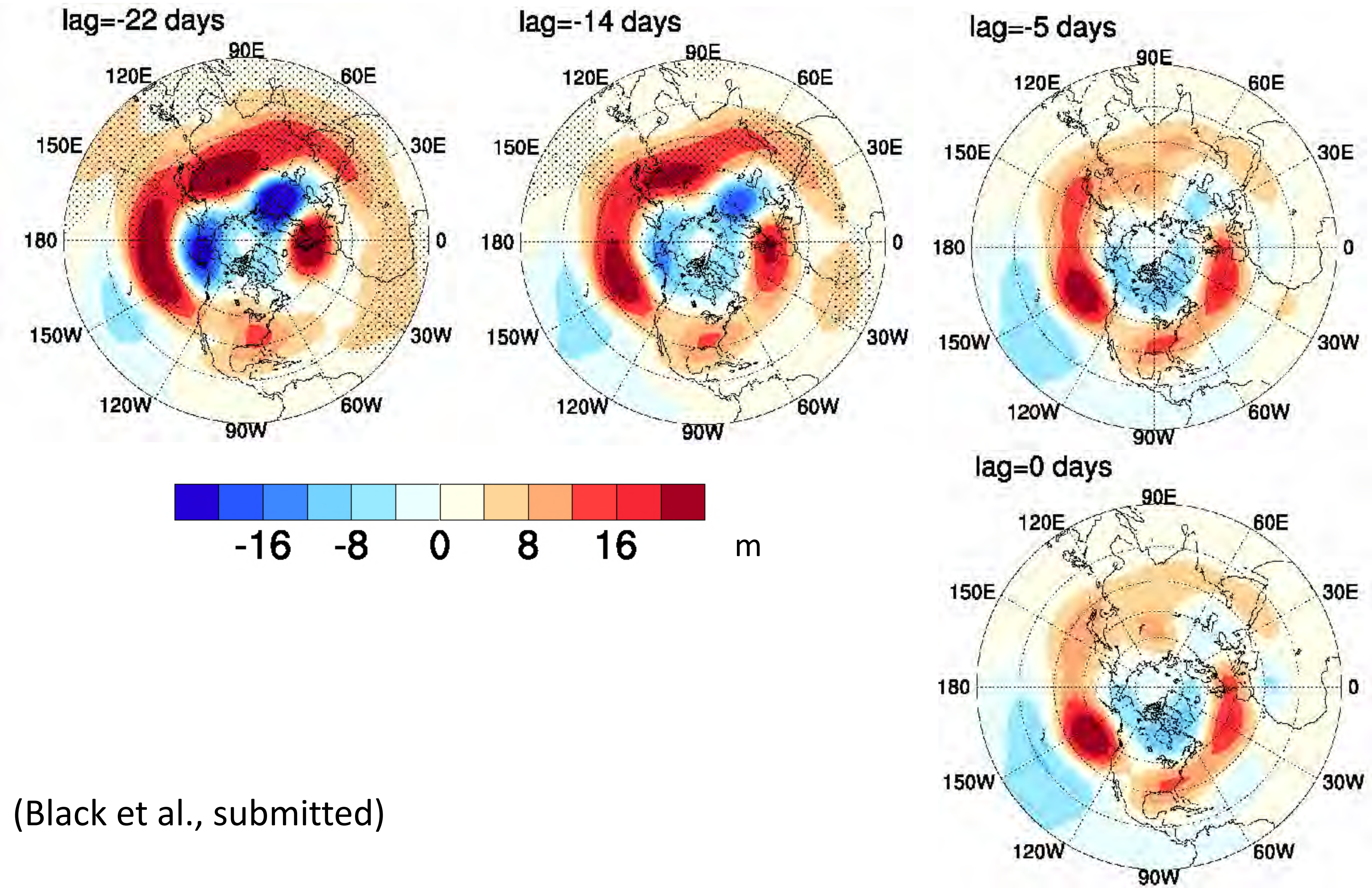




Similar skill for Weeks 3-4 and beyond

(Black et al., submitted)

