ESTIMATION AND CORRECTION OF SYSTEMATIC MODEL ERRORS IN GFS

DEPARTMENT OF
ATMOSPHERIC &
OCEANIC SCIENCE

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Goals

(i) Estimate the model deficiencies in the GFS that lead to systematic forecast errors

(ii) Implement an online correction (i.e., within the model) scheme to correct GFS following the methodology of Danforth and Kalnay, 2008.

(iii) Provide guidance to optimize design of subgrid-scale physical parameterizations. The empirical correction scheme can then be replaced by these.

Motivation

SYSTEMATIC FORECAST ERROR IN GFS

SYSTEMATIC MODEL ERRORS

Forecast Errors

Numerical weather prediction models are limited by errors in model forecast resulting from

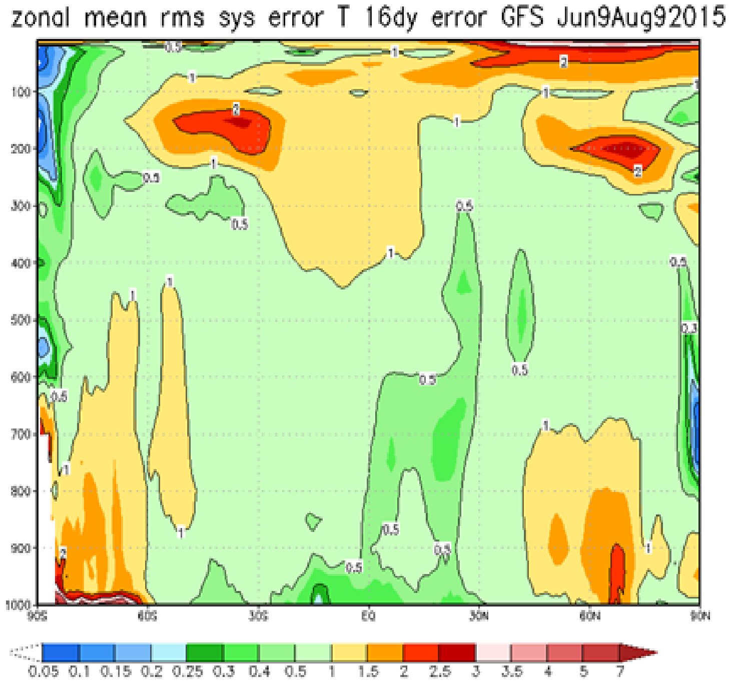
- Model bias
- Inaccuracies in initial condition

- **Forecast MSE**
  - **Systematic component** $(\overline{x_f} - \overline{x_t})^2$
    - **Model Bias**
    - **Observation bias**
  - **Random component** $\overline{(x'_f - x'_t)^2}$
    - **Analysis Errors**
    - **Chaotic growth**

Initially small, but as the model is integrated in time the errors grow and interact nonlinearly with systematic and random errors until the model loses all forecast skill.

Systematic Forecast Errors in GFS

- Systematic forecast errors are a significant portion of the total forecast error in weather prediction models, such as the Global Forecast System (GFS).



