Improving NMME forecast skill using Calibration, Bridging, and Merging (CBaM)

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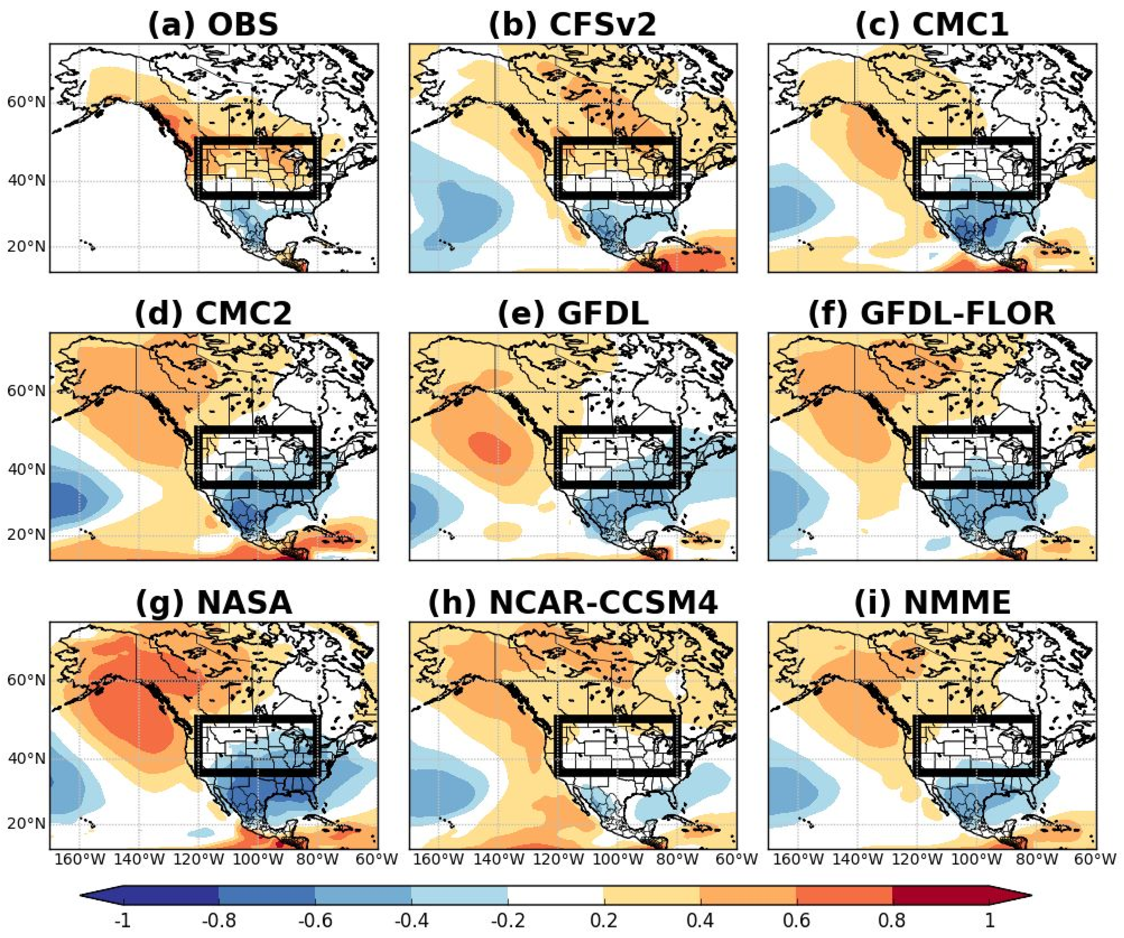
Motivation

