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An Assessment of Subseasonal Forecast Using Extended Global Ensemble Forecast System (GEFS)

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1. Introduction

The National Oceanic and Atmospheric Administration (NOAA) is increasing its efforts to improve a numerical weather guidance for the sub-seasonal timescale. The National Centers for Environmental Prediction (NCEP) Climate Forecast System Version 2 (CFSv2; Saha *et al.* 2014) provides operational global numerical guidance at sub-seasonal and seasonal scales. Extending the NCEP Global Ensemble Forecast System (GEFS) to 35 lead days, however, enhances NCEP's subseasonal prediction capability since the GEFS has higher model resolution, a more frequent model upgrade cycle, improved stochastic physics perturbations and a larger ensemble size than the CFSv2.

In this study, four GEFS experiments (or configurations) are performed to help quantify the impacts of improved stochastic physics, boundary SST forcing and new scale-aware convective parameterization on sub-seasonal forecast skill for 500 hPa geopotential height and the Madden-Julian Oscillation (MJO). Furthermore, the impact of reforecast-based statistical post-processing on the sub-seasonal forecast skill of 2-m temperature is examined.

2. Methodology

In this study, the GEFS integration is extended from 16 days to 35 days. For days 0-8 and 8-35, the GEFS has a spectral resolution of TL574 (approximately 34 km) and TL384 (approximately 52 km), respectively, with 64 hybrid vertical levels. The operational version of GEFS has 20 perturbation members and 1 control member. The initial perturbations are selected from the operational hybrid Global Data Assimilation System (GDAS) 80-member Ensemble Kalman Filter (EnKF; Whitaker *et al.* 2008, Wang *et al.* 2013).

Of all four GEFS 35-day experiments, the control experiment (CTL) uses the same configuration as the operational GEFS (Zhou *et al.* 2017) except it is extended from 16 days to 35 days. The Stochastic Total Tendency Perturbation (STTP; Hou *et al.* 2008) scheme is used to represent the model uncertainty. The SST forcing in this experiment is initialized with the Real Time Global (RTG) SST analysis and damps to an analysis climatology at a 90-d e-folding rate (Zhu *et al.* 2017).

The second experiment replaces the STTP with the Stochastic Kinetic Energy Backscatter (SKEB; Shutts 2005), Stochastically Perturbed Parameterization Tendencies (SPPT; Buizza *et al.* 1999) and Stochastic Perturbed Humidity (SHUM; Tompkins and Berner 2008) schemes, collectively known as SPs, while keeping the boundary SST forcing unchanged. The third experiment uses SPs and replaces the operational configuration of the SST forcing with a bias corrected CFSv2 predictive SST, which considers the day-to-day evolving state of the SST with respect to lead time (Zhu *et al.* 2017). This particular kind of SST forcing is known as a "two-tiered SST". The first tier means the output is from a coupled model forecast while the second tier means that SST is prescribed to an uncoupled model. The fourth experiment uses SPs, updated SST and replaces the operational convection scheme with a new scale-aware convection scheme (Han *et al.* 2017). In addition to the experiments using an uncoupled forecast system, the current stage of the fully coupled CFSv2 is also compared to these four GEFS experiments. The CFSv2 consists of 4 members, but 12 lagged members are added so that the ensemble size is more consistent with GEFS.

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These four experiments are each initialized every 5 days from May 1st, 2014 to May 26th, 2016. MJO is also evaluated from these four experiments using the traditional real-time multivariate (RMM) MJO index (WH index; Wheeler and Hendon 2004; Gottschalack *et al.* 2010). The MJO skill is calculated using the bivariate anomaly correlation between the forecast and analysis RMM1 and RMM2 (Lin *et al.* 2008; Li *et al.* 2018).

