U.S. NAVAL RESEARCH LABORATORY

Using Analysis Increments for Bias Correction and Model Uncertainty

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NRLMMD Mission: To better understand the atmosphere, the coupled environment, and their mission impacts so that they can be better simulated, better predicted, and ultimately help Navy personnel make better decisions (basic through applied research)

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Background on Model Bias and Model Uncertainty

Correct Model Bias

- **Post-processing (after the fact)**
  - Hamill et al. (2022) article on recent GEFS reanalysis and references therein
  - Vannitsem et al. (2022) review article on statistical post-processing
- **In-line (during forecast integration)**
  - Saha (1992) similar impact on bias and RMSE for post-processing and in-line corrections
  - Danforth and Kalnay (2008), in-line and off-line have similar impacts on bias, but in-line also reduces random errors (RMSE)
  - DelSole et al. (2008) suggest that the impact on random errors through in-line bias correction will depend on magnitude of the bias.
- **Both depend upon an accurate estimate of model bias, which may be conditional upon the model state.**

Account for Model Uncertainty in an Ensemble: See Berner et al. (2017) review article

- **Many methods, e.g.**
  - Stochastically perturbed parameterization tendency scheme (Buizza et al. 1999)
  - Stochastic Kinetic Energy Backscatter Scheme (Shutts, 2005)
  - Stochastically Perturbed Parameterizations (Ollinaho et al. 2017)
- **Stochastic forcing can change model climate, reduce model biases (Weisheimer et al. 2014)**

Use of Analysis Increments

Use short-forecast tendency errors or analysis increments to diagnose model biases (Dee and Da Silva, 1998; Cherpurin et al., 2005; Rodwell and Palmer 2007; Mapes and Bacmeister 2012; Klocke and Rodwell, 2014; Cavallo et al., 2016; Bhargava et al., 2017). **Overall findings – not perfect but can be useful.**

Analysis increments (short-term forecast errors, or tendency errors) have been used for in-line bias correction and to enhance ensemble performance

- DelSole et al. (2008) use short-term tendency errors to reduce biases in S2S forecasts of temperature and soil moisture in a coupled land-atmosphere model, but did not see an impact on random error variance.
- Batté and Déqué (2016) use additive perturbations from randomly sampled model error corrections to reduce bias and improve ensemble spread and North Atlantic variability in seasonal forecasts.
- Chang et al. (2019) – Inline bias correction using NASA GMAO GEOS model reduced biases, improved storm-track activity, but only modest at best improvements in subseasonal and seasonal forecast skill.
- Piccolo et al. (2019) use random analysis increments to account for model uncertainty in ensemble forecasts, improves skill and reduces biases in short-term deterministic and ensemble forecasts.
- We will use Analysis Correction-based Additive Inflation to correct for model bias and improve ensemble spread and skill following Bowler et al. (2017) and Crawford et al. (2020)

Analysis Correction-based Additive Inflation (ACAI)

- **Goal: decrease model bias and increase spread* in ensemble forecasts**

  – Compute $\delta x_m^F = \overline{\delta x^a} + \alpha\left[\delta x_m^a - \overline{\delta x_e^a}\right]$

  Seasonal (3-month) average analysis correction; address bias
  same for all ensemble members

  stochastic component; address ensemble spread
  randomly sampled from same 3-month period as $\overline{\delta x^a}$
  different for each ensemble member (m)

- **Incrementally add $\frac{\delta x_m^F}{T}$ at each time step (T = time steps/6-hr forecast) to T,U,V,Q,P**

