Ensemble-based Observation Impact Development at EMC

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The ensemble forecast sensitivity to observations (EFSO) formulation (Kalnay et al. 2012) has been implemented (Ota et al. 2013 and Groff et al. 2017) in the source code that provides ensemble square root filter (EnSRF) (Whitaker and Hamill 2002) functionality at the National Centers for Environmental Prediction (NCEP). As with the adjoint-based forecast sensitivity observation impact (FSOI) approach, the ensemble-based observation impact approach effectively enables a simultaneous computation of estimated forecast impacts and sensitivities for any and all observations assimilated in a numerical weather prediction (NWP) system. The NCEP GFS applies 4D ensemble-variational (4DEnVar) data assimilation (Kleist et al. 2015), and as such, requires an ensemble of short range forecasts to provide flow-dependent background uncertainty information. As currently configured, the EnSRF data assimilation algorithm is applied to assist in the assignment of initial conditions for the aforementioned ensemble of short range forecasts. In the context of 4DEnVar GFS cycling and following the EFSO approach described in Kalnay et al. 2012, the ensemble of analyses resulting from the EnSRF update have been used in representation of analysis-error covariance, and accordingly in approximation of the EnSRF Kalman gain. EFSO calculations are then based on the projection of this approximate Kalman gain to an evaluation forecast time using the gfs forecast model.

A complication with applying EFSO in the aforementioned context is that the set of observations and observation types assimilated in the GFS applied configuration of EnSRF are not representative of what is assimilated during the variational minimization (Todling and Diniz 2018). A variance-reduction based approach to discarding observations during the EnSRF update accounts for most of this discrepancy. To alleviate this impediment to achieving representative EFSO datasets for the aforementioned context, beta testing has been performed for GFS applied EnSRF configurations in which the variance-reduction based data discarding is disabled. Moving forward, modified pure ensemble sensitivity-based approaches will be explored to achieve a more robust observation impact approach.

In the EFSO approach, cross-covariances between perturbations in observation space and perturbations for a choice of metric in state space at the evaluation forecast time are employed to enable comparison of background states and individual observations at the evaluation forecast time. As such, taking advantage of the simultaneity aspect of EFSO datasets enables an objective basis for identifying where and when assimilated observation types are relatively more (less) efficient in reducing forecast error. Figures 1 and 2, see captions, show partitioning of 24 hour EFSO datasets (i.e. estimates for reduction of 24 hour forecast error) for the moist total energy norm (Ehrendorfer et al. 1999) by location and innovation. Similarly, EFSO simultaneity can be applied as a basis for hyperspectral IR channel selection. 24 hour EFSO calculations for IASI, AIRS and CrIS (not shown) indicate that assimilated 11 µm surface channels and 9.6 µm ozone band channels are relatively inefficient in reducing forecast error for the moist total energy norm.

Although the EFSO methodology provides an objective basis for estimating observation forecast impacts, the extent to which the approach provides representative information for improving global forecast system (GFS) or global ensemble forecast system (GEFS) forecast skill has yet to be rigorously tested. As such, it is planned that several EFSO guided experiments will be performed in the next year.

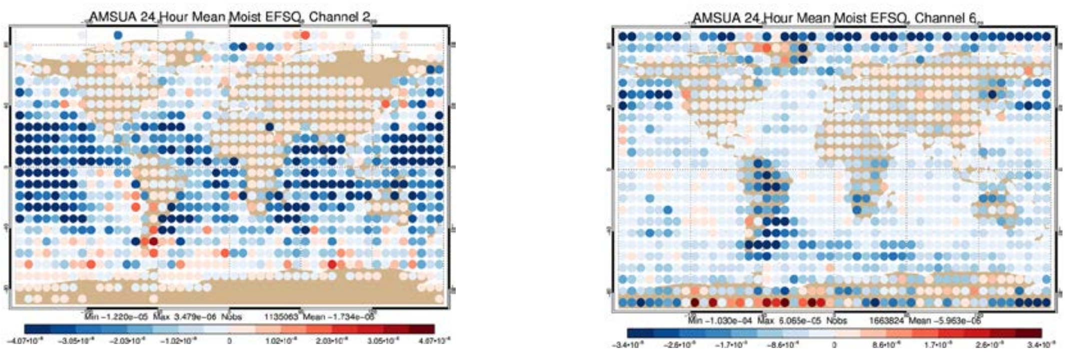

Figure 1. 7.5° by 7.5° Composite mean of 24 hour EFSO for the moist total energy norm, AMSU-A channel 2 (left panel) and AMSU-A channel 6 (right panel), the plots are for a several day sample from December 2014.

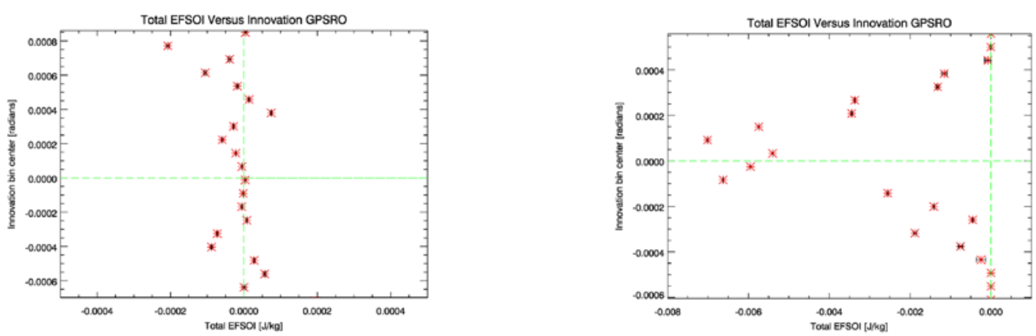

Figure 2. Total per cycle 24 hour EFSO for the moist total energy norm versus innovation bin, GPS RO Observations located below 700 hPa (left panel) and GPS RO observations located above 300 hPa (right panel), the plots are for a several day sample from January 2015.

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