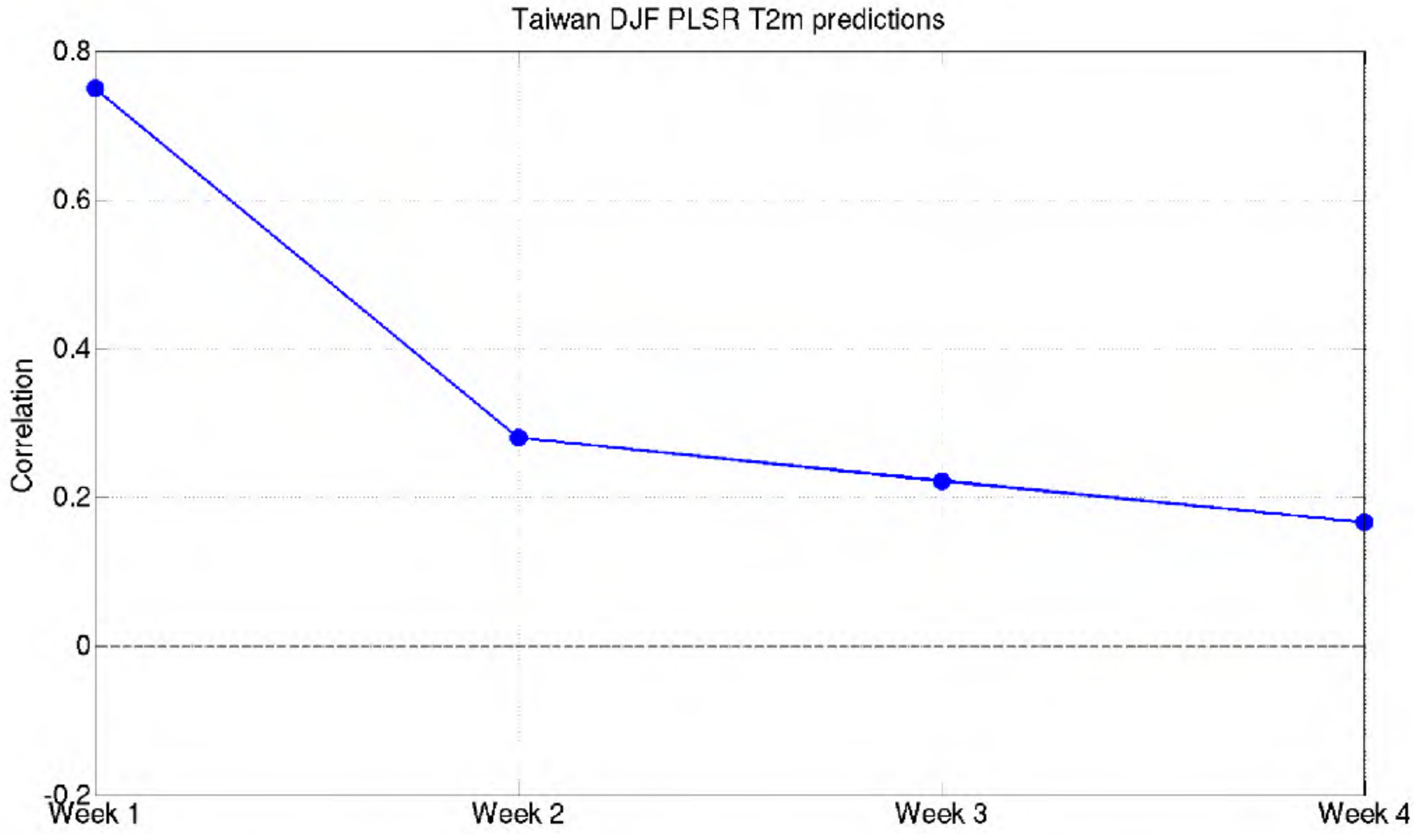
An important z300 predictor of the AO in weeks 3-4



(Black et al., submitted)

Preliminary PLSR forecasts of DJF temperatures for Taiwan

- Taiwan area mean temperature anomaly, 1980-2015
- Forecasts for Weeks 1-4
- Candidate predictors: **OLR**, **z500**, and **T2m**