- **Compute/add a new δx_m^F over each 6-hr period of the forecast**

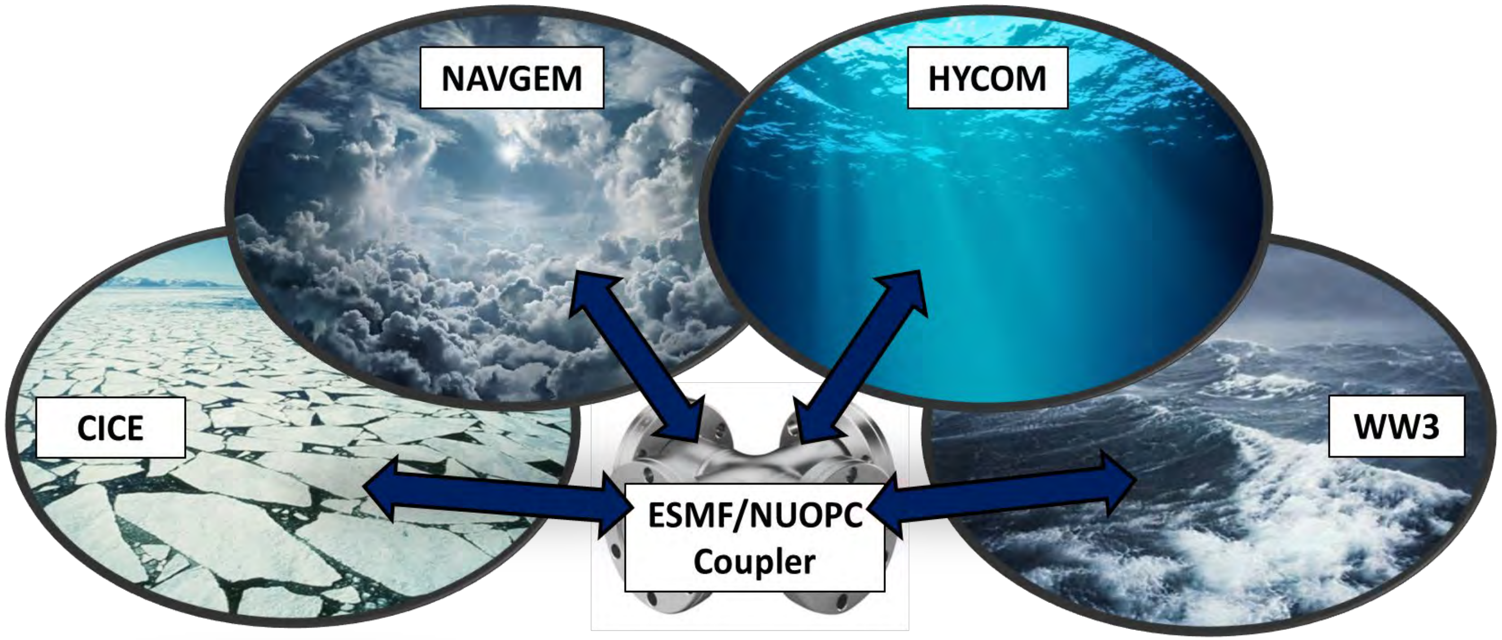
- **Sample from a 1-year archive of analysis corrections**

*More accurate representation of model uncertainty in our ensemble

$\delta x^a =$ analysis correction (or increment)
$\delta x^a = x^a - x^f$
analysis - forecast

