Stochastic Representation of NCEP GEFS to Improve Subseasonal Forecast

Contribute to the book of
Current trends in the Representation of Physical Processes in Weather and Climate Models
Editors: David A. Randall, J. Srinivasan, Ravi A. Nanjundiah, P.Mukhopadhyay

Yuejian Zhu, Wei Li, Xiaqiong Zhou and Dingchen Hou

Environmental Modeling Center
NCEP/NWS/NOAA

(Version 1.0 – Feb. 7 2018)

1. Introduction

With the improvement of accuracy of weather forecasting and the increasing computational capacity, a seamless forecast that range from weather to seasonal time scale is in growing interest and demanding in general public and service sectors in order to protect life and properties. Extending the weather forecast to cover sub-seasonal time scale clearly has great socio-economic significance. However, in scientific aspect, improving the forecast skill on this time scale is quite challenging. This gap in the forecast skill between weather and climate is partially due to the limitation of forecast predictability (Lorenz 1969) and less sensitivity to the initial condition which benefits the weather scale yet insufficient sensitivity to the boundary and external forcing which benefits the seasonal and longer lead time (Vitart 2014, Johnson et al. 2014; Liu et al. 2016; Troccoli 2010; Tian et al. 2017). Imperfectness of the representation of the model dynamics and physics, however, should be considered as the major source of uncertainties and errors for all lead time (Buizza and Palmer 1999). The approaches that aim to reasonably represent the model uncertainty thus become a practical method to reduce the model errors in recent years. The efforts in this regards include a multi-model ensemble method (Shin and Krishnamurti 2003; Palmer et al. 2004; Kirtman et al. 2014) that represents the overall uncertainty from different models; a stochastic total tendency perturbation method (STTP, Hou et al. 2008) that represents the uncertainty related to both dynamic and physics in single model; a stochastic physics perturbation tendency scheme (SPPT, Buizza et al 1999; Palmer et al. 2009) that represents the uncertainty related to toal model physical process; In addition to the stochastic perturbation on the tendency, Stochastic Kinetic Energy Backscatter (SKEB, Shutts and Palmer, 2004; Shutts 2005; Berner et al. 2009; Shutts et al. 2015) is another way to present forecast uncertainty through considering the energy at non-resolved scales which can not cascade to larger scales due to the model's finite resolution. All these methods have been in used in operational centers and research community (Palmer et al. 2009).

Since was implemented into operation in 1992, the NCEP GEFS has been widely used as probabilistic forecast guidance for the forecast within 2 weeks (Zhou et al, 2017). Regardless of the initial perturbation, the operational version of GEFS uses STTP to represent the model uncertainty. With the contribution of both initial uncertainties and perturbation in total tendency, the ensemble mean forecast of GEFS has been outperformed the GFS deterministic forecast on the anomaly correlation of forecast lead at Day-8 of Northern Hemisphere 500hPa geopotatial height to represent mid-level general circulation for past few years (Fig.1).

2. Stochastic Physics Perturbation schemes tested in NCEP GEFS 35-day forecast

To be aligned with NOAA's mission of generating an unified coupled forecast system to cover the time scale from weather to seasonal, GEFS has carried out investigations on the strategy to potentially improve the forecast skill on week 3&4 time range (sub-seasonal time-scale), and further to cover monthly forecast. A recent investigation is testing the impact of different stochastic perturbation schemes that represent the model uncertainty on the performance of sub-seasonal forecast (Zhu et al. 2017; Zhu et al. 2018; Li et al. 2018)). The motivation for this work came from the concerns of the under-dispersion (or overconfidence) of the current operational version of GEFS (GEFS v11 with EnKF initial perturbation + STTP) on medium range forecast especially over the tropics (Hou et al, 2008, Zhou et al. 2016, 2017).

Although STTP scheme compensates the less error growth from initial perturbations to some degree, the impact of the STTP is mainly over extra-tropics during boreal winter season with less impact on the spread over tropical region. It is well known that MJO is a major source of the predictability on sub-seasonal time scale. Therefore, to improve the representation of the model uncertainty over tropics is a possible pathway to potentially improve this source of sub-seasonal predictability. A suite of three widely accepted stochastic perturbation methods (SPs hereafter) are thus applied to GEFS to represent the model uncertainty instead of STTP more efficiently (Table 1, second row). The scheme of SPs are SKEB with consideration of making up sub-scale energy lost due to imperfect computation algorithms; SPPT with five different spatial and temporal scales (Fig. 2); and 3) Stochastic Perturbed Humidity (SHUM; Tompkins and Berner, 2008) with single spatial-temporal scale, and near model boundary layers. These schemes have already been implemented in the National Center Environmental Prediction (NCEP) Global Forecast System (GFS) model for use in the hybrid-EnKF data assimilation system, making them readily available for use in the GEFS. A detail descriptions of these schemes are as following.

The SKEB scheme has been used to represent dynamical uncertainty from subgrid-scale processes that propagate upscale. This is done via a stream function forcing based on the total dissipation rate. Unlike other implementations of SKEB, the GFS implementation of SKEB only considers numerical dissipation (i.e. the diffusions). Perturbations are generated independently on each vertical level, and then vertically smoothed to provide some vertical coherence. The inclusion of SKEB improves the power spectrum of the global model, which otherwise exhibits damped power near the truncation frequency.