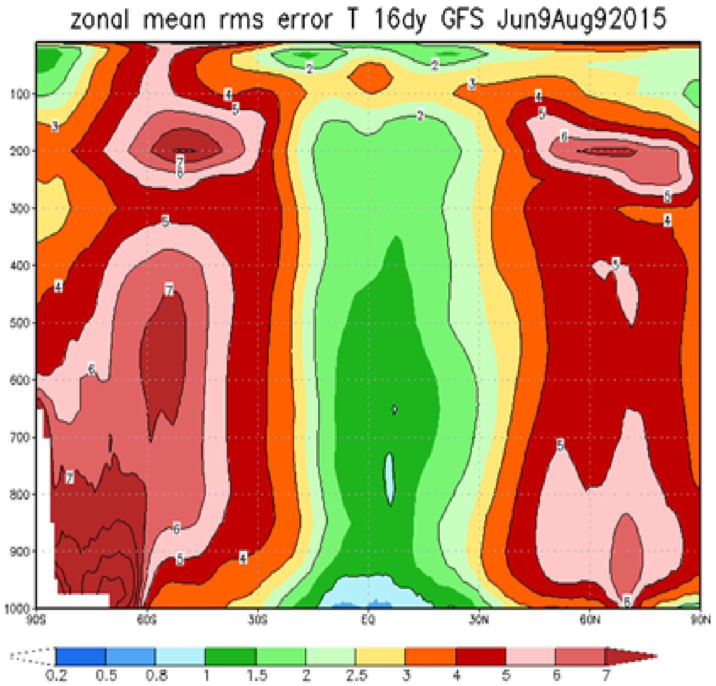


Figure 1. Zonal mean RMS systematic error (left) and total error (right) in temperature after 16 days. The range of temperature systematic errors is ~1/3 of total temperature error range after 2 weeks. (Courtesy of Dr. Glenn White).

Characterizing model error (after Danforth and Kalnay, 2008)

Our goal is to estimate the three components of the systematic error

$$x_m^e = b + \sum_{l=1}^{L} \beta_l(t) e_l + \sum_{n=1}^{N} \gamma_n(t) f_n + x_m^{rand}$$

Constant term: Time mean

Random Error

Periodic errors described using leading EOFs

State-dependent model error given by the leading SVD modes f_n of the covariance of the coupled model state anomalies and corresponding error anomalies

Past Studies

CORRECTION SCHEMES

Correction Schemes

OFFLINE CORRECTION SCHEME

- Apply a statistical correction for each forecast length after the forecast is completed
- Allow forecast errors to grow until the end of the forecast cycle
- Physical origin obscured as errors grow non-linearly after short time

ONLINE CORRECTION SCHEME

- Estimate and correct the bias during the model integration
- Continuously corrected forecasts at all lead times
- Reduces non linear error growth of bias
- Large forcing might disturb physical balance of model variables

Previous Studies (Online vs Offline)

Johansson and Saha (1989)	• Both methods removed systematic model errors • Online method reduced random errors significantly
Saha (1992)	• Online method performs as well as offline but doesn't reduce random errors
Li et al. (2009)	• Online bias removal with additive noise enhance the performance of LETKF, outperform the inflation schemes • Performs well in data sparse regions
DelSole et al. (2008)	• Online method reduced systematic model errors • Postulated that it is impossible to reduce random errors in realistic systems

Previous studies … (Danforth & Kalnay 2007, 2008ab)

Methods Used

- Time averaged analysis correction: the average correction that the observations make on the 6hr forecast

$$\dot{x}(t) = M[x(t)] + \frac{\overline{\delta x_6^{ai}}}{6\ hr}$$

- Periodic component correction (diurnal correction): linearly interpolated leading EOFs (low dimension approach)
- State dependent correction: introduced new method using SVD of coupled analysis correction and forecast state anomalies (low dimension approach)

Results

- Online correction performance was slightly better than the operational statistical method applied a posteriori
- Correcting bias also reduced random errors

Proposed Method for GFS

ESTIMATE MODEL DEFICIENCIES IN GFS WITH AN. INCREMENTS

CORRECT GFS ONLINE FOR MODEL DEFICIENCIES

Estimation of model deficiencies

- Model biases are estimated from the time average of the 6-hr analysis increments (AIs)
- AIs are the difference between the gridded analysis and forecast: the corrections that the observations make on the 6-hr forecasts

$$\boldsymbol{\delta x_{ai}^{6} = x_a^6 - x_f^6}$$

Time mean

- Estimate seasonal model bias as the seasonal average (DJF, MAM, JJA, and SON) of the AIs for surface pressure, temperature, winds and specific humidity during the five years 2012-2016

Periodic Component: periodic AIs at sub-monthly scales

- First calculate the anomalies of the 6-hourly AIs with respect to their monthly averages
- Decompose these anomalies into a complete set of 120 Empirical Orthogonal Functions (EOFs) and corresponding principal component time series

