Using analysis corrections as a representation of model error

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Project Overview

◆ **Project/Model Summary**

- The Naval Research Laboratory (NRL) is currently developing a sub-seasonal forecast capability for a coupled ocean-atmosphere-ice model (Navy ESPC).
- 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:
  1. Atmosphere - NAVGEM (40km/60 vertical levels)
  2. Ocean – HYCOM (~9km/41 vertical levels)
  3. Ice – CICE (~4km resolution)
- The ensemble uses initial conditions generated using the method of perturbed observations (similar to 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).

◆ **Goals**

- Implement a method to address model bias and stochastic model error using analysis correction-based additive inflation (ACAI).
- To begin, we test the use of ACAI in our stand-alone system (NAVGEM) in both deterministic and ensemble-based forecast settings.
- By including ACAI in our global coupled ensemble forecasts, we hope to reduce model biases while also increasing the spread-skill of the ensemble at extended ranges (~45 days)
- 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 coupled model.
- Moving forward, we will combine ACAI with other known methods of accounting for model error (i.e. RTPP & SKEB) to asses the additive impact

ACAI Methodology

Research at the UK Met Office (Bowler et al., 2017) suggests use of Analysis Correction-based Additive Inflation (ACAI) to address model error

1. Begin with archive of analysis corrections, $\delta x_i^a \; ; i = 1, 2 \ldots N_a$
2. For each ensemble member (m), randomly select δx^a from archive (same season, different year) and compute:

$$\delta x_m^F = \underbrace{\overline{\delta x_s^a}}_{\text{(i)}} + \alpha \underbrace{\left[\delta x_m^a - \overline{\delta x_e^a}\right]}_{\text{(ii)}} \quad (1)$$

where:
$\overline{\delta x_s^a}$ = seasonal mean analysis correction
$\overline{\delta x_e^a}$ = mean of randomly sampled analysis corrections
α = tuning parameter

3. Add $\frac{\delta x_m^F}{T}$ 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

- Examples of the bias captured by the mean analysis corrections are given below for the uncoupled and coupled forecasting systems
- One notable difference in structure is the reduction of increments to the trade winds (30ºS-30ºN) between the two systems

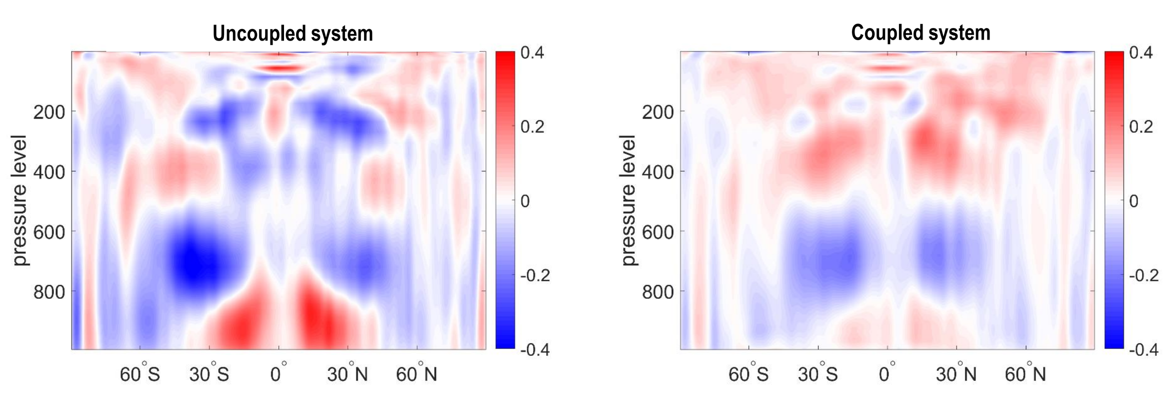

Figure 1 : Average analysis increments from the uncoupled (left; NAVGEM only) and coupled systems right; Navy ESPC)