The SPPT scheme perturbs the combined tendencies of wind, temperature, and water vapor in each time step produced by the GFS all physics parameterizations (excluding clear-air radiation). Our implementation of SPPT combines five different random patterns with different correlation length scales and/or time scales to determine the perturbations. The patterns are uniform in the vertical, except they are reduced in magnitude near the surface and taper to zero near and above the tropopause. The maximum amplitudes of five scales are 0.8, 0.4, 0.2, 0.08 and 0.04 respectively. An example of the individual independent scale random patterns and combined 5-scale random pattern is shown in Fig. 2.

The SHUM scheme only perturbs the near-surface humidity state; based on the idea that uncertainty in humidity can have nonlinear impacts as thresholds in physical parameterizations are crossed (e.g., convective initiation). SHUM uses the same random pattern generator as SPPT, but only a single spatial-temporal scale is used with maximum amplitude of 0.006. The perturbation is a maximum in the lowest model level and decreases exponentially with height. However, it's impact transports rapidly to upper level of troposphere.

To understand the contributions of each stochastic scheme in SPs and STTP, figure 3 shows the impact of the individual stochastic schemes on ensemble spread at 120 hours (average of 6 spring cases and 6 fall cases) when compared to ensemble spread without introducing stochastic perturbations (noSP, top row). The stochastic system used in the control (same as operational GEFS with STTP), produces additional spread in the extratropics but has little impact in the tropics (row 2). Of the components in the stochastic physics suite, SKEB produces additional spread in similar areas as STTP (though slightly muted; row 3). The other two components, SPPT (row 4) and SHUM (row 5), both increase spread in the tropics where the control system is deficient. SPPT also has an impact in the spring/summer hemisphere. In combination, these stochastic schemes generally improve forecast uncertainty, particularly in the tropics, which may lead to improvements in tropical forecast skill.

Apparently, the SPs (combined three stochastic schemes) presents forecast spread globally, especial for tropical area when compares to NCEP operational GEFS solo stochastic scheme (STTP). The statistical scores for tropical zonal winds of 850hPa and 250hPa show huge improvements from introduced SPs for 2 years experiment periods (figure 4). For both of upper and lower atmosphere levels, increased forecast spread does also result in the reduced forecast error (root mean square error - RMSE; left plots of figure 4); and higher continuous ranked probability skill scores (CRPSS; right plots of figure 4). Moreover, the spreads are more closed to forecast errors (left plots of figure 4) indicates representation of forecast uncertainty is more realistic than current operational GEFS (STTP).

3. Other strategies on improving ensemble forecast on sub-seasonal time scale

The sub-seasonal forecast has different dependence from the short-term forecast. While the short-term forecast largely relies on the initial condition, the sub-seasonal forecast more and more relies on the boundary and external forcing. As such, for an uncoupled forecast system on sub-seasonal time scale, an accurate representation of the prescribed Sea Surface Temperature (SST) is of great importance (Li et al., 2001; Ling et al., 2015). The operational version of GEFS uses a prescribed SST that is initiated from analysis data and damps to climatology. Taking into account the day-to-day variability of the SST and as an intermediate stage between uncoupled and coupled forecast system, the underlying SST is updated using the bias-corrected SST from coupled model forecast (i.e. two-tiered SST, Table 1, third row).

As for the forecast system, an accurate representation of the physical process is critical to the forecast skill, the last strategy (or configuration) (Table 1, fourth row) that was tested is combining new SPs; two-tiered SST; and an upgraded Simplified Arakawa-Schubert (SAS) cumulus parameterization scheme that is both scale- and aerosol-aware (Han et al, 2017). The highlights of this upgraded convective parameterization scheme include: 1) the change of the rain conversion rate; 2) the change of convective adjustment time in deep convection; 3) cloud base mass flux in the shallow convection scheme is now a function of mean updraft velocity; 4) convective inhibition (CIN) in the sub-cloud layer is an additional trigger condition to suppress unrealistic spotty rainfall; and 5) convective cloudiness is enhanced by suspended cloud condensate in an updraft.

The performance of the different GEFS configurations is demonstrated in Fig. 5-6. Since the Madden Julian Oscillation (MJO) is the dominant mode on the sub-seasonal predictability, MJO and its associated components are one of the emphases to evaluate the capability of the forecast system on sub-seasonal time scale. Compared to STTP scheme, the performance of the 850hPa zonal wind over the tropics indicated a significant improvement associated with the increase of the spread in SPs (Fig.4). The skill of the upper level zonal wind showed similar improvement (Figure not shown. please confirm), indicating a positive impact of the SPs on the MJO associated circulation. The RMM MJO skill increased from ~12.5 days in STTP scheme to 16.8 days in SPs. Combing SPs and updated SST further result in the increased the MJO skill to 18.5 days. Combing SPs with updated SST and updated convection scheme lead to increase the MJO skill to 22 days (Fig.5, Table 2). The impact of the different configuration on the Northern Hemisphere large-scale circulation indicated the consistent result as the MJO (Fig.6), with the improvement from STTP to SPs. The statistics, in terms of NH 500hPa geopotential height anomaly correlations for average period of week-2 (days 8-14) and weeks 3&4 (days 15-28), include NCEP Climate Forecast System version 2 (CFSv2). The results indicate 1). All three new configurations shows similar or better score than GEFS operation (ctl) for week-2, but much better than CFSv2; 2) All there new configurations demonstrate the very valuable skills for weeks 3&4 than GEFS operation (ctl), and much better than CFSv2.