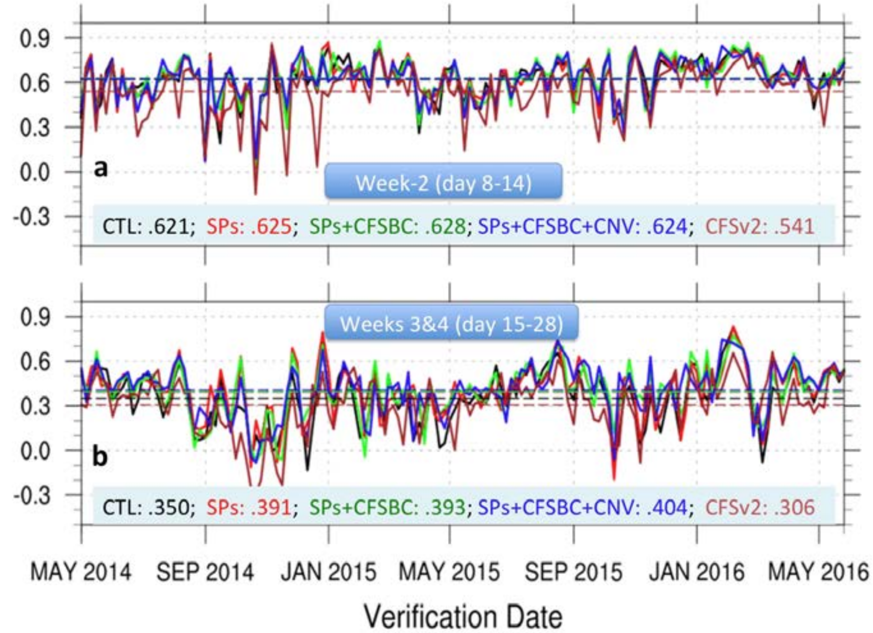

Fig. 1 Pattern Anomaly Correlation (PAC) for Northern Hemisphere 500 hPa geopotential height for lead (a) week 2 and (b) weeks 3&4. CTL is black, SPs is red, SPs+CFSBC is green, SPs+CFSBC+CNV is blue and CFSv2 is brown with period average PAC scores for each configuration (numbers in the bottom of each plot with different color).

Near-surface variables such as 2-m temperature are challenging to forecast on subseasonal scales, since enhancing stochastic physics, SST and convection has minimal effect on improving the performance (Zhu *et al.* 2018). Therefore, 2-m temperature needs to undergo statistical post-processing (Guan *et al.* 2018). In this study, 11-member 2-m temperature reforecast data with the same configuration as the fourth experiment from 2011 to 2015 is used to calibrate 2016. The reforecasts within this period are initialized once per week with the Global Data Assimilation System (GDAS). A climatological mean forecast error calculated from this reforecast dataset is used to calibrate 2-m temperature (Guan *et al.* 2018). A 31-day window is used and centered on each day being considered to calculate the reforecast climatology (Guan *et al.* 2015; 2018).

3. Results

3.1 500 hPa height forecast skill

Anomaly correlation is used to measure the potential skill of the 500 hPa geopotential height. For lead week 2 over the northern hemisphere, combining SPPT, SKEB and SHUM demonstrate an increase in the potential skill (Fig. 1). Updating the bias-corrected SST and the scale-aware convection scheme further enhances the anomaly correlation. Furthermore, all four GEFS experiments perform better than the CFSv2 over the northern hemisphere. Therefore, improving the representation of the the stochastic physics, SST and convection in GEFS outperforms the current stage of CFSv2.

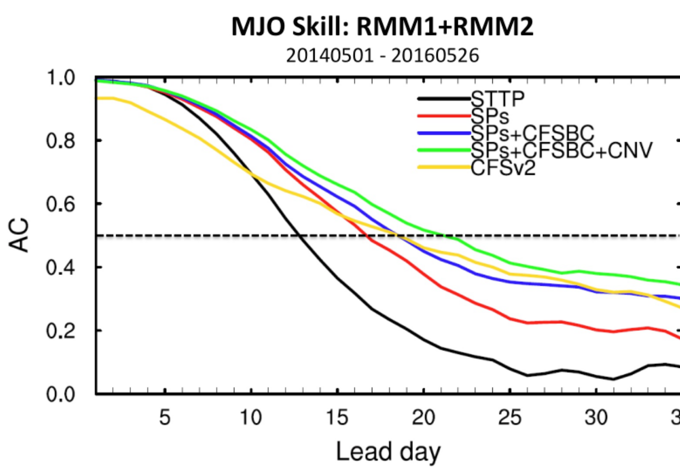

Fig. 2 MJO forecast skill as a function of lead time for the period of May 1st, 2014 to May 26th, 2016.