Comparison to measured bias

- ACAI is predicated on the idea that the seasonally averaged analysis corrections are representative of the true bias
- Comparison with radiosonde measurements indicates that the analysis corrections correctly capture the sign of the bias, but that they generally under estimate the magnitude

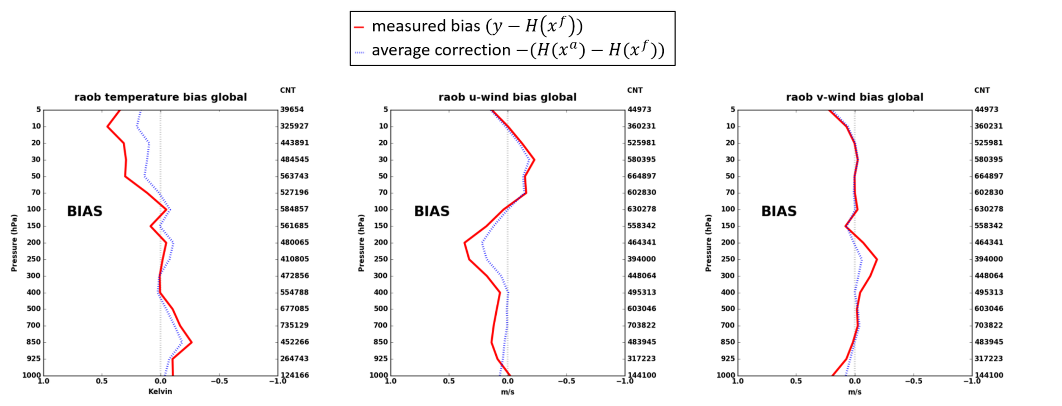

Figure 2: Global mean profiles of background departures from radiosondes (red) and negative of analysis corrections at observation locations (blue-dashed) averaged over 15 Dec. 2016 -31 Mar. 2017.

Results in deterministic system

- We have implemented ACAI in our stand-alone atmospheric forecasting system for use in both deterministic and ensemble forecasts
- Scorecards indicate significant improvement to both Bias and RMSE in the deterministic scorecards shown below.