Crawford et al. 2020 MWR; Bowler et al. 2017 QJRMS

U. S. Navy ESPC Experiments



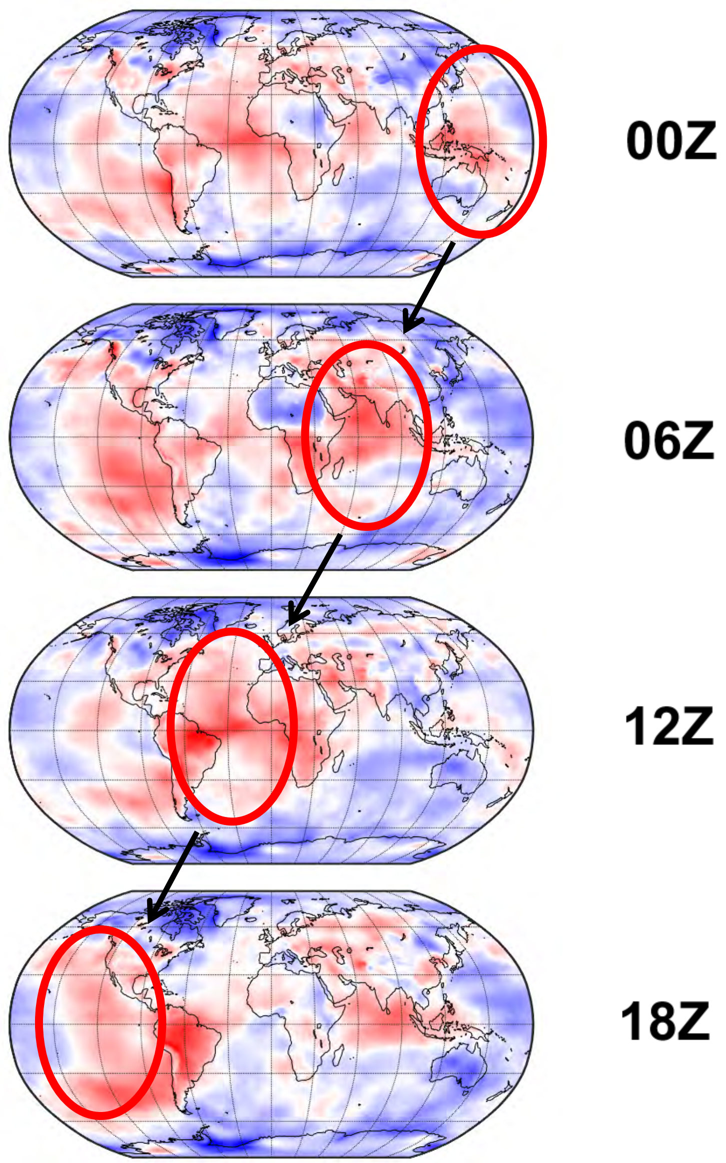
Test ACAI in NAVGEM and Navy Earth System Prediction Capability (Navy ESPC)

- Atmospheric res is 37km, ocean and sea ice res decreased to ¼ deg for computational reasons (1/12 deg in operations).
- 7-member 45-day ensembles once per week from 1 Feb 2017-31 Jan 2018
- Control Ensembles: No model uncertainty
- ACAI Ensembles: Started from the same initial conditions as CTL, but includes ACAI in NAVGEM

Structure of Average Analysis Corrections

$$\delta x_m^F = \overline{\delta x^a} + \alpha\left[\delta x_m^a - \overline{\delta x_e^a}\right]$$

- Mean analysis corrections to surface pressure as a function of time of day (right)
- Large dependence on time-of-day
- Average corrections show a clear migration westward between 00Z and 18Z
- We now use analysis corrections relative for the forecast time-of-day to produce the ACAI perturbations