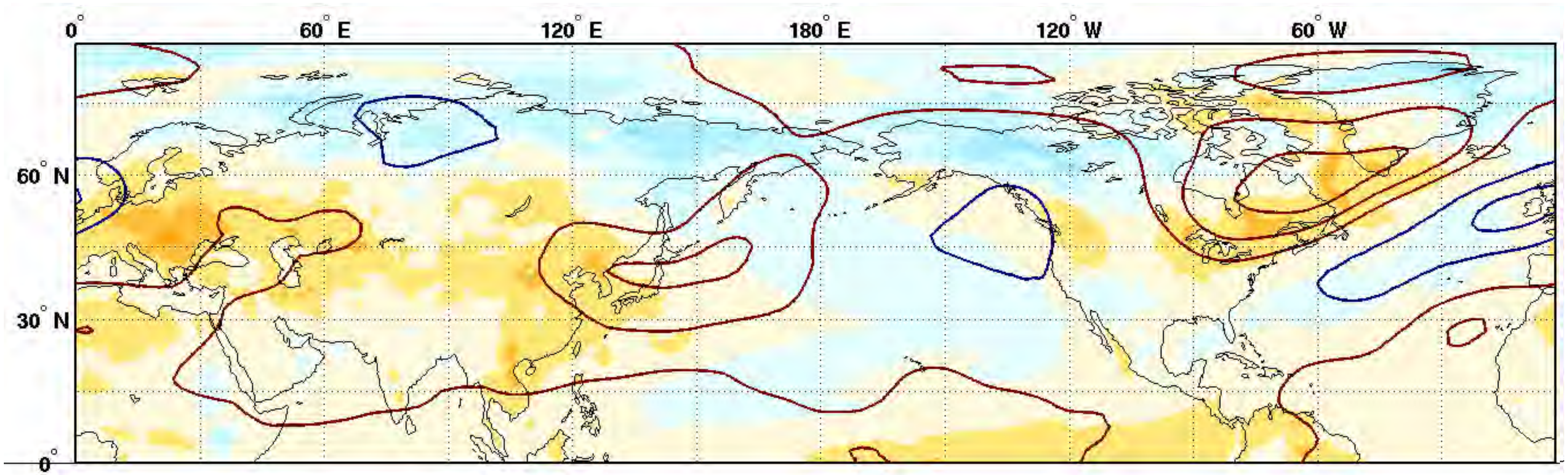


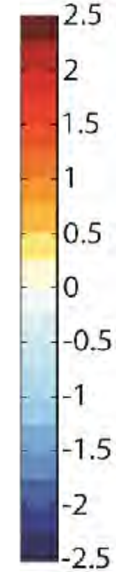
DJF week 3 z500 predictor pattern for Taiwan temperature

z500 (CI = 5m) and T2m (color shading)

Lag 0(initialization)