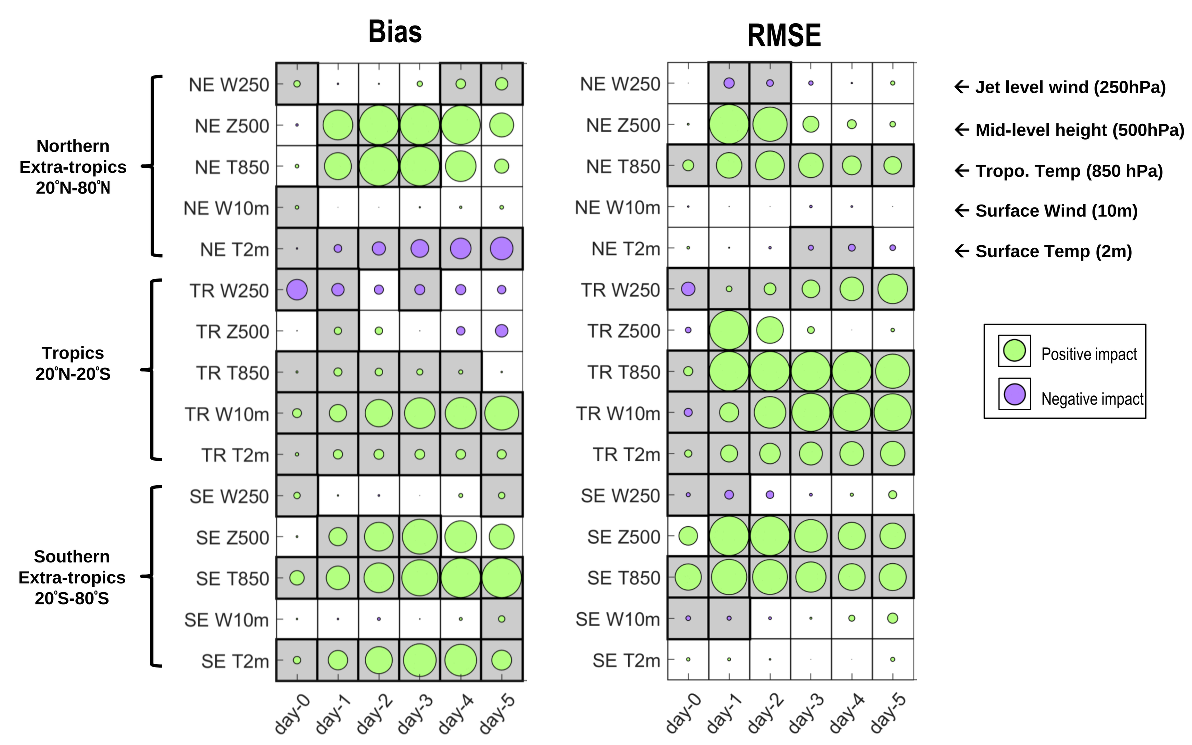

Figure 3: Scorecards presenting change in Bias (left) and RMSE (right) for ACAI-based experiments compared to control. Grey shading represents significance at the 95% level. Circle size maximum for Bias (RMSE) is 50% (5%).

- We also see that the localized impacts of ACAI can be quite large
- Changes in 10m wind speed bias between the control and ACAI-based experiment are ~1.25 m/s in the tropical region

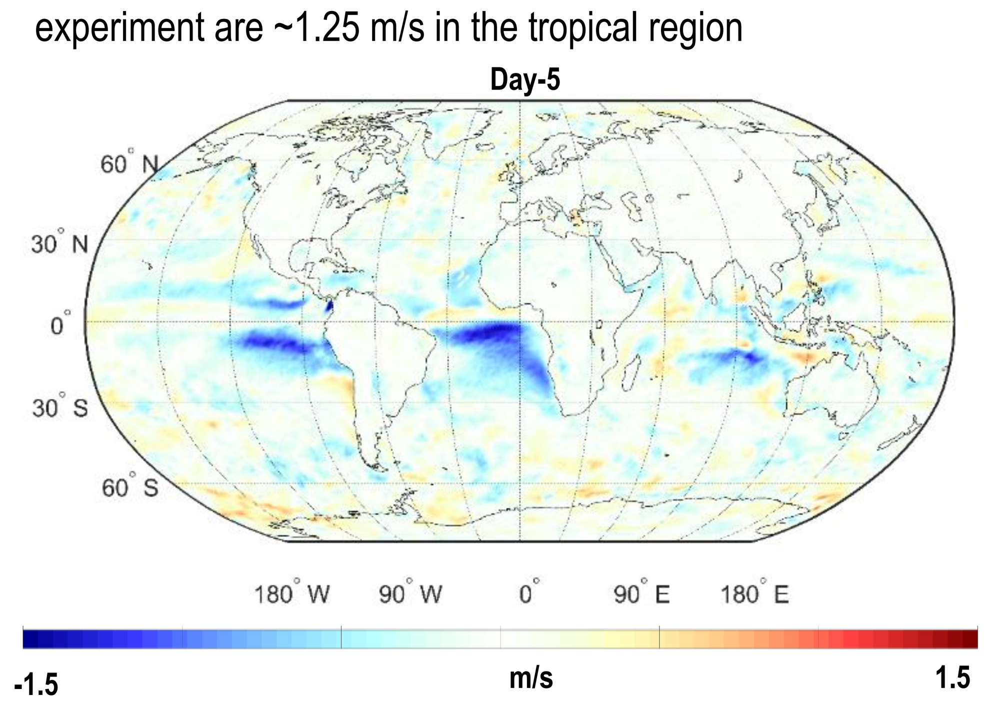

Figure 4: Difference in magnitude of 10m wind speed bias in deterministic forecasts at day 5 |DETacaibias| - |DETctrlbias|. Blue (red) colors indicate an improvement (degradation) to the bias.