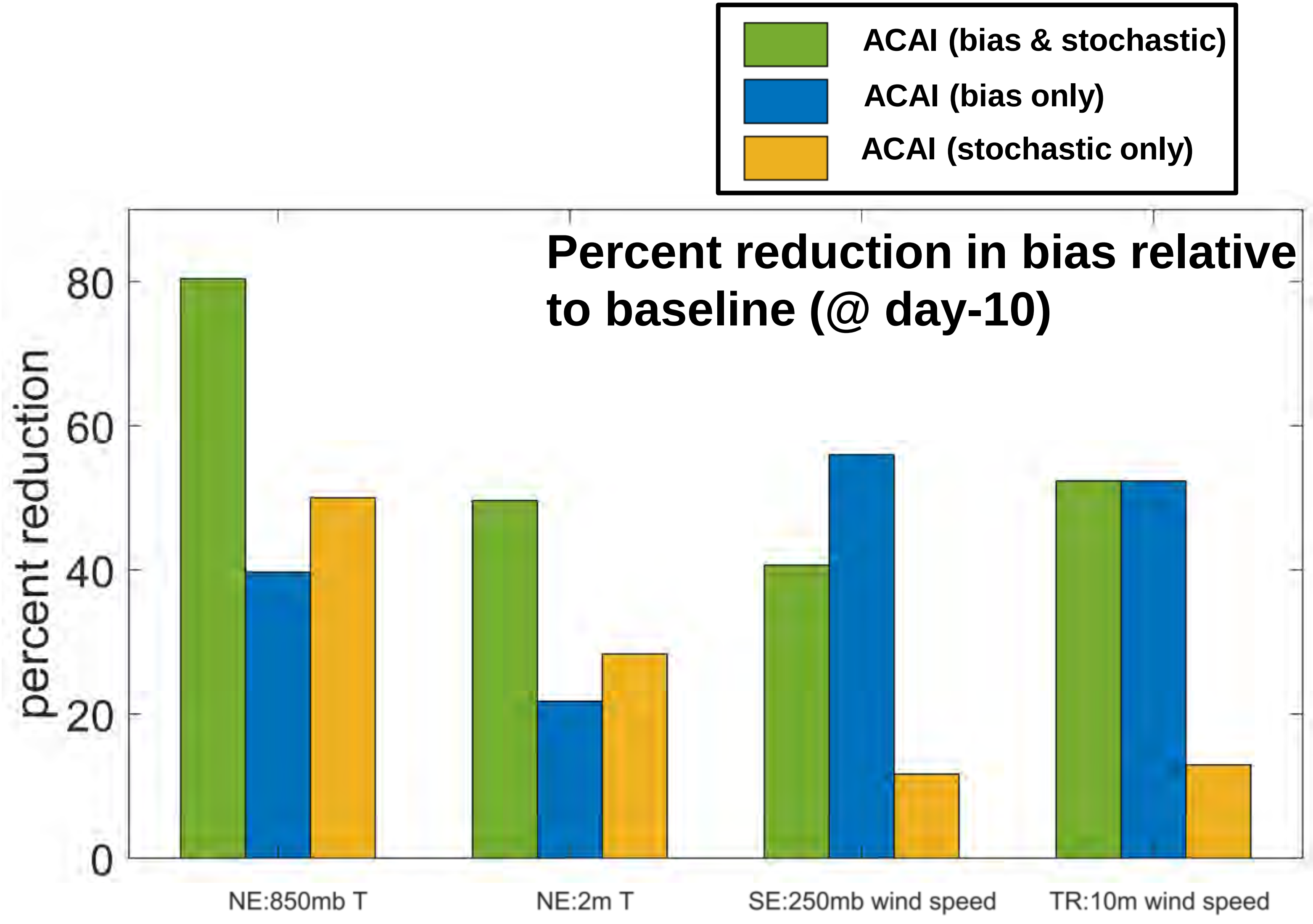


ACAI in Stand-Alone Atmosphere

- **First experimented with ACAI in our stand-alone system**
- **Ran experiments using only the bias or random components of the ACAI perturbations**