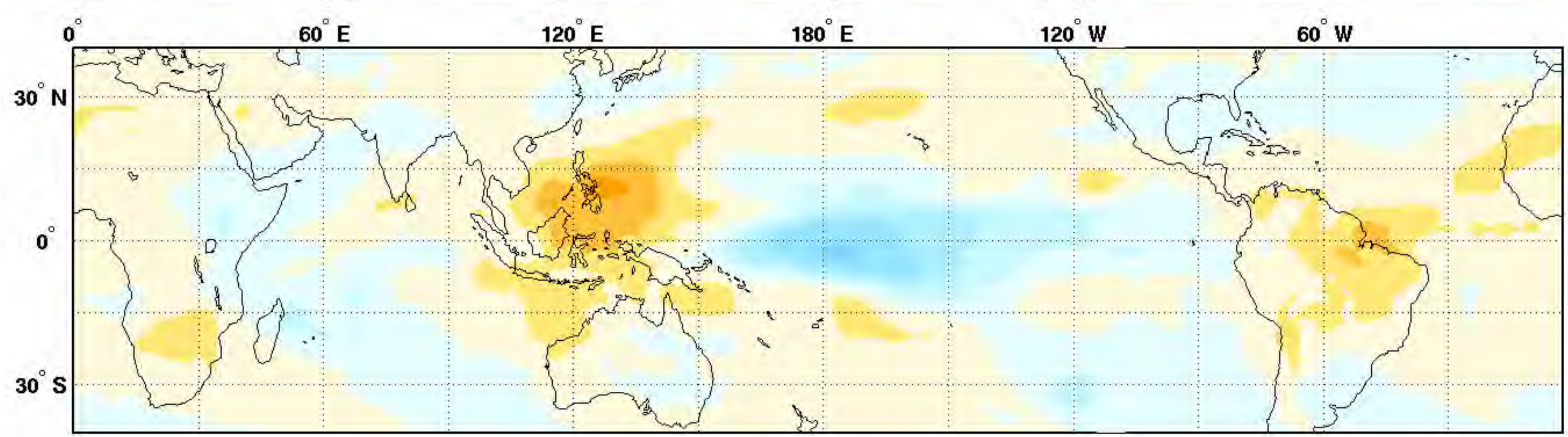
Week 1

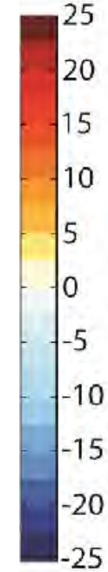




°C

OLR





Wm^{-2}

Future work

- Analysis of forecast skill in dynamical models: how well do they identify forecasts of opportunity beyond two weeks?
- Development of hybrid dynamical-statistical models?
- Studying the mechanisms of subseasonal predictability

Subseasonal-to-seasonal (S2S) prediction activities at GFDL

The 3–4-Week MJO Prediction Skill in a GFDL Coupled Model

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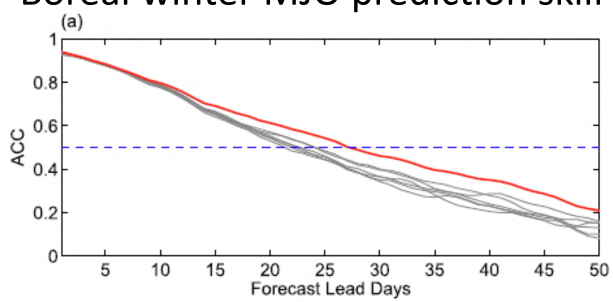
Boreal winter MJO prediction skill



FV3 to Help Revolutionize NOAA's Weather Forecasting

Simulation and Prediction of Category 4 and 5 Hurricanes in the High-Resolution GFDL HiFLOR Coupled Climate Model