4. Towards physically based stochastic parameterization

As we demonstrated in section 2 for various stochastic perturbation schemes, most of them are in current operational ensemble forecast system that is still preliminary approach to assimilate model-based uncertainties. There are many limitations in practical application, for example, the SKEB scheme highly depends on the accumulation of dissipation in the numerical integration from computational accuracy, the schemes of horizontal and vertical diffusions, parameters of gravity wave drag and mountain blocking and et al. A contribution of SKEB will be greatly reduced when model resolutions are increased and when numerical schemes are improved. Another example of the limitation is: in SPPT, the perturbation varied with model physical process, tendency of total physical processes, spatial and temporal de-correlation of the stochastic patterns thus does not really reflect uncertainty associated with individual physical process.

Figure 7 is a schematic diagram which demonstrates the current status of the stochastic perturbations, and the approach that represent the model uncertainties through realistic stochastic parameterization most possibly be applied in the future. In the same time, two valuable studies have been done based on operational ECMWF ensemble forecast system to apply 1). Independent random pattern to perturb different physical processes (or iSPPT). It is a similar procedure to current stochastic schemes (SPPT) but accounting stochastic for each individual physical process (Christensen et. al. 2017); 2). Stochastic perturbed selected 20 physical parameters (SPP) (Leutbecher et. al. 2017). Both of them increase ensemble spreads in general. The later one could change vertical distributions of forecast uncertainties significantly thus may represent model uncertainties through the interaction of physical processes more realistically.

With the rapid progress in ensemble forecast system development and better understanding on the model physical process, the representation of forecast uncertainties from model dynamics and physics should be more approach to realistic atmosphere. Following this progress, many other sources of uncertainties, such as soil moisture and soil temperature from land model, sea surface temperature from ocean model, reflectivity of snow and sea ice from sea-ice model will be considered to improve weather forecast and subseasonal-climate prediction.

5. Summary

Stochastic perturbation is important processes that can help to improve subseasonal prediction after it succeed for weather forecast. It advanced MJO skills significantly and associated tropical atmospheric circulation (850hPa and 200hPa zonal winds). It also enhanced extratropical prediction skills for weeks 3&4 average. In contrast to NCEP CFS v2 that is a coupling system with lower model resolution and older model physics, latest GEFS configuration has taken great advantage with new SPs, two-tired SST and new convective parameterization in terms of tropical and extratropical, weather and subseasonal prediction. There are two areas we should focus on in near future: 1). Improve current physical tendency perturbation scheme to represent physical processes more realistically; 2). Consider other sources of uncertainties from land, sea and other surface boundary.

Acknowledgements:

The authors would like to thank all of helps from EMC ensemble team members, and Dr. Bing Fu helps to provide figures 2 and 3; Mr. Eric Sinsky provides figures 4 and 6 in particularly. This study is partially supported through NWS OSTI and NOAA's Climate Program Office (CPO)'s Modeling, Analysis, Predictions, and Projections (MAPP) program

References:

Berner, J., G. J. Shutts, M. Leutbecher, and T. N. Palmer, 2009: A spectral stochastic kinetic energy backscatter scheme and its impact on flow-dependent predictability in the ECMWF ensemble prediction system, J. Atmos. Sci., 66 (3), 603 – 626,

Buizza, R., M. Miller, and T. Palmer. 1999: Stochastic representation of model uncertainties in the ECMWF ensemble prediction system, Q. J. R. Meteorol. Soc., 125 (560), 2887 - 2908

Christensen, H, M., S.-J. Lock, I. M. Moroz, T. M. Palmer, 2017: Introducing independent patterns into the Stochastically Perturbed Parametrization Tendencies (SPPT) scheme, Q. J. R. Meteorol. Soc., Part A. 143(706), 2168-2181

Guan, H., Y. Zhu, E. Sinsky, W. Li, X. Zhou, D. Hou, C. Melhauser, R. Wobus, 2018: Systematic Error Analysis and Calibration of 2-m temperature for the NCEP GEFS Reforecast of SubX Project, Submit to Mon. Wea. Rev. (in process).

Han, J., W. Wang, Y. C. Kwon, S.-Y. Hong, V. Tallapragada, and F. Yang, 2017: Updates in the NCEP GFS Cumulus Convection Schemes with Scale and Aerosol Awareness, Wea. and Forecasting, https://doi.org/10.1175/WAF-D-17-0046.1

Hou, D., Z. Toth, Y. Zhu, and W. Yang, 2008: Evaluation of the impact of the stochastic perturbation schemes on global ensemble forecast. Proc. 19th Conf. on Probability and Statistics, New Orleans, LA, Amer. Meteor. Soc. [Available online at https://ams.confex.com/ams/88Annual/webprogram/Paper134165.html.]

Hou, D., M. charles, Y. Luo, Z. Toth, Y. Zhu, R. Krzysztofowicz, Y. Lin, P. Xie, D. Seo, M. Pena, and B. Cui, 2014: Climatology-Calibrated Precipitation Analysis at Fine Scales: Statistical Adjustment of Stage IV toward CPC Gauge-Based Analysis. J. Hydrometeor., 15, 2542–2557

Johnson, N.C, D. Collins, S. Feldstein, M. L'Heureux, E. Riddle, 2014: Skillful wintertime North American temperature forecasts out to 4 weeks based on the state of ENSO and the MJO. Weather Forecast 29:23–38. doi:10.1175/WAF-D-13-00102.1

Kirtman B.P., D. Min, and J. M. Infanti, 2014: The North American Multimodel Ensemble: Phase-1 seasonal-to-interannual prediction; Phase-2 toward developing intraseasonal prediction. Bull Amer. Meteor. Soc. 95:585–601

Li, H., L. Luo, E. F. Wood, and J. Schaake, 2009: The role of initial conditions and forcing uncertainties in seasonal hydrologic forecasting. J. Geophys. Res., 114, D04114, doi:10.1029/2008JD010969.