- **Find that the random component can have as large of an impact on the bias as the mean component**

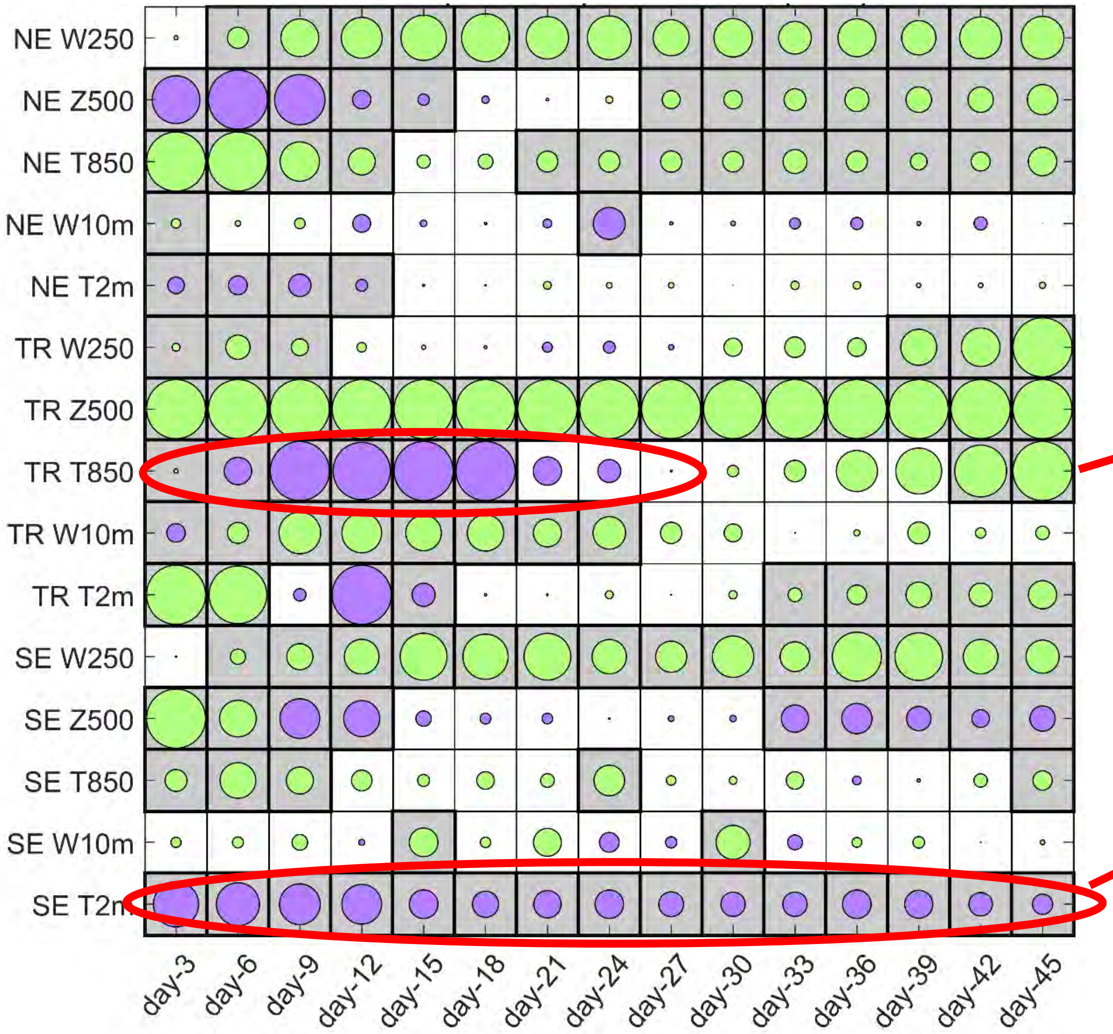
$$\delta x_m^F = \overline{\delta x^a} + \alpha\left[\delta x_m^a - \overline{\delta x_e^a}\right]$$

