Applying Multi-Model Superensemble Methods
to Global Ocean Operational Systems

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1. Introduction

A number of international organizations are currently running global Operational Ocean Forecast Systems in near-real-time modes. The daily nowcast and forecast data sets for a variety of oceanographic prognostic parameters are now available to the public through large data servers. Ongoing studies conducted as part of the GODAE OceanView Class-4 intercomparison (Ryan et al., 2015) are demonstrating that these OOS offer complimentary predictive skills. There is also well-documented literature that shows combining multiple forecasts using simple combinations can help to substantially increase accuracy (or reduce error) of such forecasts (Clemen, 1989, Galmarini et al., 2004).

A previous study (Spindler, Mehra, Tolman 2013) employed simple and weighted means and k-means clustering algorithms (Hartigan, 1975; Arthur and Vassilivitski, 2006) to improve nowcast error and bias in SST by processing a month of nowcast fields from five global OOS. This study is an extension of that work into the feasibility of applying simple numerical techniques as well as more sophisticated resampling methods to four global OOS (UKMET GloSea5, US Navy HYCOM, Mercator-Ocean Global, and NCEP Global RTOFS) that offer near-real-time nowcast and forecast data to assess the potential for reducing error and bias in both the current ocean state and forecasts of global SST and North Atlantic potential temperatures to depths of 500 m.

2. Method

Nowcasts and 6 days of forecasts from the member models were processed daily, using 30 prior days of model data to feed into the clustering algorithm. All members were interpolated to the reference data set grid. The global SST ensemble used Nearest Neighbor KD-Tree interpolation, whereas bilinear interpolation both horizontally and vertically was used for the regional ensemble. The external reference field for the global SST was GHRSST at 1/10° resolution, and FNMOC High Resolution Ocean Analysis for GODAE was used for the regional ensemble. Three ensemble methods were compared: simple average, weighted average (using inverse RMSE as the weight), and K-Means cluster-based weighted averaging (which also used inverse RMSE as the weight). Daily RMSE, Bias, and Cross Correlation was computed for both ensembles. For the regional model with depth-dependent fields, vertical temperature profiles were extracted and matched against ARGO profiles used in the GODAE Class-4 intermodel comparison project.

3. Results

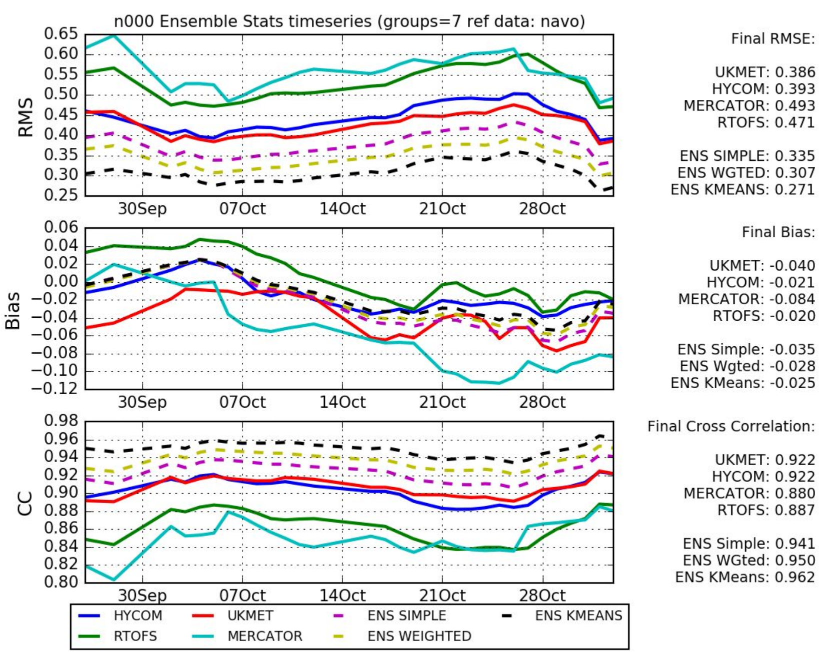

Figure 1. Global SST Ensemble: RMSE, Bias, and Cross Correlation statistics analyzed from one month of model runs. All three methods resulted in reductions in RMSE, improvements in cross-correlations, and with the ensemble bias remaining within the envelope of the members' bias values. The global SST K-Means ensemble exhibited the best improvements, with nowcasts and forecasts showing about a 30% improvement in RMSE, mid-range bias, and about a 10% improvement in the cross-correlation.