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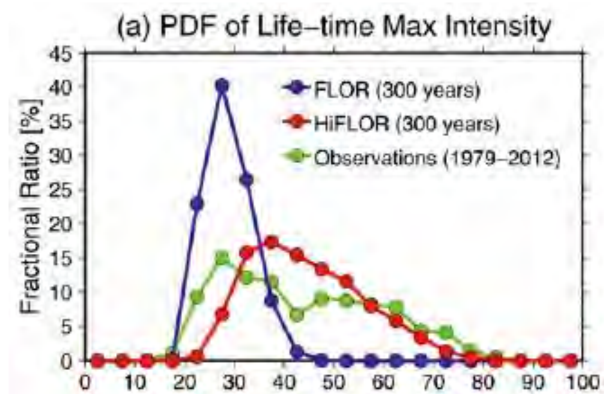
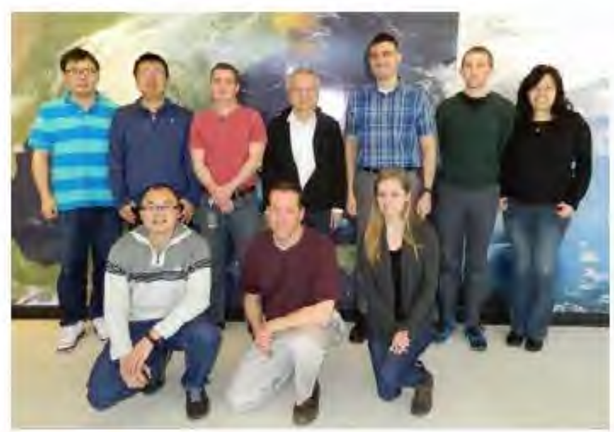
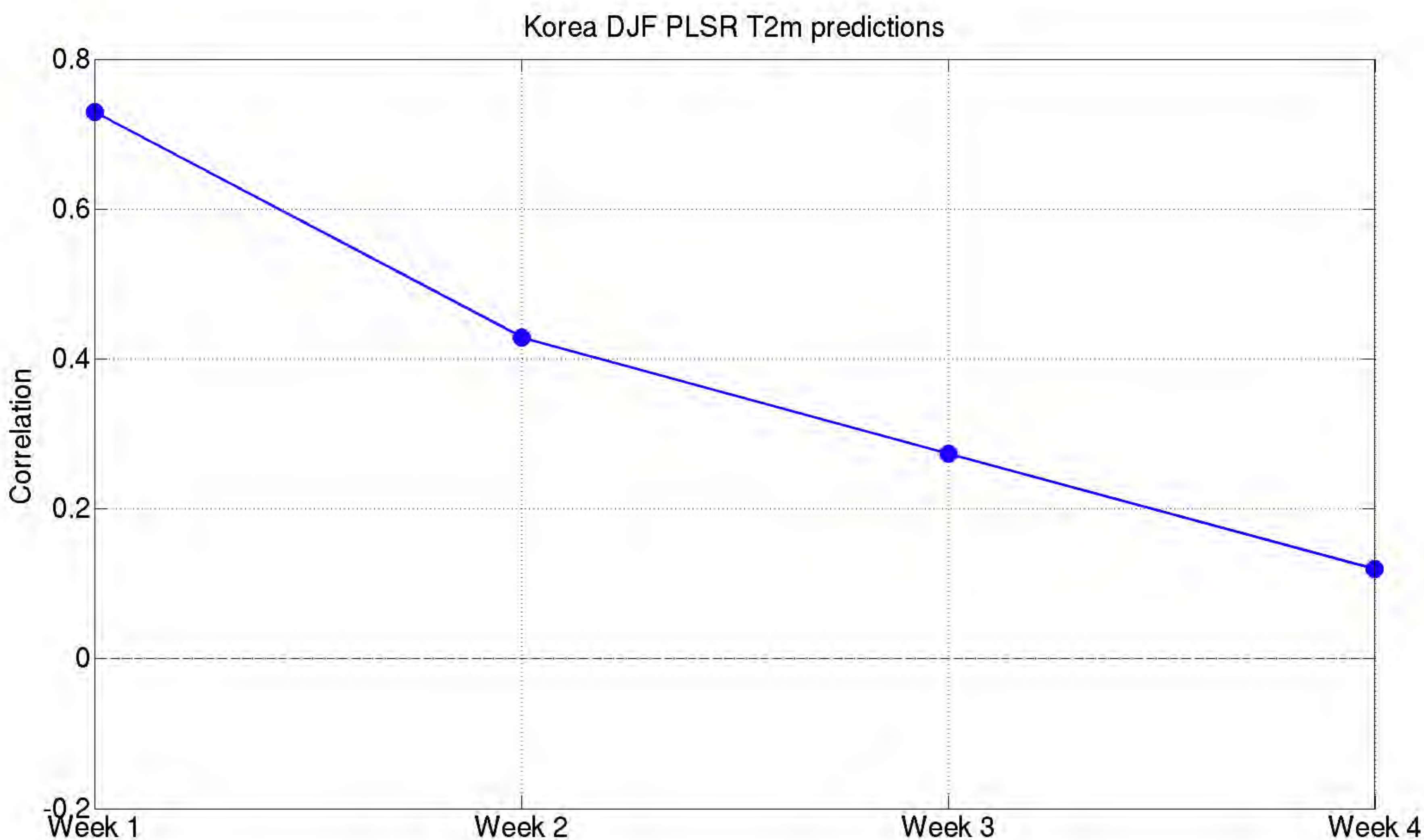


Tropical cyclone intensity



Conclusions

- A recent emphasis on subseasonal prediction for lead times beyond two weeks has resulted in the push to develop new forecast products in the U.S.
- An empirical MJO/ENSO-based statistical model has undergone successful transition to operations in NOAA CPC's Experimental Week 3-4 Outlooks and has become a key component of the forecasting process.
- Partial least squares regression (PLSR) models have been constructed to produce skillful forecasts of the PNA, NAO, and AO indices out to ~5 weeks.
- Preliminary work using similar statistical approaches suggests that there may be "forecasts of opportunity" in weeks 3-6 over East Asia.