- If ACAI is performing as expected, the prior in ACAI-based experiment should be closer to "truth" and the increments added by the 4D-Var system should be smaller on average.
- Figure 5 below illustrates that the globally averaged increments are smaller in the ACAI-based experiment for T, Q, U and V.

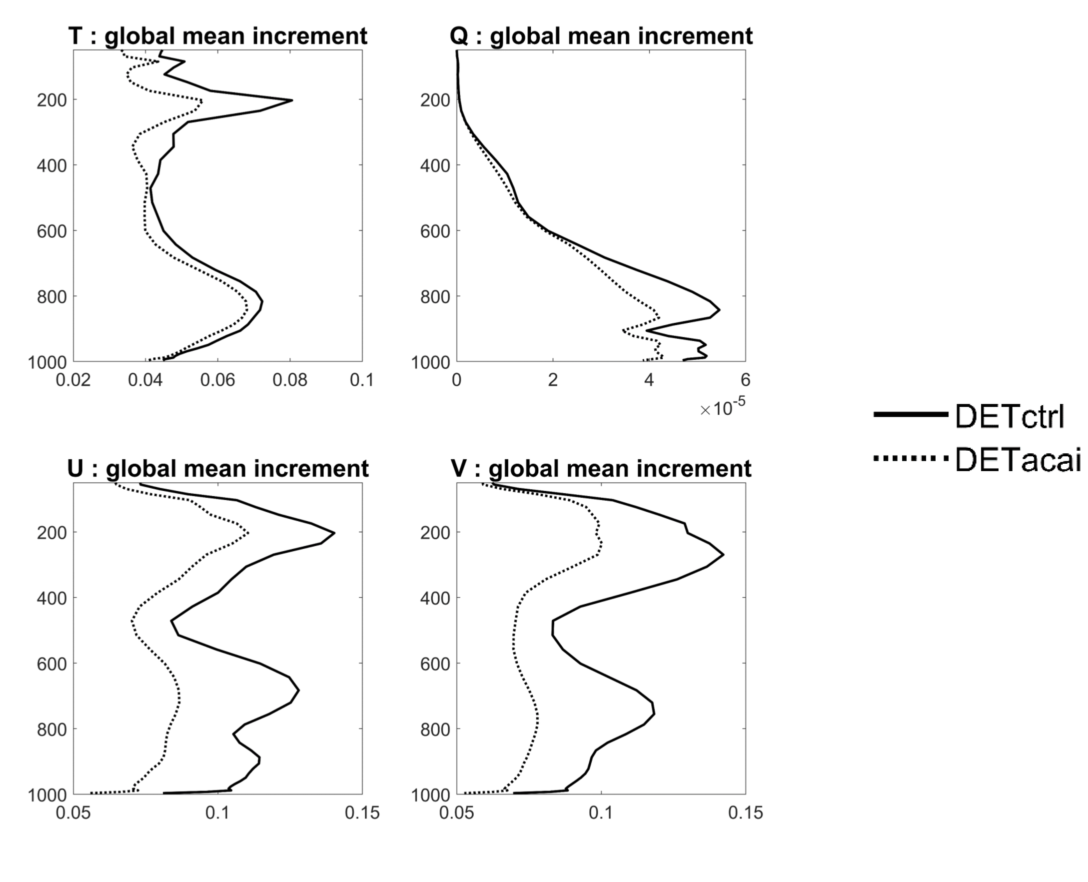

Figure 5: Global mean profile of absolute magnitude of temperature (T), humidity (Q), zonal velocity (U) and meridional velocity (V) analysis corrections. DETctrl (solid); DETacai (dotted).

Impact of individual perturbation components

- To test the impact of the individual components of the ACAI-based perturbations, we conducted 4 ensemble based tests; (1) control, (2) ACAI perturbations using eq. 1, (3) stochastic component of ACAI perturbations set to 0 and (4) bias component of ACAI perturbations set to 0.
- Interestingly, we find that the random component of the perturbations can be as effective as the mean component at reducing bias in the ensemble based forecasts.