Li, W., R. Yu, H. Liu, and Y. Yu, 2001: Impacts of diurnal cycle of SST on the intraseasonal variation of surface heat flux over the western Pacific warm pool, Adv. Atmos. Sci., 18(5), 793–806.

Li, W., Y. Zhu, X. Zhou, D. Hou, E. Sinsky, C. Melhauser, M. Pena, H. Guan and R. Wobus, 2018: Evaluating the MJO Forecast Skill from Different Configurations of NCEP GEFS Extended Forecast. Submitted to Journal of Climate (in process)

Ling, T., M. Xu, X.-Z. Liang, J. X. L. Wang, and Y. Noh, 2015: A multilevel ocean mixed layer model resolving the diurnal cycle: Development and validation, J. Adv. Model. Earth Syst., 07, doi:10.1002/2015MS000476

Liu X, Wu T, Yang S, Li T, Jie W, Zhang L, Wang Z, Liang X, Li Q, Cheng Y, Ren H, Fang Y, Nie S, 2016: MJO prediction using the sub-seasonal to seasonal forecast model of Beijing Climate Center. Clim Dyn. doi:10.1007/s00382-016-3264-7

Lorenz, E., 1969: The predictability of a flow which possesses many scales of motion. Tellus, 21, 289–307, doi:10.1111/j.2153-3490.1969.tb00444.x

Palmer, T. N., et al., 2004: Development of a European multi-model ensemble system for seasonal to inter-annual prediction (DEMETER), Bull. Am. Meteorol. Soc., 85, 853–872.

Palmer, T., N., R. Buizza, F. Doblas-Reyes, T. Jung, M. Leutbecher, G. Shutts, M. Steinheimer, and A. Weisheimer, 2009: Stochastic parametrization and model uncertainty. Tech. Rep. ECMWF RD Tech. Memo. 598, 42 pp. [Available online at http://www.ecmwf.int/publications/.]

Shin, D. W., and T. N. Krishnamurti, 2003: Short- to medium-range superensemble precipitation forecasts using satellite products: 1. Deterministic forecasting, J. Geophys. Res., 108(D8), 8383, doi:10.1029/2001JD001511.

Shutts, G., and T. N. Palmer, 2004: The use of high-resolution numerical simulations of tropical circulation to calibrate stochastic physics schemes. Proc. ECMWF/CLIVAR Simulation and Prediction of Intra-Seasonal Variability with Emphasis on the MJO, Reading, United Kingdom, European Centre for Medium-Range Weather Forecasts, 83 – 102.

Shutts, G. 2005: A kinetic energy backscatter algorithm for use in ensemble prediction systems. Q. J. R. Meteorol. Soc. 131, pp. 3079–3102

Shutts, G. 2015: A stochastic convective backscatter scheme for use in ensemble prediction systems. Q. J. R. Meteorol. Soc. Part A. 141 (692), 2602–2616

Tian, D. W., Eric and X. Yuan, 2017: CFSv2-based sub-seasonal precipitation and temperature forecast skill over the contiguous United States. Hydrol. Earth Syst. Sci., 21, 1477–1490.

Tompkins, A. M., and J. Berner, 2008: A stochastic convective approach to account for model uncertainty due to unresolved humidity variability, J. Geophys. Res., 113, D18101.

Troccoli, A.: Seasonal climate forecasting, 2010: Meteorol. Appl., 17, 251–268, doi:10.1002/met.184

Vitart, F., 2014: Evolution of ECMWF sub-seasonal forecast skill scores. *Quart. J. Roy. Meteor. Soc*., 140, 1889–1899, doi:https://doi.org/10.1002/qj.2256.

Zhou, X. Y. Zhu, D. Hou, and D. Kleist 2016: Comparison of the Ensemble Transform and the Ensemble Kalman Filter in the NCEP Global Ensemble Forecast System. Wea. and Forecasting, Vol. 31, 2058-2074

Zhou, X. Y. Zhu, D. Hou, Y. Luo, J. Peng and D. Wobus, 2017: The NCEP Global Ensemble Forecast System with the EnKF Initialization. Wea. and Forecasting, Vol. 32, 1989-2004.

Zhu, Y. 2005: Ensemble Forecast: A New Approach to Uncertainty and Predictability. Advance in Atmospheric Sciences, Vol. 22, No. 6, 781-788

Zhu, Y. X. Zhou, M. Pena, W. Li, C. Melhauser, and D. Hou, 2017: Impact of Sea Surface Temperature Forcing on Weeks 3 & 4 Forecast Skill in the NCEP Global Ensemble Forecasting System. Wea. and Forecasting, Vol. 32, 2159-2173DOI: 10.1175/WAF-D-17-0093.1

Zhu, Y., X. Zhou, W. Li, D. Hou, C. Melhauser, E. Sinsky, M. Pena, B. Fu, H. Guan, W. Kolczynski, R. Wobus, and V. Tallapragada, 2018: An Assessment of Subseasonal Forecast Skill Using an Extended Global Ensemble Forecast System (GEFS), Submitted to Journal of Climate (in process)