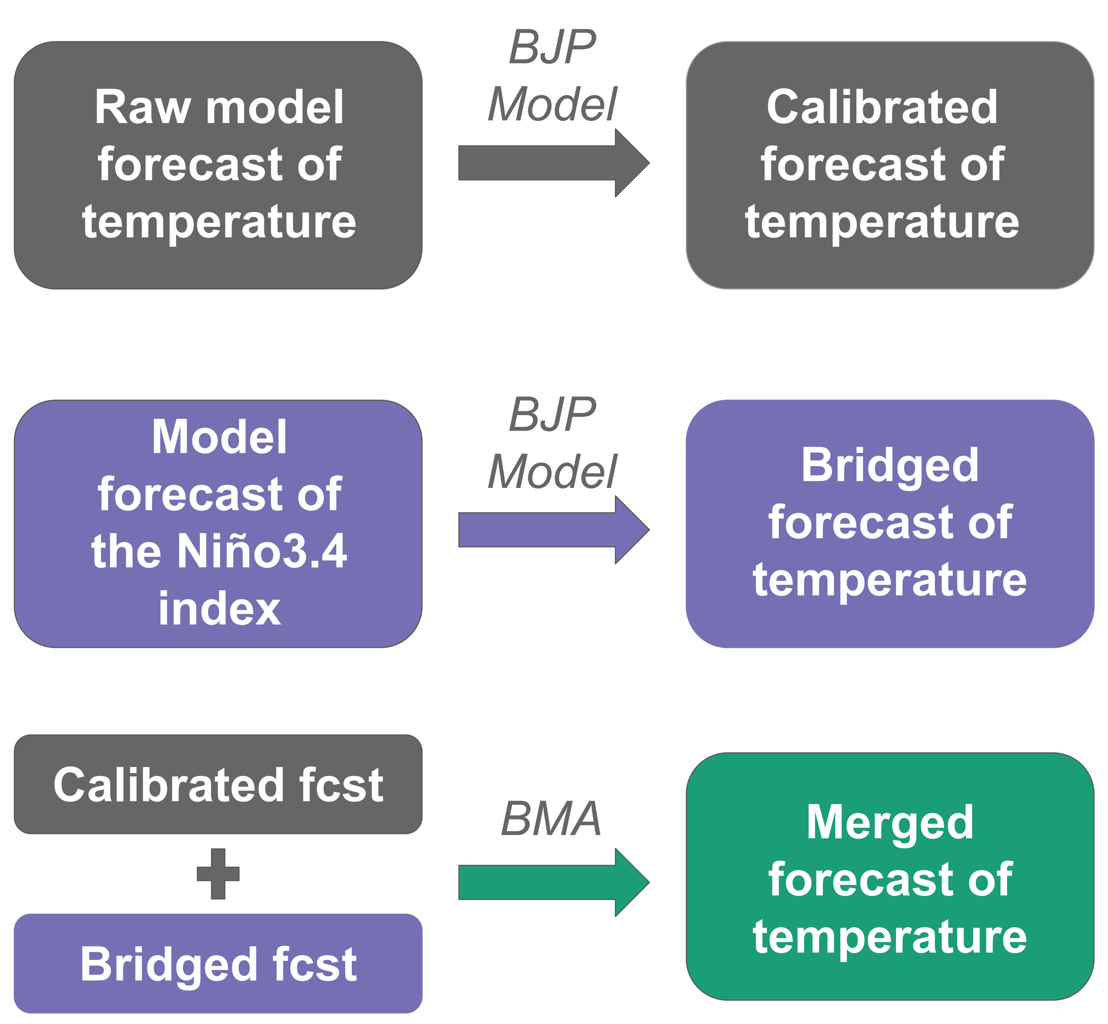
Climate models sometimes fail to reproduce observed teleconnection patterns associated with key drivers of North American climate (e.g., ENSO), which may reduce forecast skill. As an example, ***Figure 1*** shows the 1-month lead forecast December-January ENSO-temperature teleconnection pattern from the NMME (b-i) compared to the observed pattern (a). We address this problem by applying Bayesian statistical post-processing to model forecast fields.



Data and Methods

We use monthly mean 2-m temperature and SST forecast fields from the NMME to calculate seasonal mean forecast fields for the 12 3-month overlapping seasons over the NMME hindcast period, 1982-2010. Observed data from the GHCN-CAMS data set are used for verification.

We employ Bayesian joint probability (BJP) modeling to generate calibrated and bridged forecasts (see below). We then merge the calibrated and bridged forecasts using Bayesian model averaging (BMA).