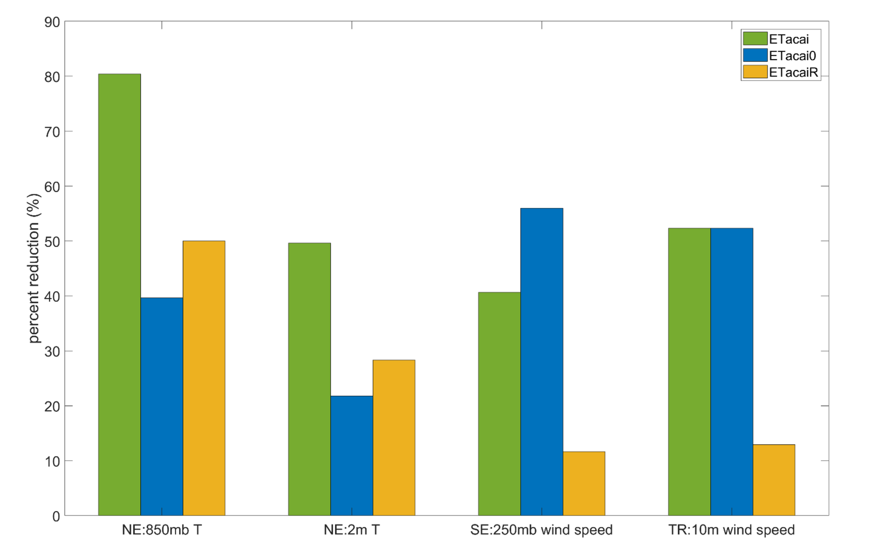

Figure 6: Percent reduction in day-10 bias in for experiments using the full ACAI perturbations (green), bias only (blue) and random only (orange). Reduction computed relative to a control experiment without ACAI.

Results in coupled ensemble system

- We have now implemented ACAI in our global coupled ensemble forecasting system (Navy ESPC) and have begun looking at the impacts on extended range forecasts (45 days)
- We see significant improvement to many ensemble performance diagnostics including the ensemble mean RMSE (below)