Correcting GFS online for model deficiencies

- Plan to follow the methods comprehensively developed by Danforth and Kalnay [DKM07; Danforth and Kalnay, 2008(GRL) and Danforth and Kalnay, 2008(JAS)]

$$\dot{\boldsymbol{x}}(\boldsymbol{t}) = \mathbf{M}[\mathbf{x}(\boldsymbol{t})] + \frac{\overline{\boldsymbol{\delta x_{ai}^{6}}}}{\boldsymbol{6-hr}}$$

- Correcting diurnal and semi-diurnal bias using low dimensional estimate

$$\sum_{l=1}^{N} \boldsymbol{\beta_l(t) e_l}$$

  - e_l : leading EOFs from the anomalous error field (time independent term)
  - β_l : time dependent amplitude, estimated by averaging over the daily cycle in the training period
  - N : number of leading EOFs

Preliminary Results

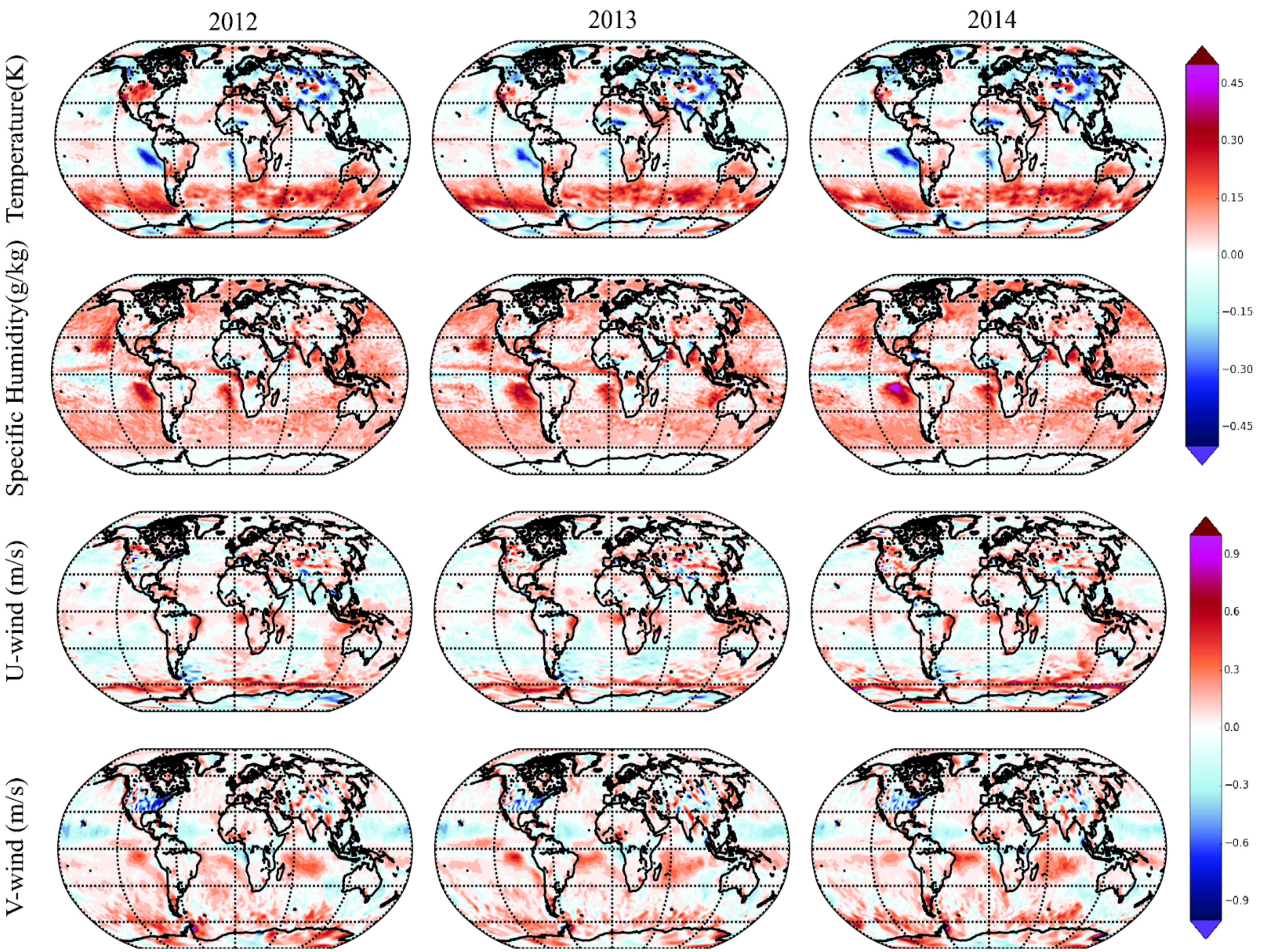
SEASONAL BIAS ESTIMATION

PERIODIC BIAS ESTIMATION

Seasonal Bias Estimation

- Significant biases that are **geographically anchored** with **continental scales** in the GFS.
- Despite major changes made to the data assimilation scheme in May 2012, the **bias corrections retain their major features throughout 2012 to 2014**

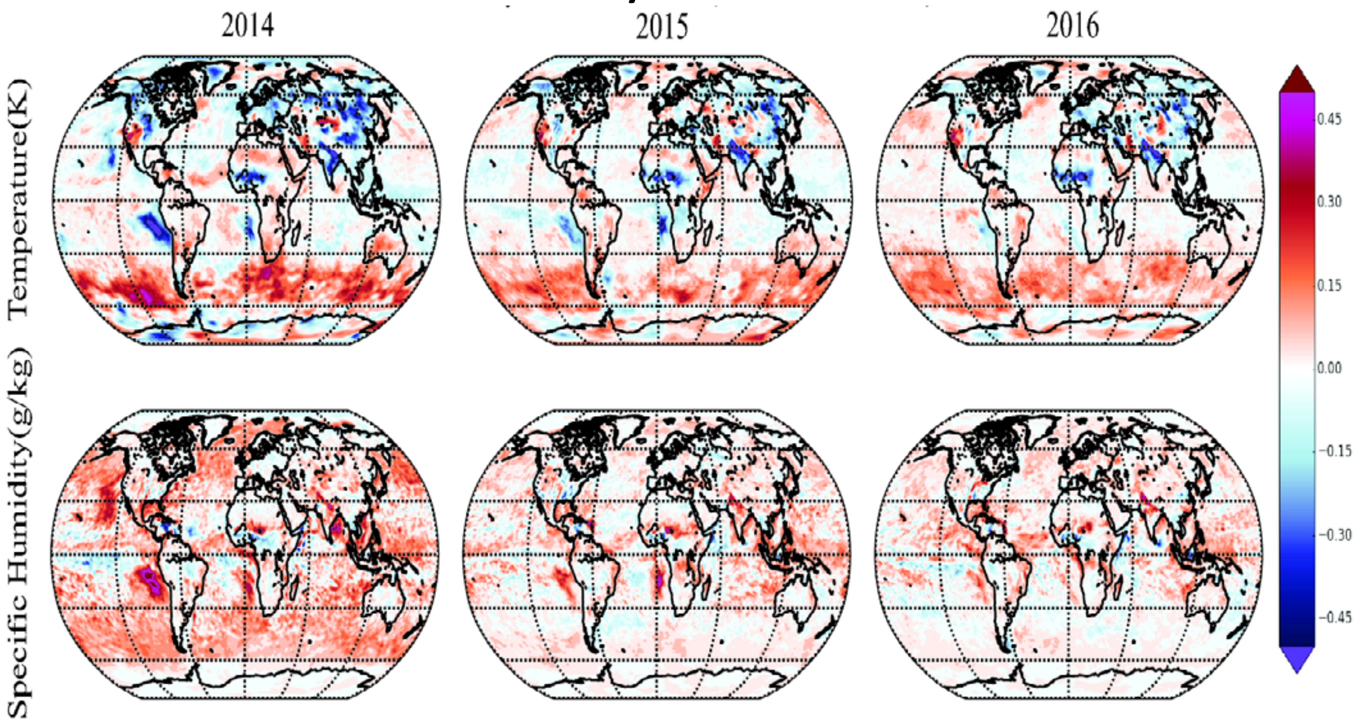
JJA mean 6-hr Analysis Increment at ~850mb