3.2 MJO forecast skill

MJO is the dominant mode in sub-seasonal variability in tropics. As such, the performance of the MJO in the forecast system is evaluated. The MJO skill over the 2-year period shows that SPs outperforms STTP

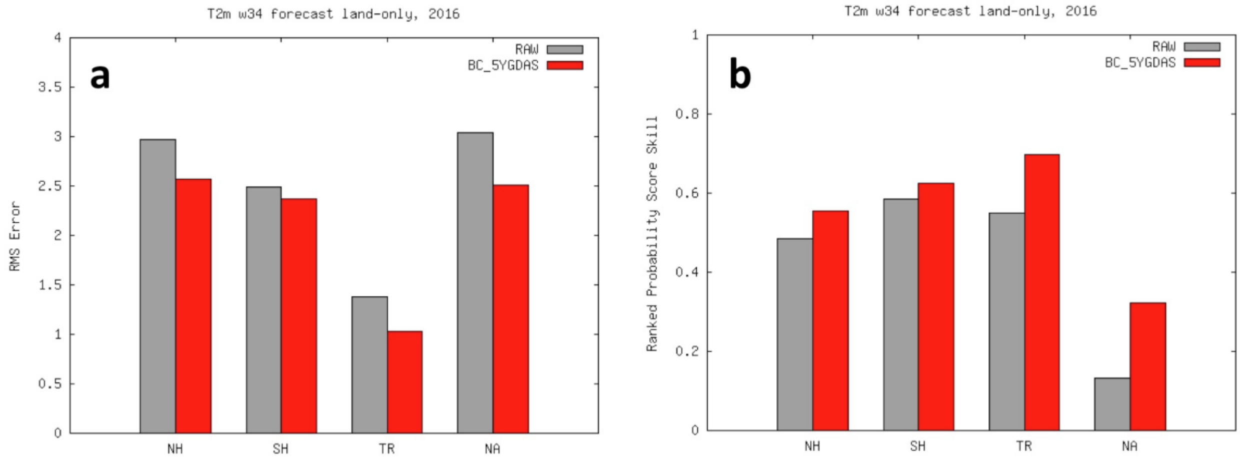

Fig. 3 Raw (grey) and calibrated (red) regional 2-m temperature (a) RMS Error and (b) RPSS. (a,b) are averaged temporally and spatially over a 1-year period and over each region (land only) for weeks 3&4, respectively.

(CTL; Fig. 2). The CTL and SPs remain to have a skillful MJO forecast for 12.5 lead days and 16.8 lead days, respectively (AC ≧ 50%). Adding a bias-corrected SST to SPs reaches a skill around 19 days. When combining SPs, the bias-corrected SST and the scale-aware convection, the MJO skill of SPs+CFSBC+CNV (21.5 days) exceeds the MJO skill of CFSv2 (19 days).

3.3 2-m temperature calibration

Calibrating the 2-m temperature using the reforecast bias method shows substantial improvement over all domains (land only) for the week 3-4 lead time (Fig. 3). The North America (land only) RMS error and RPSS (Ranked Probabilistic Skill Scores) benefit the most from the calibration. These improvements in 2-m temperature demonstrate the importance of using reforecast information for calibration.

4. Summary

The NCEP GEFS has been extended from 16 to 35 days to predict sub-seasonal timescales. It has been found that improving the stochastic physics perturbations, using a predictive SST and a scale-aware convection scheme substantially improves the extra-tropics forecast and MJO skill for the sub-seasonal scales, without degradation of weather forecast. The GEFS has also outperformed the CFSv2 in the extratropical and MJO skill.

Although updating the model configuration improves 500 hPa height and MJO prediction, surface variables such as 2-m temperature require statistical postprocessing in order to be significantly improved. In this study, reforecast information is used to calibrate 2-m temperature. The fourth configuration generally has the best performance, and therefore is used for the extended GEFS forecast configuration with 18 years hindcast to support the SubX project. It has been found that using the GEFS reforecast information for bias correction has greatly improved the 2-m temperature, which demonstrates the high value of using reforecast information for calibration.

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