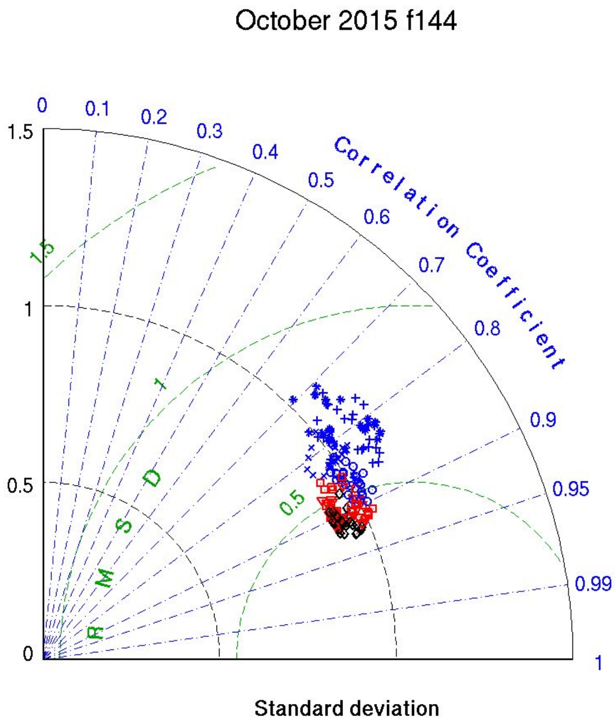

Figure 2: Global SST Ensemble: Taylor Diagram of the model members and ensemble methods for the 144 hour forecasts for the month of October, 2015. All points have been normalized by the standard deviation of the observations.

Blue: Model members
Red: simple and weighted ensemble
Black: K-Means ensemble

The diagram shows significant reductions in the spread of the ensemble RMSE as well as improved cross-correlations of the ensemble forecast as compared to the individual member forecasts. Of the three ensemble methods, the K-Means ensemble shows the lowest RMSE spread and the highest cross-correlation. The model member forecast spread in RMSE was found to increase over the forecast period at a faster rate than the ensemble RMSE spread.

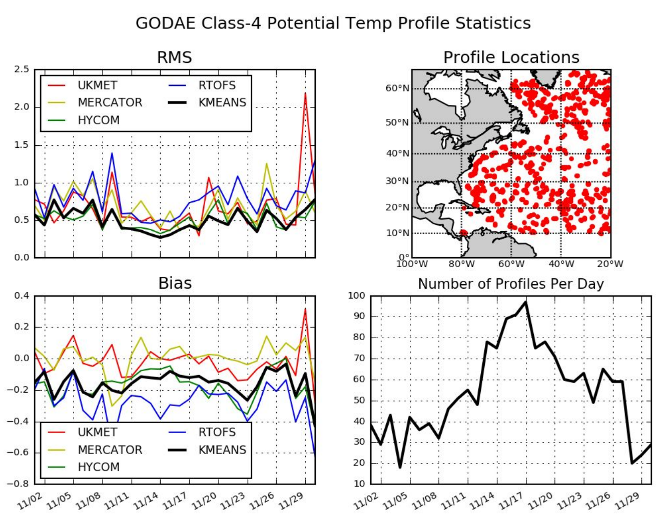

Figure 3: Regional North Atlantic Ensemble: GODAE Class-3 ARGO temperature profiles are compared to co-located profiles extracted from the Regional Ensemble. The upper right panel shows the locations of all of the profiles, the lower right panel shows the number of profiles per day over the course of the month. RMSE of the ensemble profiles showed improvement, but remained just within the envelope of the member values.

4. References

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