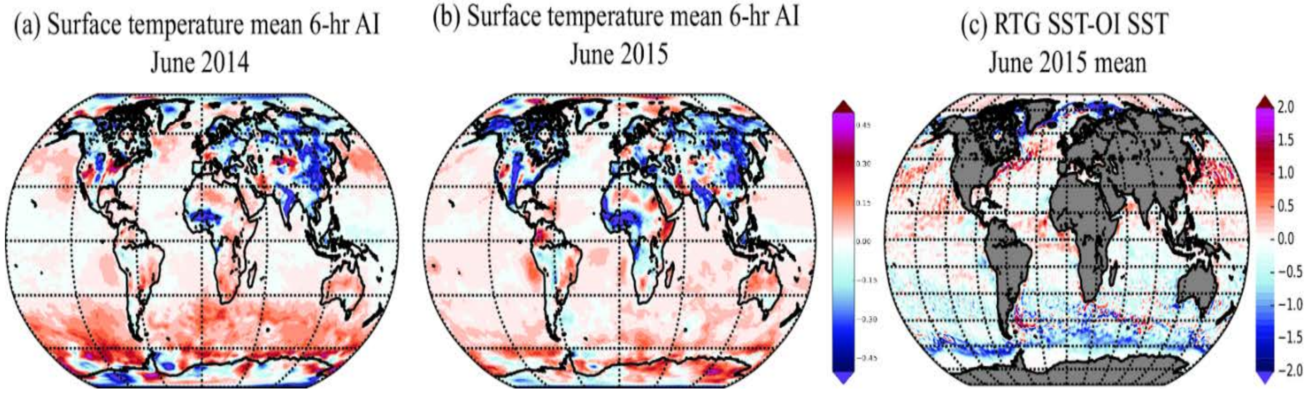
Seasonal Bias Estimation …

- Amplitude of the bias **declines in 2015, especially over the ocean**
- In north, the reduction might be due to change in the SST boundary condition
- In south, the reduction in bias is due to updating of the Community Radiative Transfer Model and improvements in radiance assimilation
- Bias represented by AIs over oceans in 2012-2014 also arise from bias in prescribed SSTs