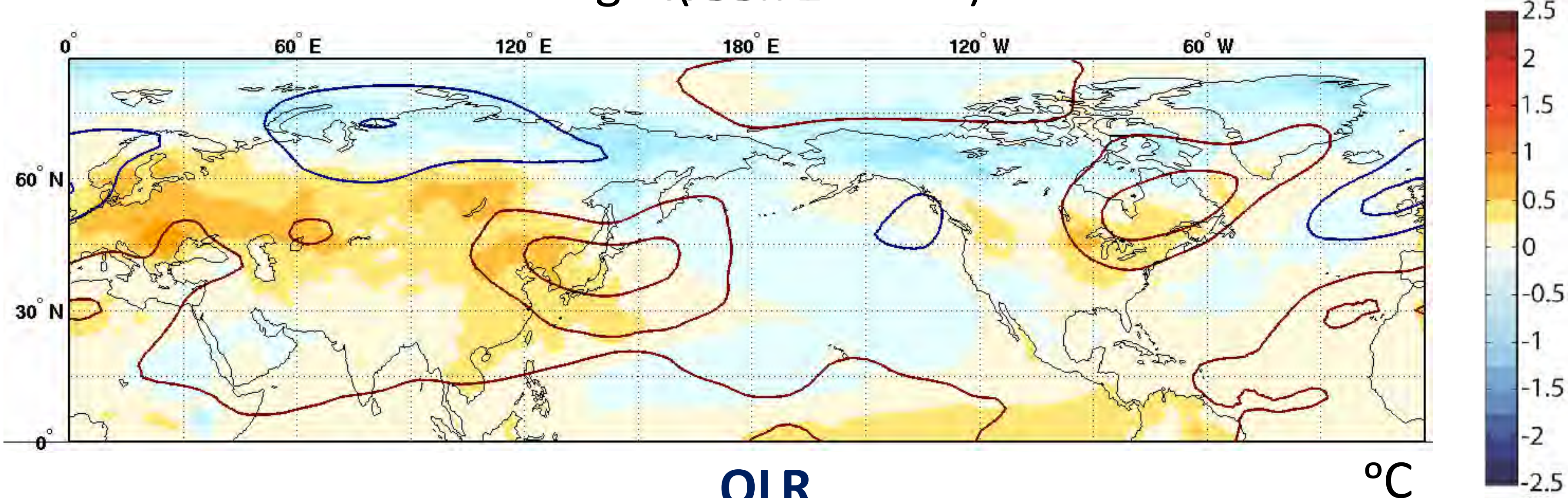
Korea DJF PLSR T2m predictions
Correlation
0.8
0.6
0.4
0.2
0
-0.2
Week 1
Week 2
Week 3
Week 4

DJF week 3 z500 predictor pattern for Korean temperature

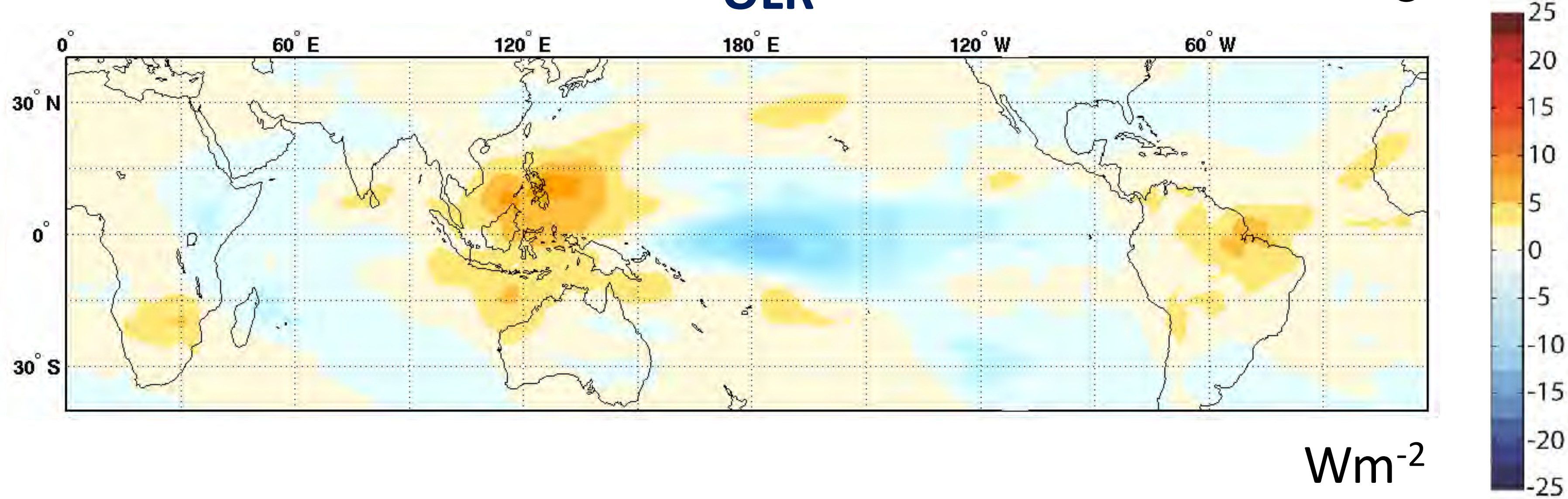
z500 (CI = 5m) and T2m (color shading)