Results

Figure 2: Calibrated forecast skill

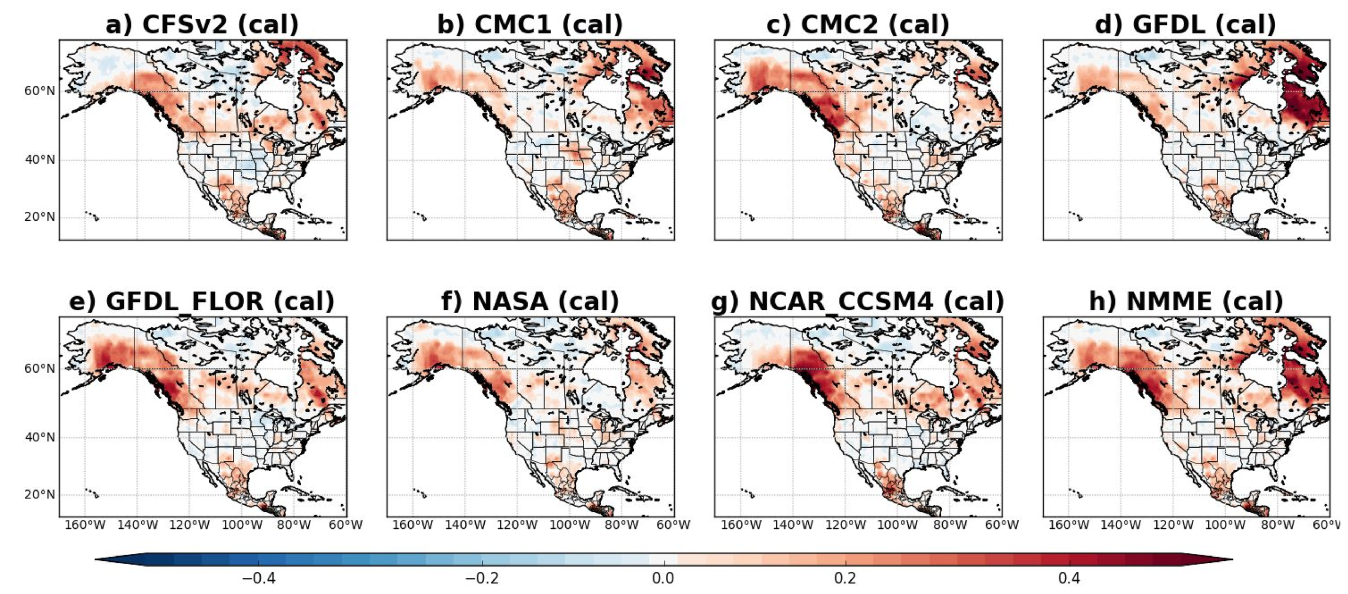


Figure 3: Bridged forecast skill

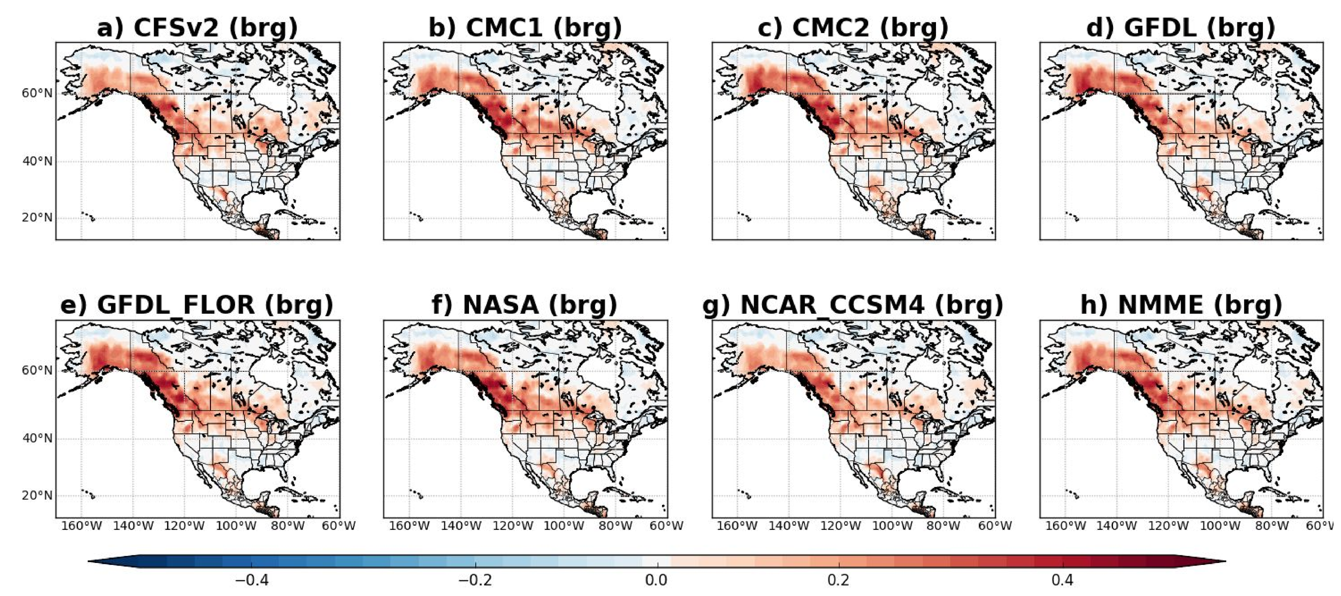
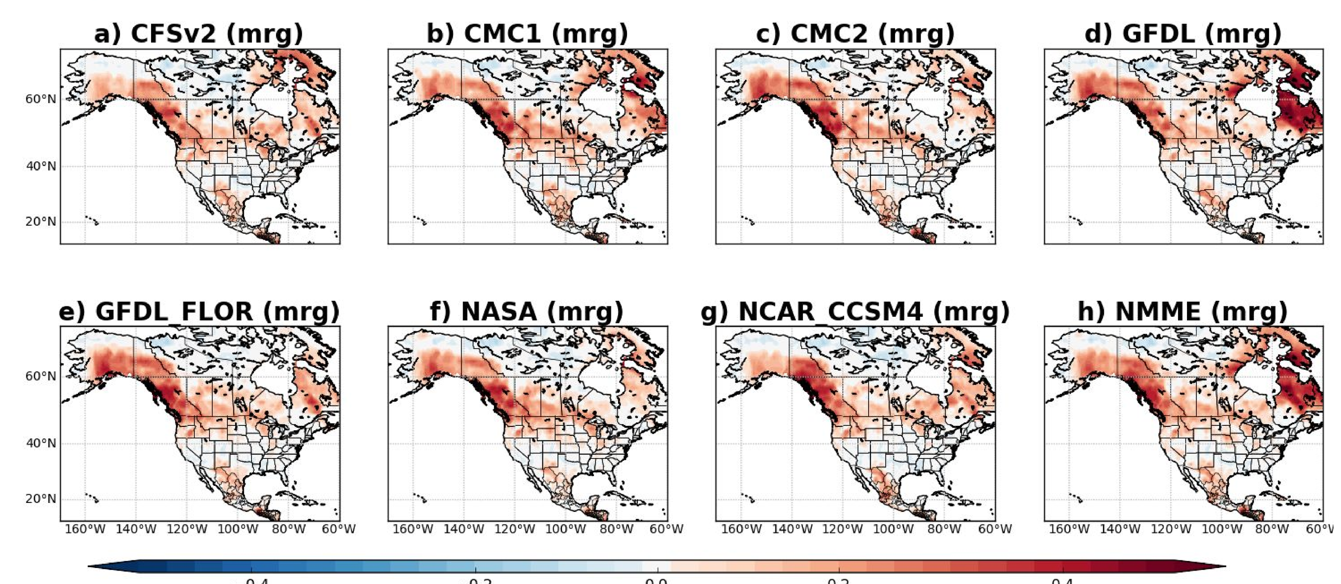


Figure 4: Merged forecast skill



Figures 2-4 (left) show Brier skill scores from probabilistic forecasts of below normal 2-m temperature over the hindcast period using calibration (**2**), bridging (**3**), and merging (**4**).

Figure 5 (below) provides reliability diagrams from probabilistic forecasts of below normal 2-m temperature over the hindcast period using calibration (gray), bridging (purple), and merging (green). The size of the circle corresponds to the number of forecasts in that predicted probability bin.

Figure 6 (bottom) depicts the percentage of grid cells for which bridged forecast skill exceeds calibrated forecast skill. Statistical-dynamical bridging (dark purple) is compared with statistical bridging (light purple).