JJA mean 6-hr Analysis Increment at ~850mb



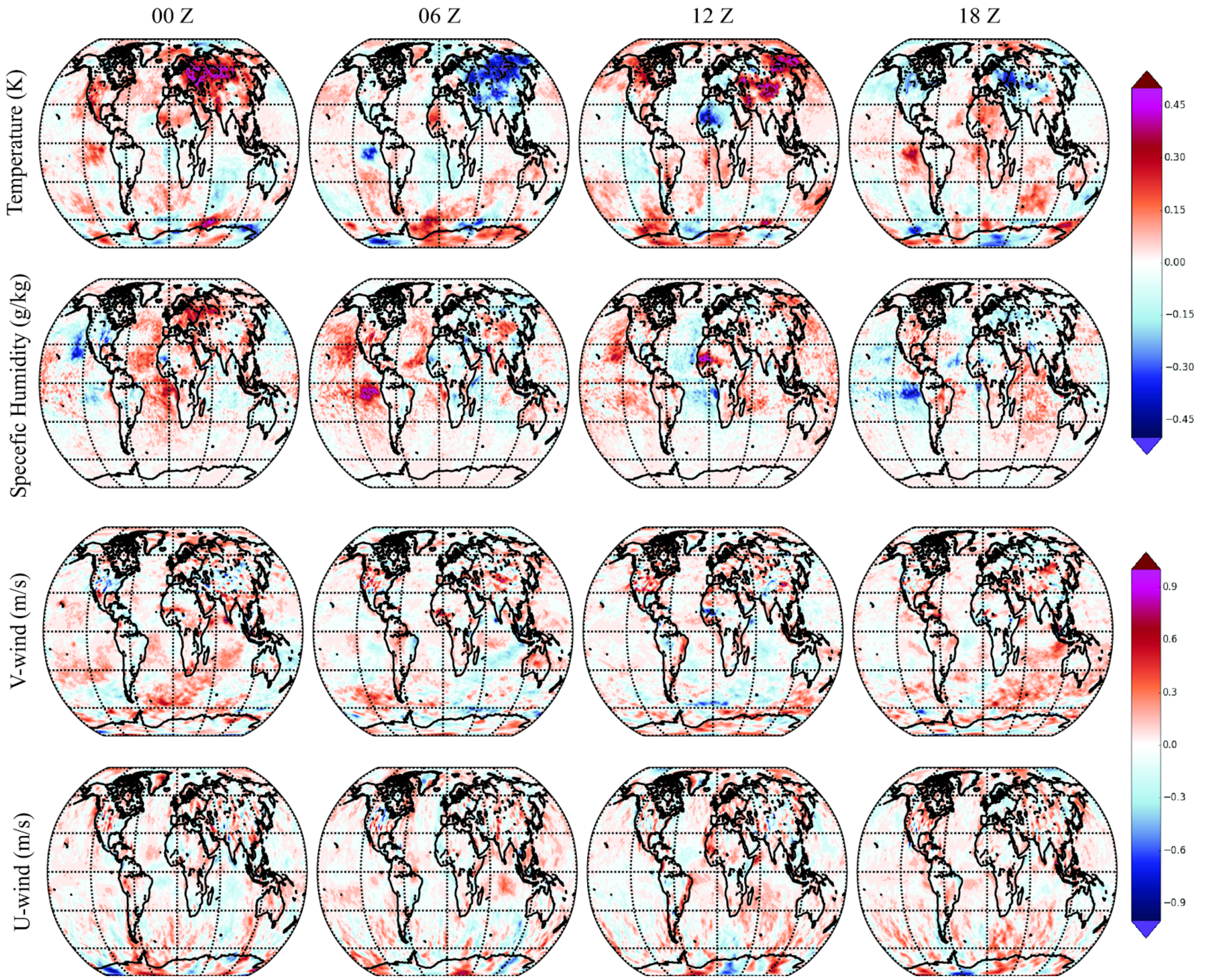
Change in surface air temperature mean bias, June 2014 (a) - June 2015(b) and the difference in RTG and OI SST (c).