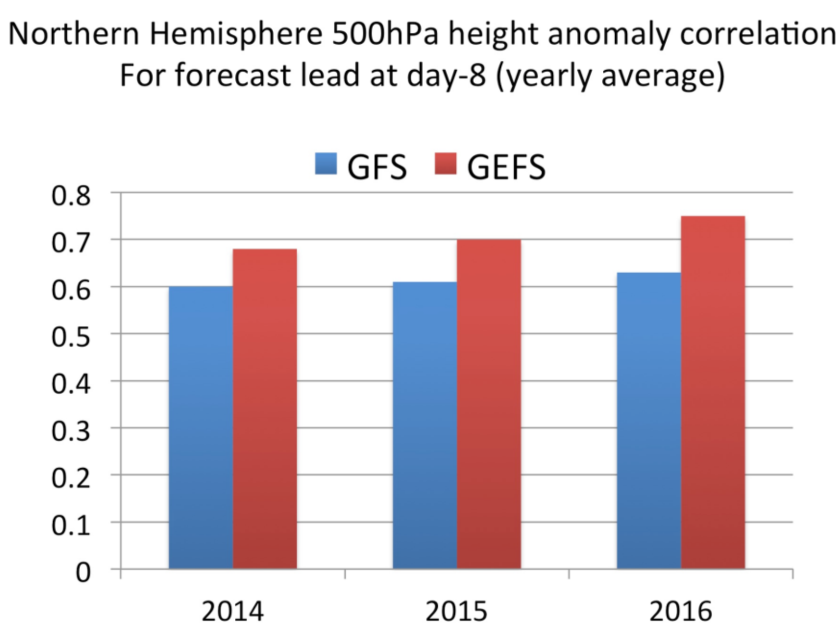

Figure 1: Northern Hemisphere 500 hPa geopotential height anomaly correlation for forecast lead at day-8 of GFS forecast (blue) and ensemble mean forecast (red) during years 2014 - 2016.

Experiments	Stochastic Schemes	Boundary (SST)	Convection
CTL	STTP	Default	Default
SPs	SKEB+SPPT+SHUM	Default	Default
SPs+SST_bc	SKEB+SPPT+SHUM	2-Tiered SST	Default
SPs+SST_bc+SA_CV	SKEB+SPPT+SHUM	2-Tiered SST	Scale Aware Convection

Table 1: The Configuration differences for four experiments

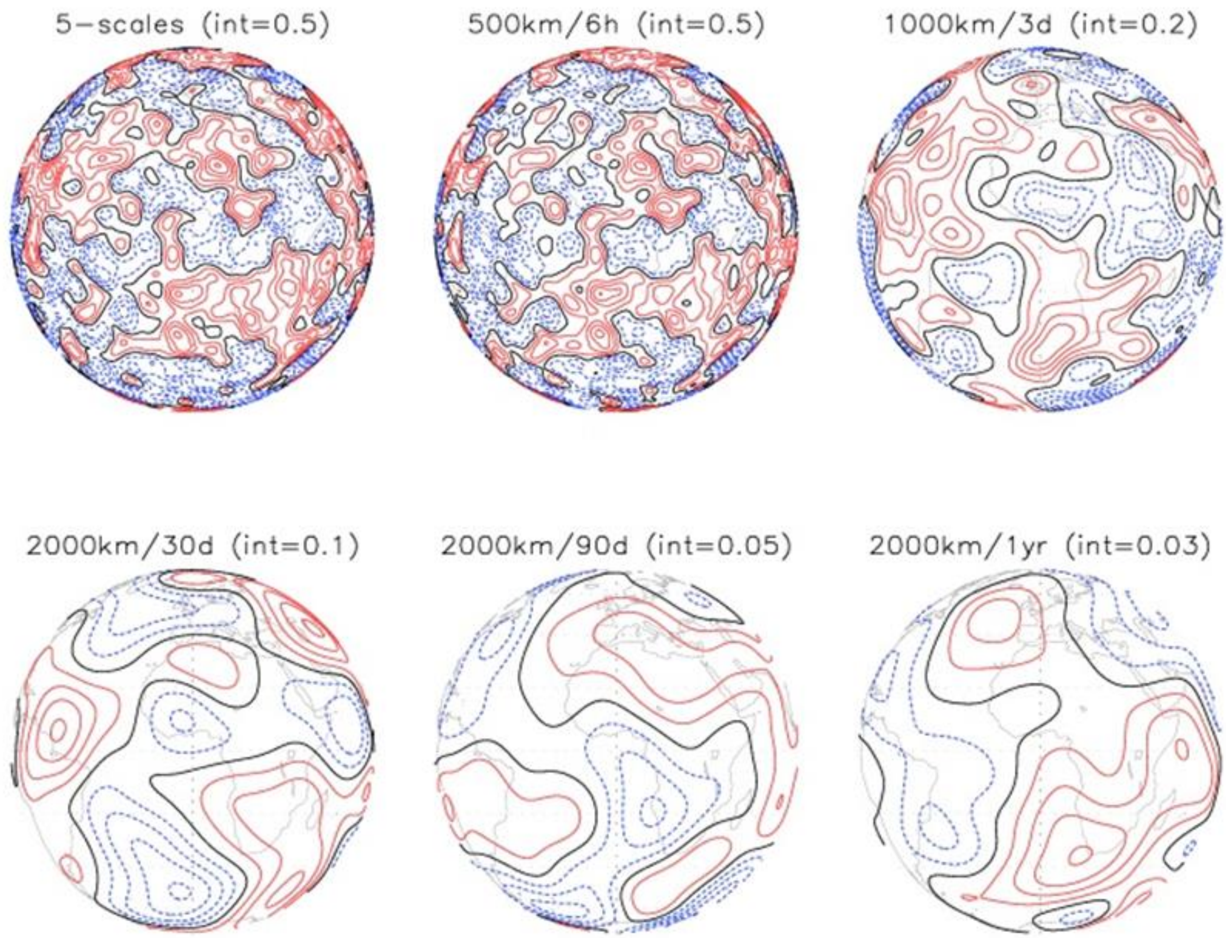

Figure 2. 5-scale random patterns used in Stochastic Perturbed Physics Tendencies (SPPT). On the top of each plot, the numbers (except for upper left) represent the scales of spatial and temporal perturbations with contour intervals in the bracket. The upper left is for combined total 5-scales