Lag 0 (Initialization)

Week 1



OLR

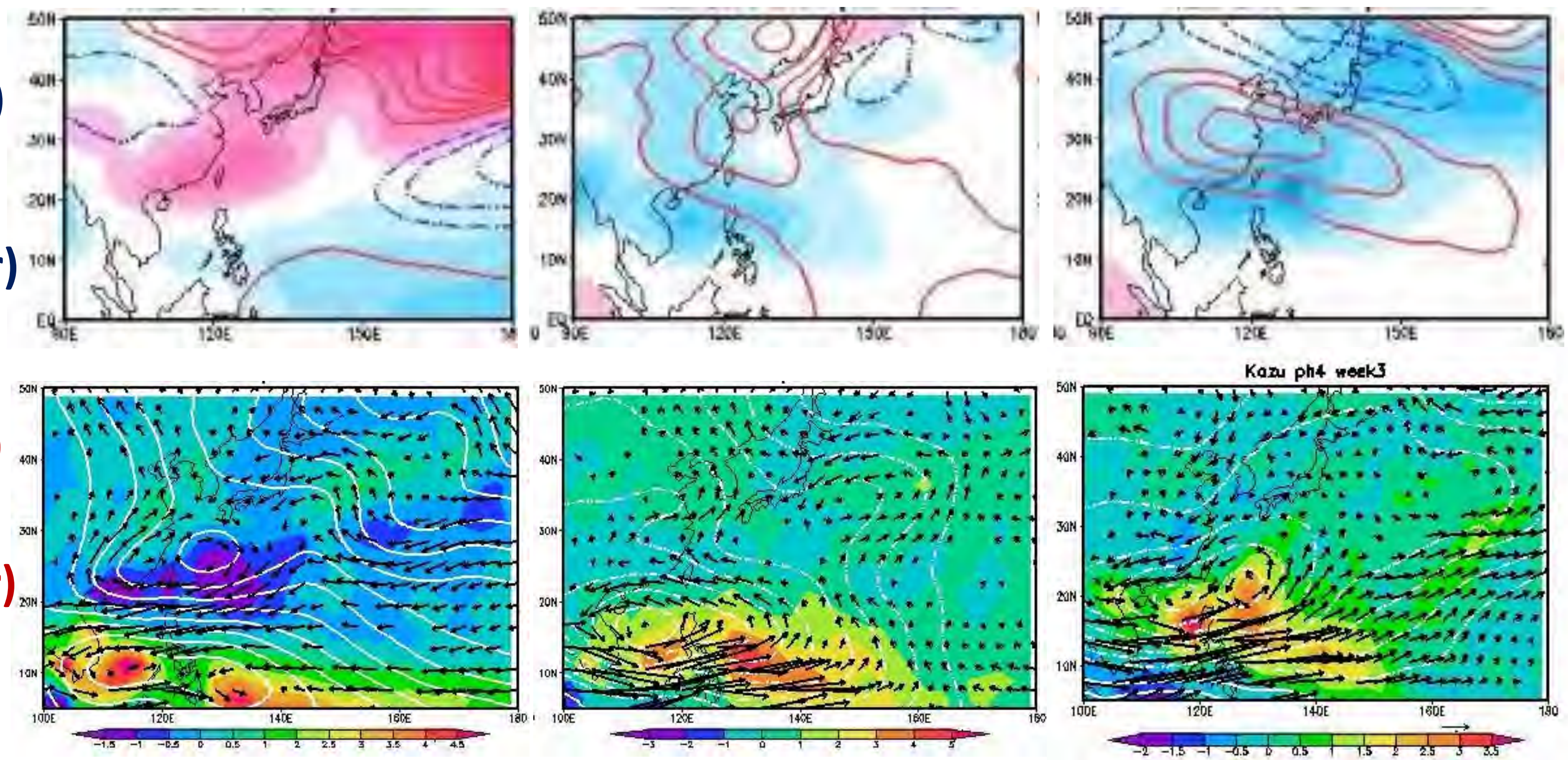


Composite evolution: **BSISO phase 4**

Week 1 **Week 2** **Week 3**

z850 (shaded)
z300 (contour)

precip (shaded)
ψ850 (contour)
u,v850



Kikuchi et al. (2012) index