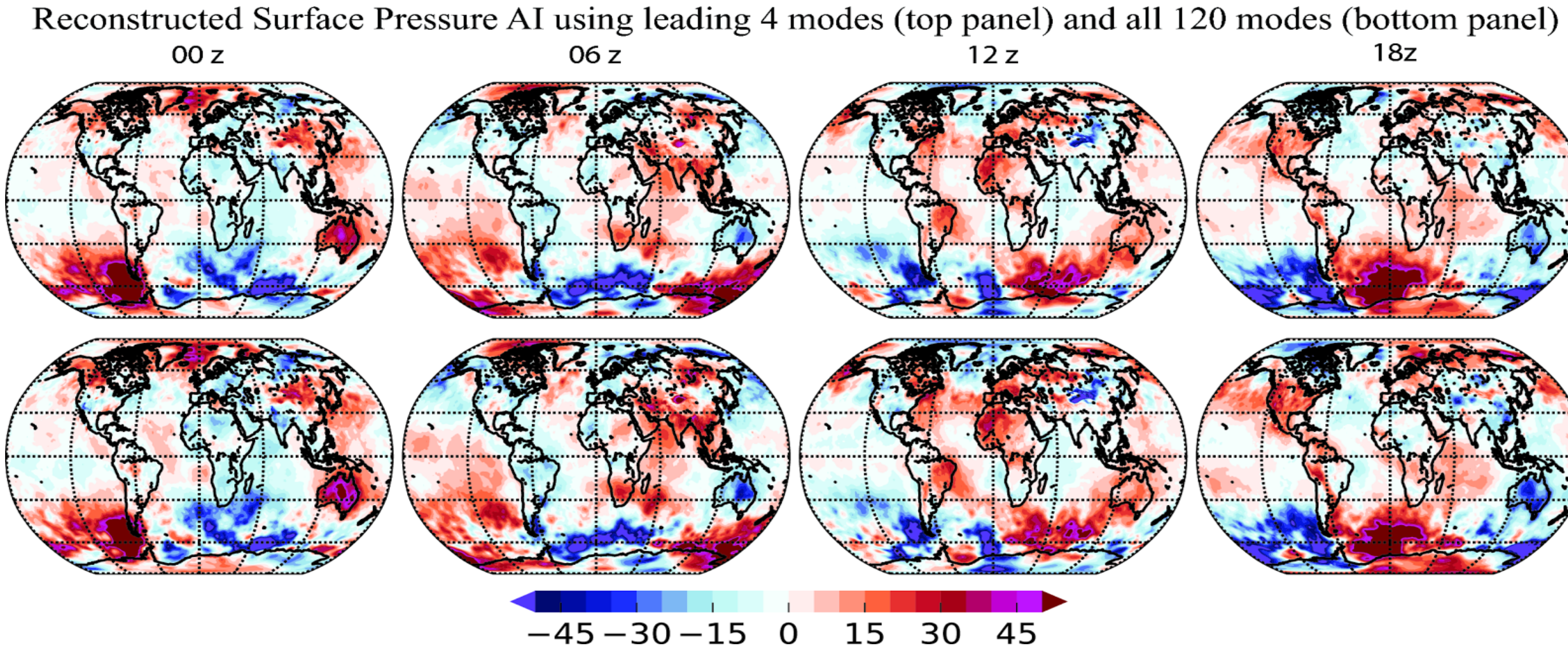
Periodic Bias Estimation

- Large **diurnal component** moves westward following the motion of the Sun. Also a significant **semi-diurnal signal**
- **Amplitude comparable to the seasonal bias**, thus making correction of diurnal and semi-diurnal bias is also critical

JJA 2014 mean 6-hr AI at ~ 850 mb



Periodic Bias Estimation: EOF Analysis



Periodic Bias Estimation: EOF Analysis

The errors in diurnal cycle represented with the first four modes are almost indistinguishable when compared with all (120) modes

Proposed Future Work

WORK PLAN

TIMELINE FOR COMPLETION OF DISSERTATION AND PUBLICATIONS

Work Plan

- Results for bias estimation in GFS support the application of the approaches used by DKM07.
- Two challenges that now arise when using them for online correction :

1. <u>Accounting for contributions of observation biases to the AIs.</u>

- AIs should be adjusted for observation biases before using them to correct the model bias.
- Erroneously correcting the model for an observation bias should result in an increase of the AI’s, this should help differentiate model and observation bias