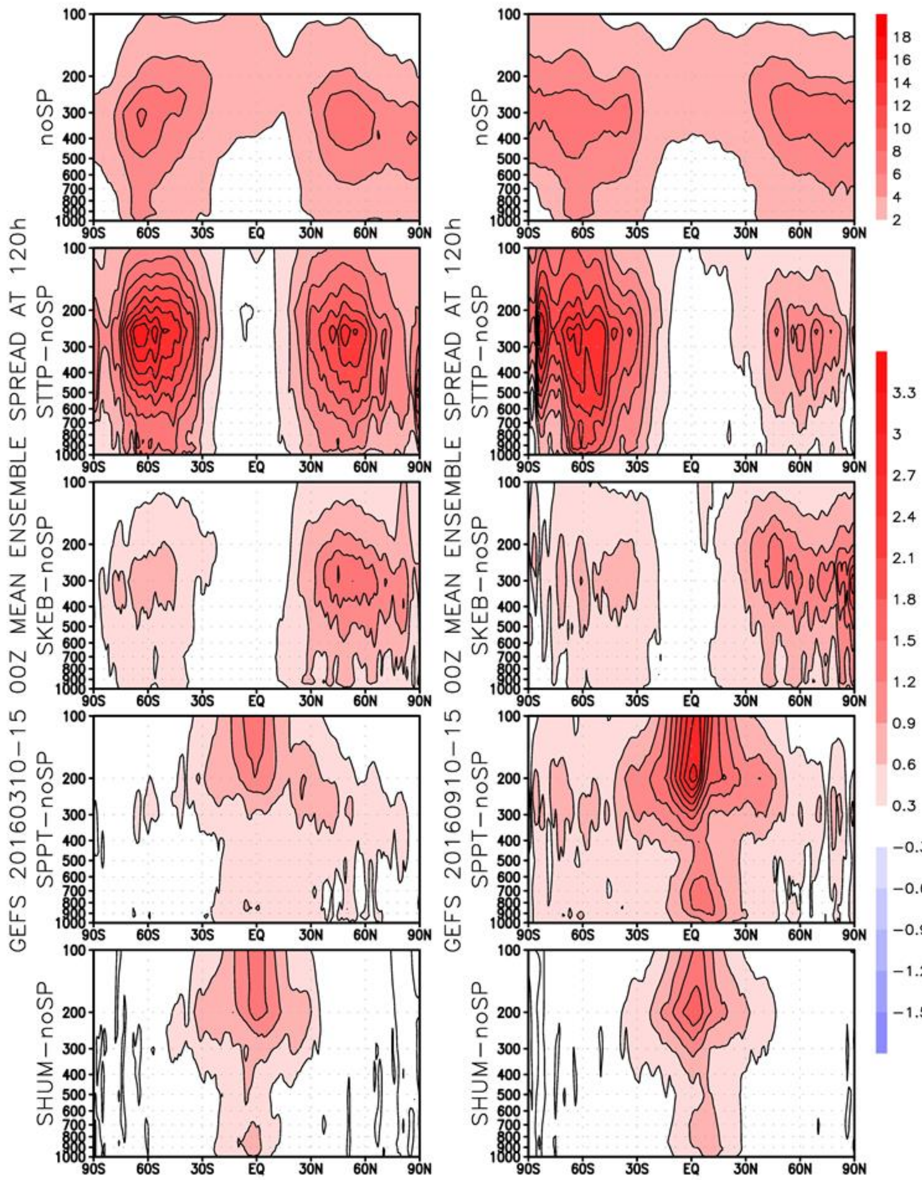

Figure 3. Global meridional cross section showing the impact of stochastic perturbations for the atmosphere (cross section) for 120 hour forecasts from six spring initializations (left) and six fall initializations (right). Paneled are the differences of zonal wind spread from CTL for (top) no stochastic physical perturbations, and the difference of STTP (upper middle); SKEB (middle); SPPT; (lower middle) and SHUM (bottom).