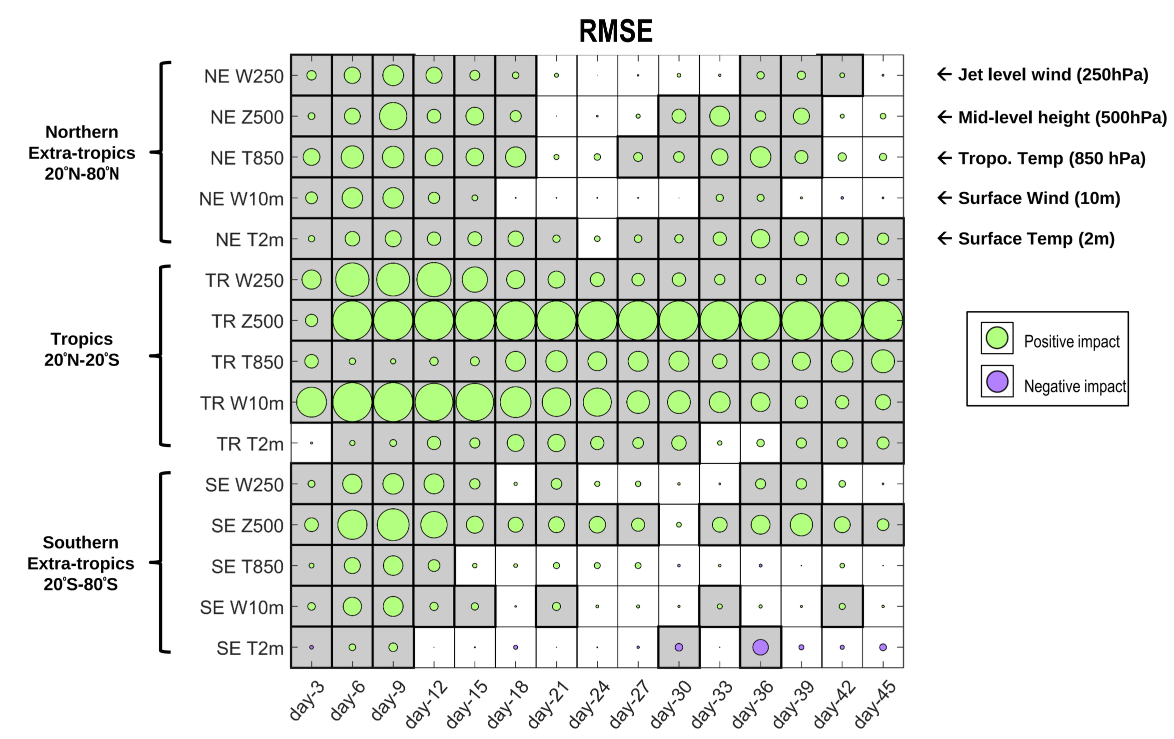

Figure 7: Scorecard presenting change in RMSE for ACAI-based EDA compared to control. Grey shading represents significance at the 95% level. Circle size maximum is 7.5%.

- As expected, ACAI also has large impacts on bias in the coupled system
- Below we see the impact on precipitable water by comparing bias in the control and the ACAI-based forecast for a single initialization in June of 2017

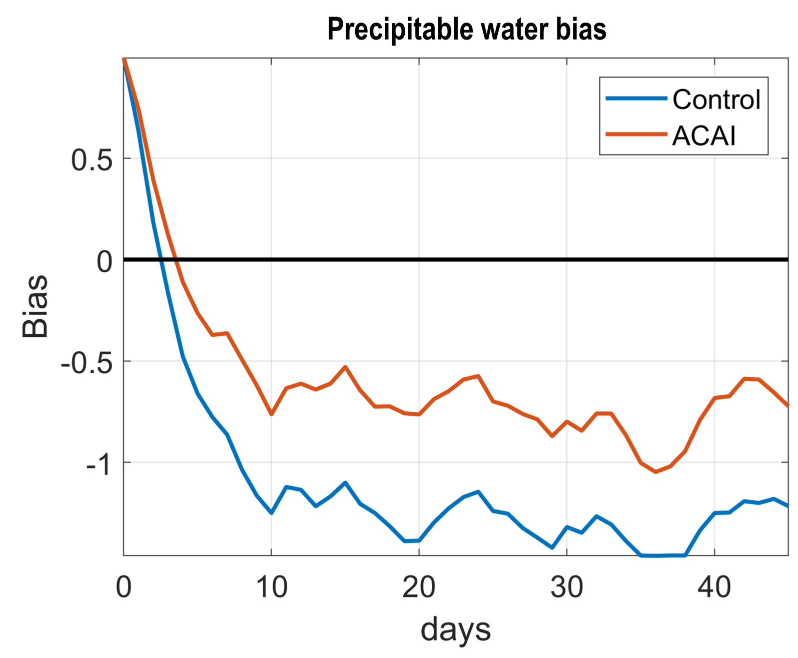

Figure 8: Bias in globally average precipitable water as a function of forecast tau for the control (blue) and ACAI-based (red) experiments

Summary and Future Work

- We have demonstrated that the mean analysis corrections reasonably capture the sign of the bias as measured by radiosondes
- ACAI has a positive impact on Bias and RMSE in the deterministic system and we find that the stochastic component of the perturbations can be as effective at reducing the bias as the mean component in the ensemble based system
- We find that ACAI also has a substantial impact on seasonal forecasts in the Navy ESPC system, with some of the largest impacts seen in precipitable water bias
- While the 6-hour estimates of bias used in ACAI seem to provide some substantial benefits to the forecasts, the estimates are not necessarily a representation of bias at later lead times and will be the topic of future research

References:

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