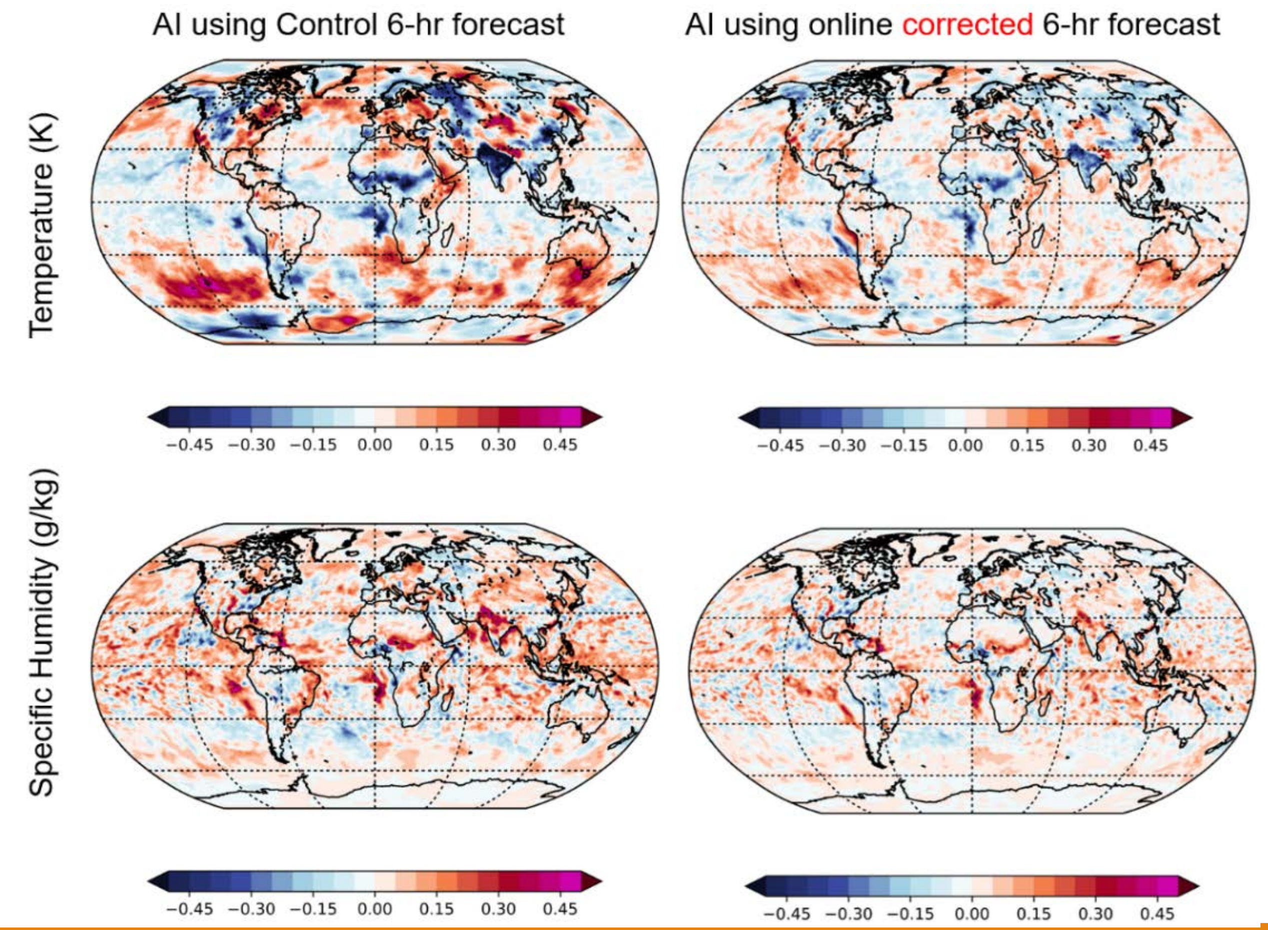
2. <u>How to utilize the past estimates to correct present models?</u>

- Plan to use the successful approach of Greybush et al. [2012], who used the rolling mean of a limited number of past AIs (e.g., the past 21 days) to correct the model online.

Utilize the past estimates to correct present models : Preliminary application

- **Training period** : rolling average for the past 21 days.
- **Spatial resolution :** T670L64
- **Temporal resolution**: Output every 6 hours until 5-day forecast.
- Forecasts initialized every 6 hours from June 1, 2015 to June 14, 2015 using the analysis from the control run.

Two week average 6-hr AIs for first 2 weeks of June 2015



Work Plan

Apply Online Correction

- Apply the same corrections to the winds and surface pressure
- Correct periodic bias (diurnal and semidiurnal errors)

After Online Correction

- Compare forecast bias improvement with statistical bias correction made *a posteriori*.
- Check whether reducing the mean and periodic bias also reduces forecast random errors during their nonlinear growth.
- Apply this method to FV3 to provide simple verification tool to optimizing physical parameterizations
- Work with EMC scientists on using the Analysis Increments as an efficient tool to facilitate testing impacts of new parameterizations on FV3.

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Thank You