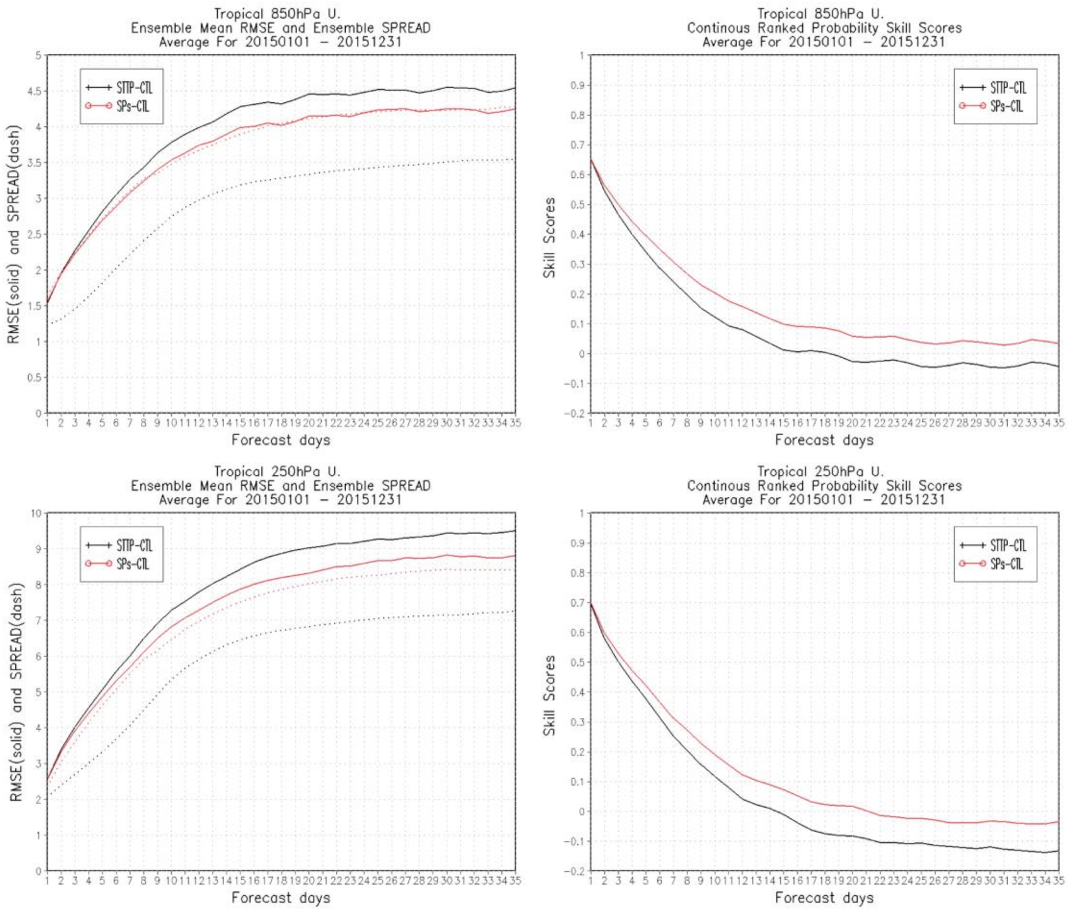

Figure 4. RMS error of the ensemble mean (solid) and the ensemble spread (dash) (left), and CRPSS (right) are plotted every 24 hours out to 35 days for 850-hPa (top) tropical (20^{o}N-20^{o}S) zonal wind during the Jan. 2015 to Dec. 2015 period comparing CTL (black) and SPs (red).

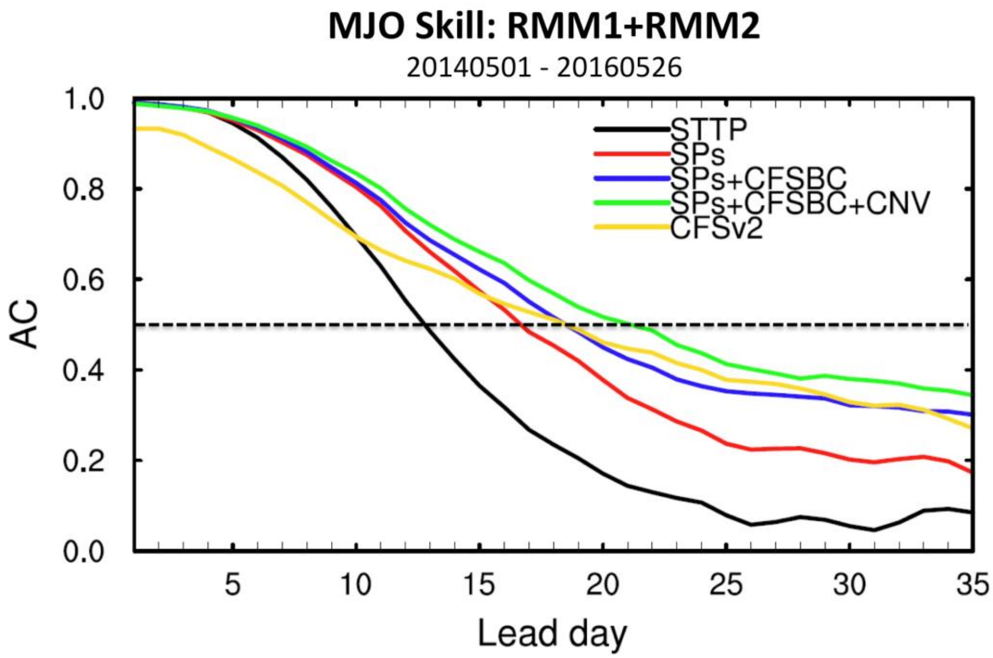

Figure 5. MJO skills of the four different configurations of GEFS and CFSv2.