Figure 5: Reliability Diagrams

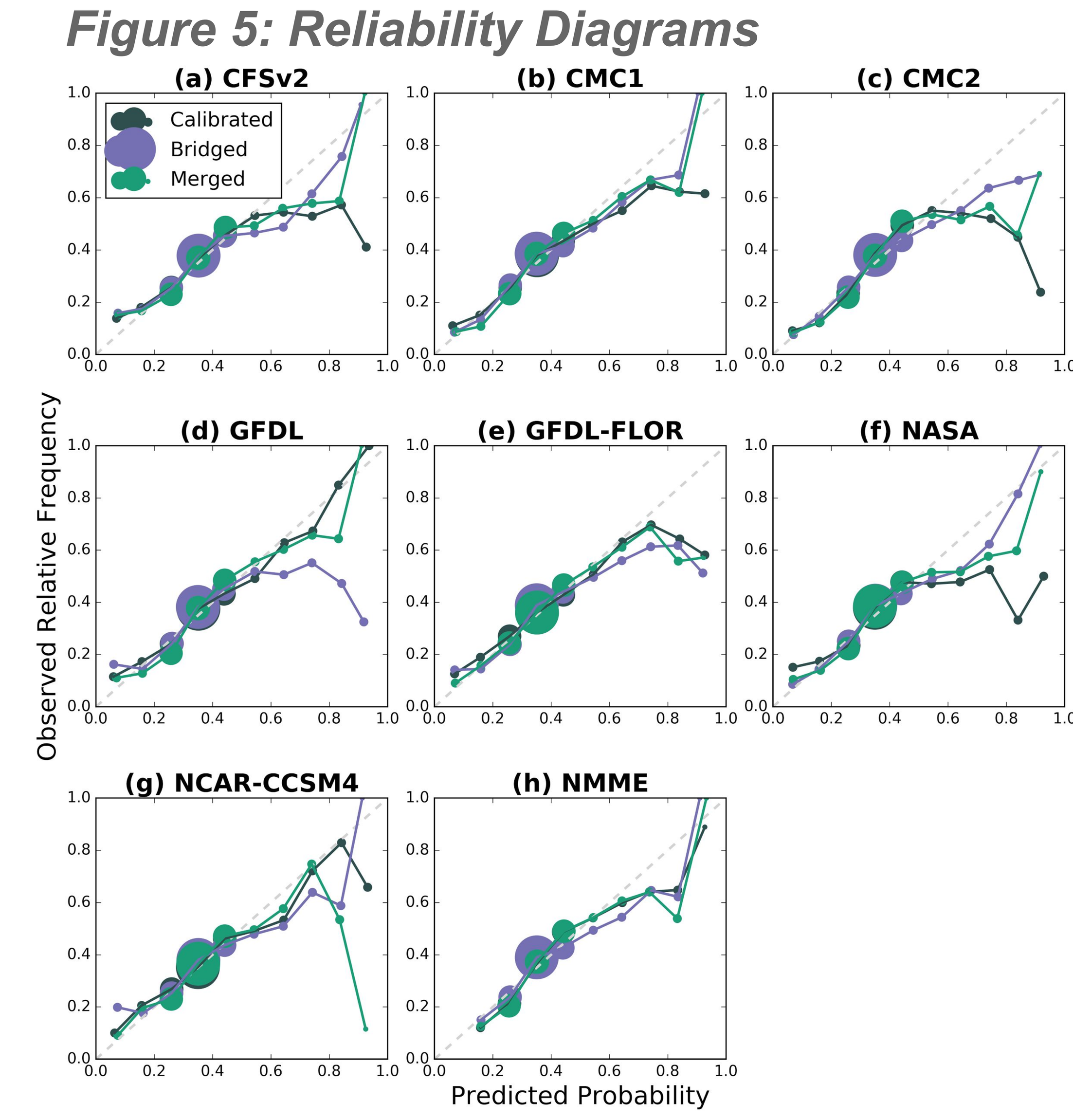
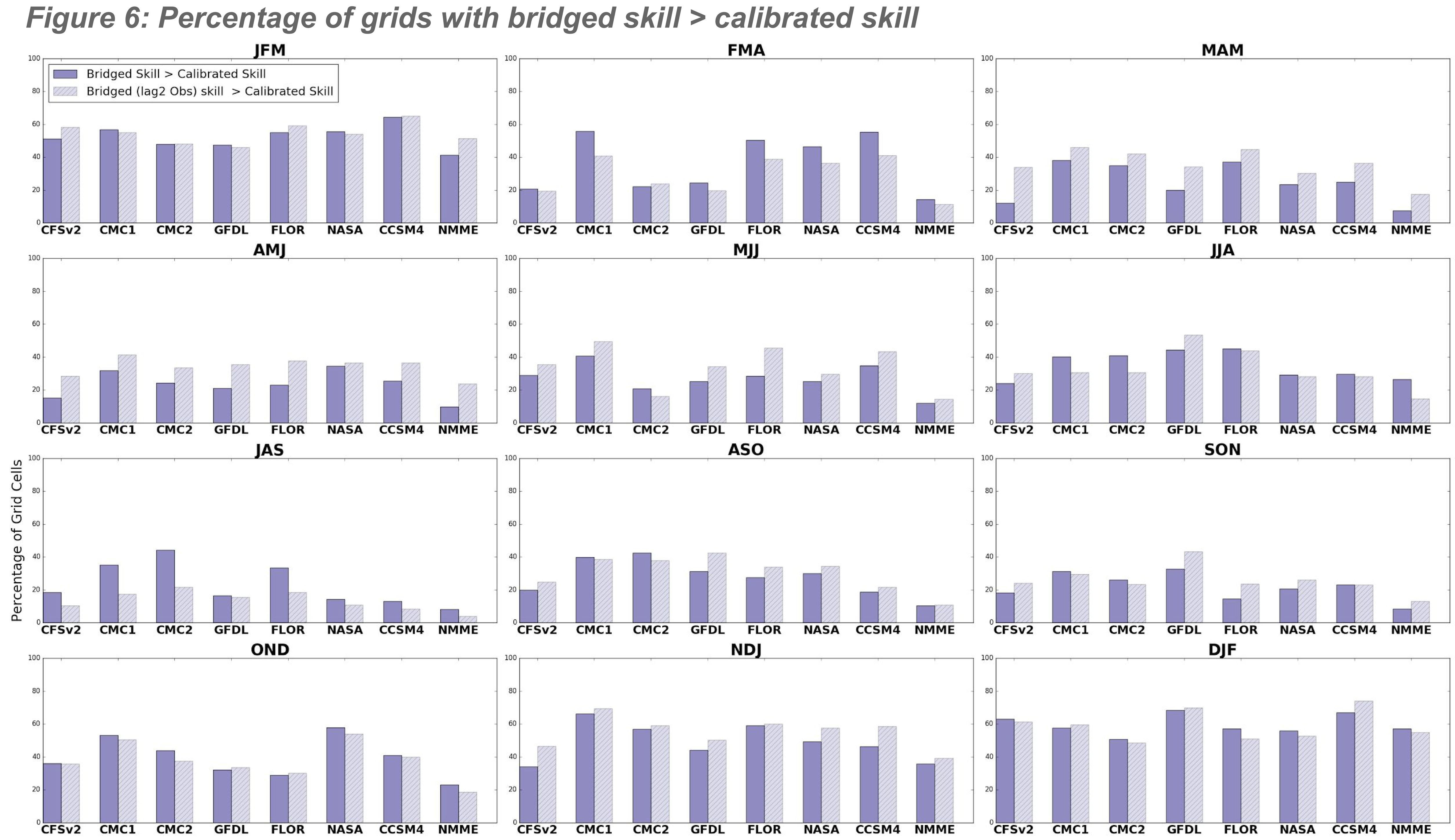


Figure 6: Percentage of grids with bridged skill > calibrated skill



Summary and Conclusions

Statistical-dynamical bridging using the forecast Niño 3.4 index improves temperature forecast skill over the Climate Prediction Center forecast domain, particularly for regions where dynamical models fail to reproduce the observed ENSO-temperature teleconnection pattern. The largest improvement occurs during the winter seasons, when the ENSO-temperature teleconnection is strongest. In contrast, very little improvement occurs during spring, summer, or early fall. Merged forecasts achieve the highest overall coverage of positive skill relative to bridged and calibrated forecasts. These results suggest that the CBaM post-processing method may help improve seasonal forecast skill, although additional testing using real-time NMME forecasts is necessary.

Acknowledgements: The CBaM method was originally developed at CSIRO by Q.J. Wang, Andrew Schepen, and others (see Schepen et al. 2017, Monthly Weather Review). This research is funded by a NOAA Climate Program Office MAPP Climate Test Bed grant.