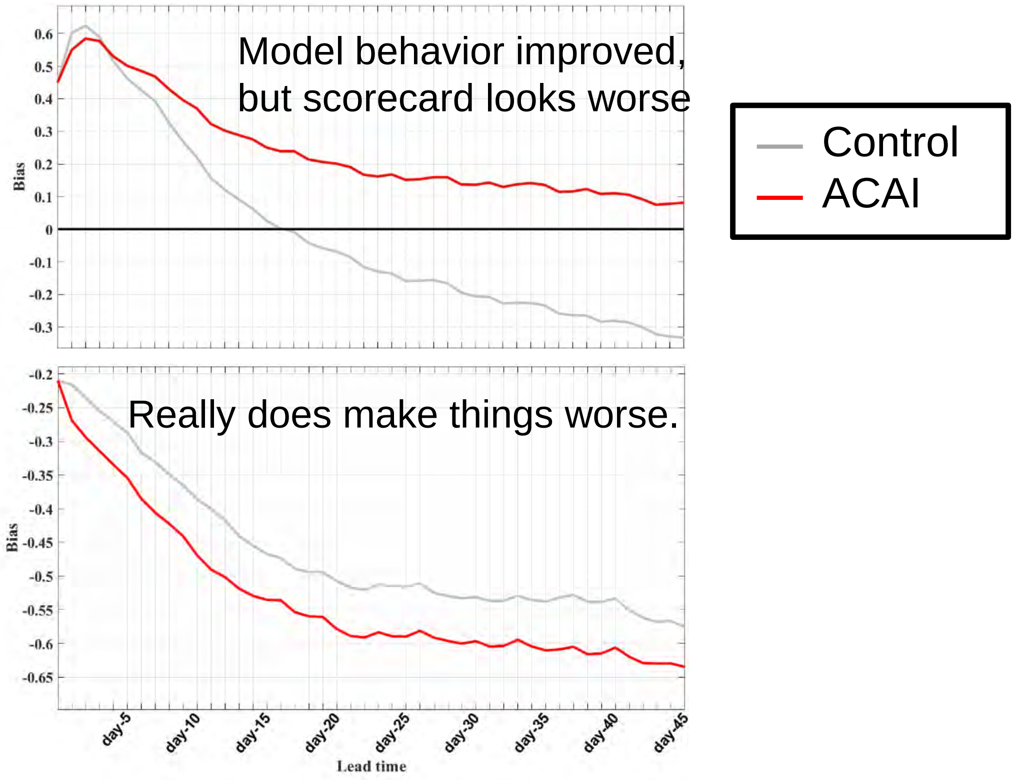
Crawford et al., 2020



ACAI in Navy ESPC Ensemble: Bias

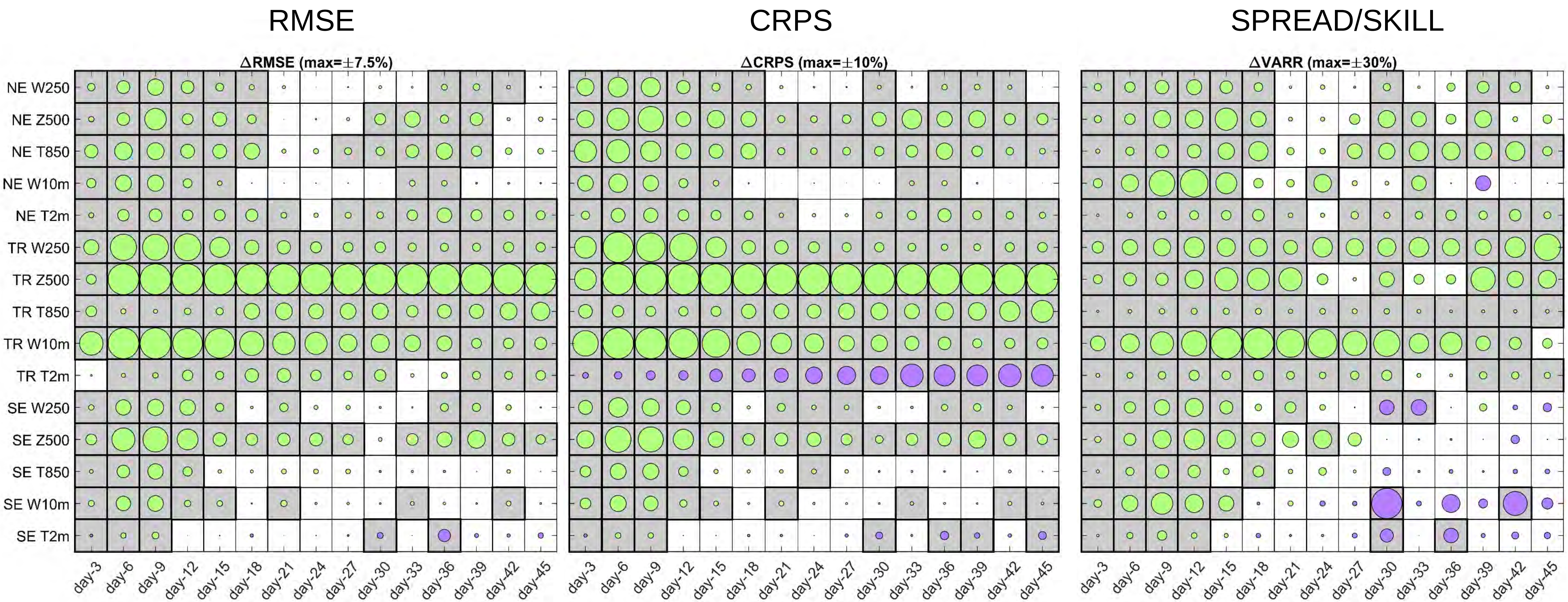
Change in Bias : ACAI vs CTRL (max=30%)





Crawford et al., In prep.

ACAI in Navy ESPC Ensemble: Spread-Skill



Overall promising performance for other metrics

Work by Stephanie Rushley and Matt Janiga show improvements for MJO and TC Potential Intensity forecasts (extra slides)

Crawford et al., In prep.

Summary

- We use analysis increments for in-line bias correction and accounting for model uncertainty in the US Navy's global atmosphere and coupled forecast system
- Overall performance very promising but it doesn't work everywhere
  - Biases can change with forecast lead time, particularly in coupled systems
  - Biases can be state (e.g., ENSO) dependent, testing "trailing" ACAI
  - In the future, larger reforecast archive and perhaps AI/ML can help better define state and time-dependent biases.
- In-line correction not a substitute for improving the model, but a strategy to enhance forecast performance given biased models
- DA increments useful in identifying model biases, useful to help improve models?