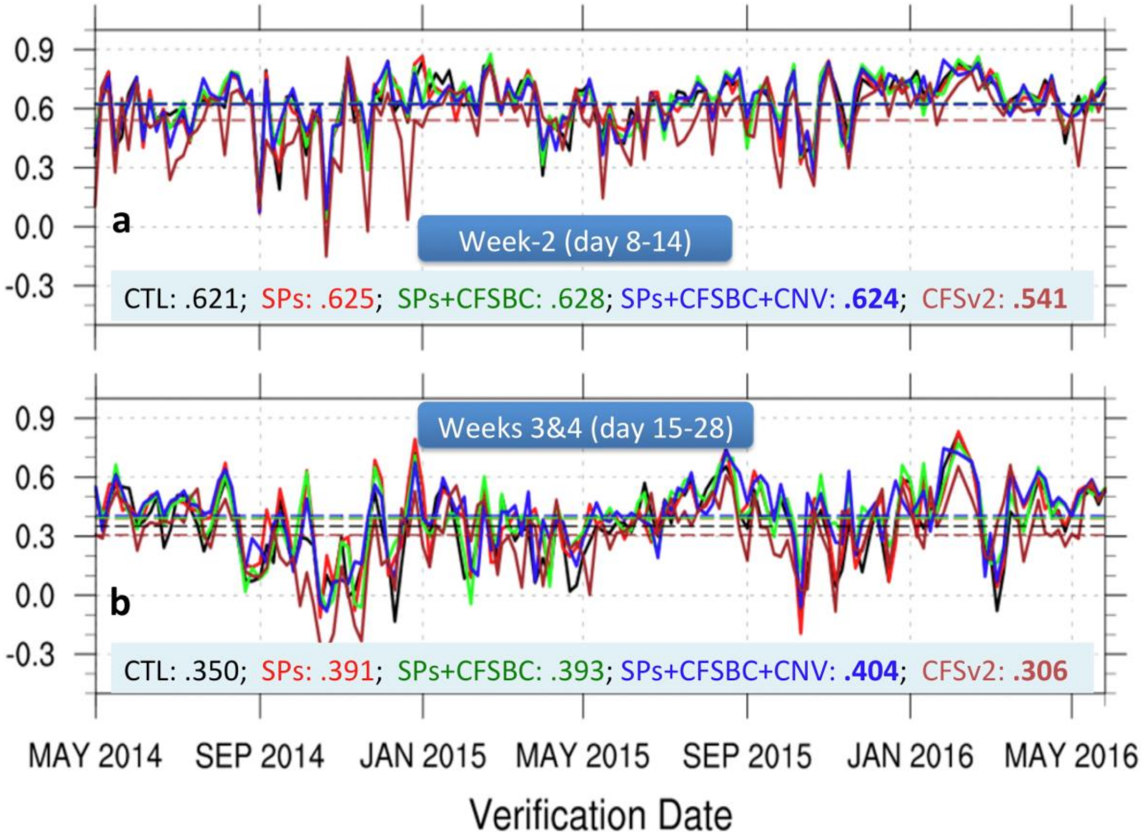

Figure 6. The time series of ensemble-mean anomaly correlation for Northern Hemisphere (20^oN-80^oN) 500hPa geopotential height from May 2014 - May 2016 for different configurations (CTL-black; SPs-red; SPs+CFSBS-green and SPs+CFSBC+CNV-purple) and CFSv2 (orange) for lead week-2 (a) and weeks 3&4 (b). Average scores are shown in the bottom of each plot.

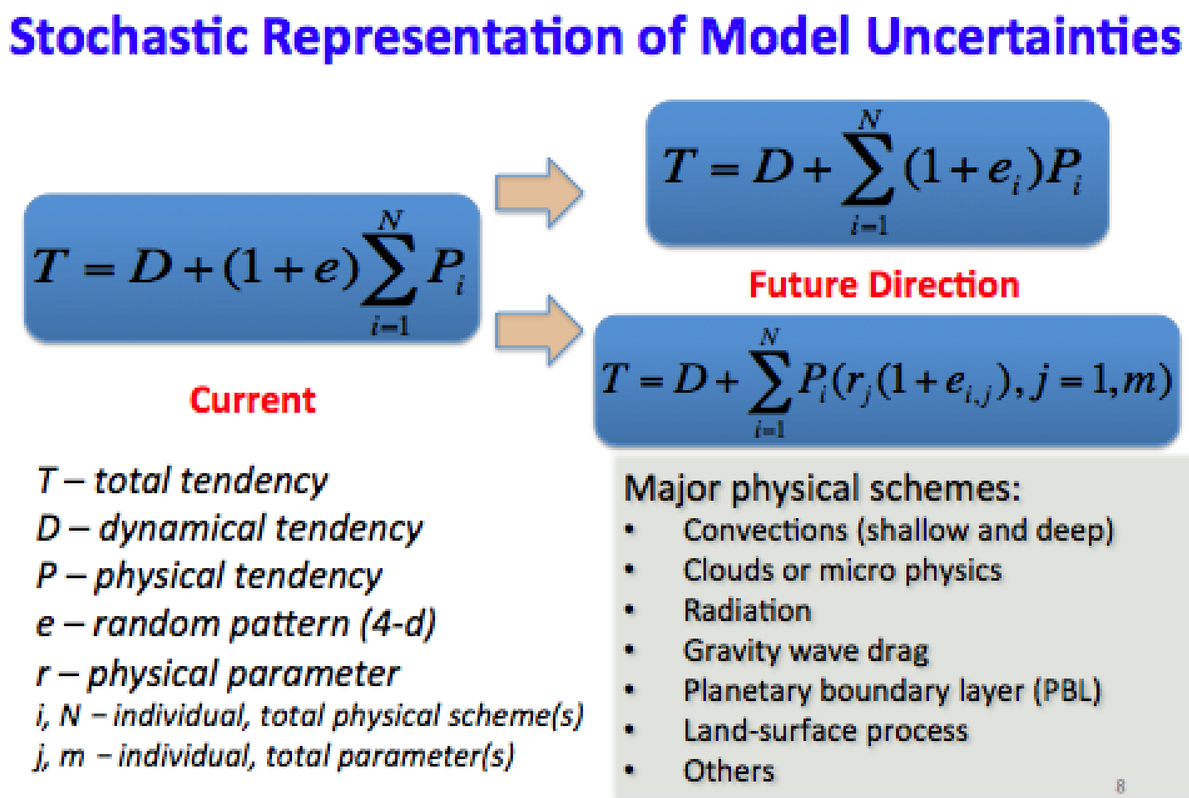

Figure 7. Schematic diagram to present current status and future direction for stochastic representation of model uncertainties.