# Using Forecast Temporal Variability to Evaluate Model Behavior

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We use simple diagnostics to quantify the temporal variability in analyses, $a_i$, and forecasts, $f_i$, for increasing time differences from $i$=1, 10 days. In addition, we introduce a diagnostic that reflects the day-to-day variability of the forecasts, $d_i$, for increasing forecast lead time $i$. In a perfect system, we expect $a_i > f_i$, and $a_1 > d_i$ due to the presence of uncorrelated analysis errors. We apply these diagnostics to control and perturbed ensemble initial states and forecasts from the NCEP and CMC global ensemble forecasting systems to demonstrate the utility of the diagnostics in quantifying aspects of forecast performance related to temporal variability. We relate the results to ensemble design and, in the case of CMC, a system upgrade.

While $a_i > f_i$ and $a_1 > d_i$ for most NCEP fields, which is expected in a perfect system, $a_i < f_i$ and $a_1 < d_i$ for several CMC fields, indicating that the CMC system may have excessive temporal variability as compared to the analyses. This is probably due to the excessive smoothing of the CMC analyses through the application of a digital filter (since replaced by 4DIAU in the deterministic global system as discussed in Buehner et al. 2015, and under development in the ensemble system). Trends in $d_i$ illustrate how both the control and perturbed NCEP forecasts show a small but steady decrease in day-to-day temporal variability with increasing forecast time. In contrast, the CMC control forecasts show increasing temporal variability for temperature and humidity during the first few days, illustrating the spin-up of the system after the initial excessive digital filter smoothing.

The diagnostics also clearly reflect the upgrade in the CMC system on 13 February 2013. Before the upgrade, $f_i$ was greater than $a_i$ in the tropics for the CMC perturbed ensemble member for height, winds and temperature, which is not expected in a perfect system. After the upgrade, $f_i$ was less than $a_i$ in the tropics for the perturbed member. The trends in $d_i$ for the perturbed member also change, remaining fairly constant or increasing before the upgrade, and decreasing after the upgrade. These differences are consistent with changes made to the stochastic physics perturbations in order to reduce excessive precipitation (Gagnon et al. 2013).

An advantage of these diagnostics is the ability to assess forecast temporal variability on different time scales without the need for very long forecast integrations. For example, the locations of the maxima in height field variability shift or extend from the North Atlantic and North Pacific jet regions for $i$=1 downstream to northern Europe and the eastern North Pacific for $i$=10. These shifts are consistent with patterns found in temporal filtering diagnostics of analyses time series that differentiate between regions of synoptic variability and blocking (e.g., Blackmon et al. 1977; Lau and Nath 1987; Cai and Van Den Dool 1991) using low-pass (>10 d) and band-pass (7-90 and 8-64 d) filters that could not be applied to the 10-d forecast integrations considered here.

Diagnostics measuring temporal variability are complementary to other diagnostics, such as those that focus on time-mean quantities or model bias (e.g., Klocke and Rodwell, 2014), spatial scale separation techniques (e.g., Harris et al. 2001), and techniques to quantify differences between forecast fields and reality as represented on the scales resolved by the data assimilation and forecast systems (e.g., Peña and Toth 2014). Using diagnostics to assess the accuracy of both temporal and spatial variability will become increasingly important as stochastic techniques to account for model uncertainty proliferate in ensemble forecasting systems, as both spatial and temporal correlations are often parameters in these schemes that need to be tuned. Potential future work includes consideration of other forecast systems, as well as an extension to a comparison with observations.

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