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Accounting for Error in an Ensemble of Seasonal Forecasts using a **High Resolution Global Coupled Model** William J. Crawford¹², Sergey Frolov², Craig Bishop², Justin McLay², Neil Barton²

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Project Overview

• Summary

- The Naval Research Laboratory (NRL) is currently developing a sub-seasonal (30-90 day) forecast capability for an oceanatmosphere-ice model (ESPC model).
- At such lead times, the deterministic predictability is lost and ensemble forecasting starts to play a key role in characterizing the probable evolution of the Earth system.
- The Navy ESPC model consists of:
 - Atmosphere NAVGEM (40km/60 vertical levels)
 - 2. Ocean HYCOM (~9km/41 vertical levels)
- 3. Ice CICE (~4km resolution) • The ensemble is produced using initial conditions generated using the method of perturbed observations (Houtekamer et al., (1996) and Kucukkaraca and Fisher, (2006)) where random perturbations are added to the observations prior to being assimilated via 4DVAR (atmosphere) and 3DVAR (ocean/ice).

Motivation and Implementation of ACAI

- Research at the UK Met Office (Bowler et al., 2017) suggests use of Analysis Correction based Additive Inflation (ACAI)
- 1. Begin with archive of analysis corrections, δx_i^a ; $i = 1, 2 \dots N_a$
- 2. For each ensemble member (m), randomly select δx^a from archive (same season, different year) and compute:



Project Status and Initial Results

- ACAI capability implemented into atmosphere only (NAVGEM) portion of the ESPC model code base
- Initial tests using a 10-day, 20-member ensemble in NAVGEM versus the current operational system at FNMOC indicates positive impact to bias and RMSE





Challenges

- The ensemble suffers from significant model biases and error • Sources include:
- Initial conditions
 - Perturbed observations known to generate initial conditions which are under spread
 - Aim to replace with relaxation-to-prior-perturbations
- 2. Model error (bias & stochastic model error)
 - Can address in two ways:
 - a) Stochastic physics methods (e.g. SKEB, SPPT, SPT); only addresses stochastic model error and are not constrained by observations
 - b) Observation based approach; based on analysis corrections from data assimilation (ACAI; see Goals)

♦ Goals

• Implement an observation based method to address both

- 3. Add $\frac{\delta x_m^r}{\pi}$ at each time step, T = time steps/6-hrs forecast
- 4. Repeat (2) and (3) for each 6-hr period of extended range forecast
 - (i) addresses model bias and (ii) addresses stochastic model error

Statistics of analysis corrections

- Statistics of analysis corrections can lend insight into systematic adjustment or bias in the model
- These represent term (i) in equation (1) above

surface pressure : mean correction







Figure 5: Change in bias (a) and RMSE (b) relative to the baseline system. Upward/green = improvement. Outside triangle represents a 100% change (a); 10% change (b). NE=northern extra-tropics; TR=+/-20°; SE=southern extra-tropics



- While overall performance is positive, bias of some variables is driven through zero (Fig. 6) resulting in a degradation at longer lead times.
- Spatially and temporally varying amplitudes of the seasonal mean corrections added to the state are currently being tested to combat this

Term (ii) in equation (1) is aimed at increasing spread throughout the forecast • Figure 7b indicates that ACAI is not always additive with the baseline method (SKEB) • α set to 0.5 in the presented results and will be increased in later experiments

model bias and model error using analysis correction based additive inflation (ACAI)

- While stochastic physics methods directly address errors in physical processes, it is not clear how to constrain with observations. These methods are typically much more difficult to implement and tune.
- In contrast, ACAI is directly driven by observations of the imperfection of model trajectories; also simple and easy to implement.
- By including ACAI in our global sub-seasonal ensemble forecast, we hope to reduce the overall bias in the model while also increasing spread throughout the length of the forecast.
- This work builds upon that of Piccolo and Cullen, (2016) and Bowler et al., (2017); however, the implementation here is of a much higher resolution, as well as, (potentially) the first implementation in a couple model.





Figure 2: Seasonal (3-month) mean analysis correction for surface pressure

- Figure 2 indicates the model is persistently adjusting the \bullet meridional pressure gradient across all seasons
- Appears to also effect the meridional component of the wind with decreased convergence (divergence) at the surface (aloft)



Figure 3: Seasonally (Oct-Dec) averaged correction to the meridional component of the wind at the surface (a) and zonal mean; all levels (b)

- Too much rain-out is a known problem in NAVGEM
- DA appears to try and compensate with reduced convergence (Fig. 3) and increased humidity (Fig. 4) in the tropics



0[°] 30[°]N 60[°]N

60[°]S 30[°]S



Figure 7: Time-series comparing ensemble spread for 10m wind speed (a) and 2m air temperature (b) in the tropics $(+/-20^{\circ})$

Summary and Future Work

- We have demonstrated improvement to the baseline ensemble system with the use of analysis correction based additive inflation (ACAI); however, more testing is necessary to prevent runaway bias at longer lead times and to increase spread in the ensemble
- Currently testing the method of relaxation-to-prior-perturbations where a weighted sum of the prior and posterior ensemble perturbations is taken to increase spread at the initial time
- Thus far have only implemented in the atmosphere and plan to begin development in HYCOM soon. Many challenges associated with this!
- Analyze nature of coupled biases and feedbacks in ESPC model



Figure 1: Schematic illustrating how correction of under spread initial conditions,

model bias and addition of stochastic model error can help attain the target ensemble variance (blue)





References:



Houtekamer P.L., et. al., 1996, A System Simulation Approach to Ensemble Prediction, Mon. Wea. Rev. 124, 1225-1242. Kucukkaraca, E., and Fisher, M., 2006, Use of Analysis Ensembles in Estimating Flow-Dependent Background Error Variances, ECMWF Tech. Mem., 492. Piccolo C. and Cullen, M., 2016, Ensemble data assimilation using a unified representation of model error. Mon. Wea . Rev. 144, 213-224. Bowler N., et. al., 2017, Inflation and Localization Tests in the Development of an Ensemble of 4D-Ensemble Variational Assimilations." Q.J.R.M.S., 143, 1280-1302.