Dynamically Weighted Hybrid Gain Data Assimilation

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1. Introduction:

Over the past 15 years, hybrid data assimilation methodologies have become more popular, particularly for use in many operational weather forecast centers worldwide. Despite its general success, hybrid DA, from a practical (and mostly operational) perspective, can become computationally expensive. Penny (2014) proposed the newest approach for the hybrid system, aiming to reduce the computational load during the composition of the final analysis. The specific algorithm proposed by Penny (2014) combines two analyses: one from the ensemble-based system and the other from the variational approach, which uses the ensemble analysis mean as the background. Thus, the final analysis is the result of this linear combination between two analyses, where the weight given to the 3D-Var is a number between 0 and 1. The goal of this work is to use what was proposed in Penny (2014), but instead of use a scalar static weight, using a dynamic weight that is a matrix based on the ensemble spread from the LETKF, giving more weight to the LETKF when it presents a small spread and weighing more the 3D-Var when the LETKF presents a large spread.

2. Methodology:

We used the SPEEDY model (Simplified Parameterizations, primitivE-Equation DYnamics), developed by Molteni (2003) in the version T30L7. The Hybrid Gain (HG) algorithm used was implemented by Wespetal (2019). It uses the LETKF from Hunt et al. (2007) and the 3D-Var from Barker et al. (2004), with a tuned background error climatology for SPEEDY computed from forecast ensemble perturbations. The HG aims to solve Equation 1 where x^a_{HG} is the Hybrid Gain final analysis, $x^a_{LETKF}$is the analysis mean from the LETKF,$x^a_{3D-Var}$is the analysis from the 3D-Var, which uses the ensemble analysis mean as the background, α is the coefficient that determines the weight that each system will have in the final analysis ($0\leq\alpha\leq1$) and is a scalar.

$$x^a_{HG}=(1-\alpha)\,x^a_{LETKF}+\alpha\,x^a_{3D-Var} \qquad (1)$$

The proposal behind the dynamical weight is to better utilize spatially and temporally dependent information provided by LETKF through the ensemble spread. Thus, this work proposes replacing the fixed alpha (a scalar) from Equation 1 with a dynamic alpha (an evolving matrix), which is adjusted at each analysis step, each grid point in each level, and for each variable.

Eight experiments were performed using the SPEEDY model: five experiments using fixed alpha were run to estimate the best performing value of alpha (0.1, 0.3, 0.5, 0.7 and 0.9), two additional experiments using only the LETKF and only 3D-Var were performed for comparison, and the experiment using the dynamic alpha (DYN).

3. Results and conclusion:

The results were very interesting. We found good results for the dynamic alpha during the analysis (Figure 1), and better results when we look to the 120 hours forecast (Figure 2). Those results should be related to the fact that the alpha dynamic analysis are better balanced than the others (Figures 3 and 4). This study presents a methodology that permits to identify geospatially varying values of alpha that give near-optimal results without any necessary tuning, although we highlight that the encouraging success of this perfect model experiment does not guarantee success with all atmospheric global models.

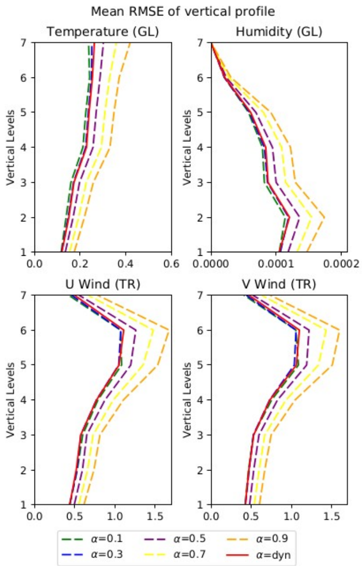

Fig 1. Vertical profiles of global temperature and humidity RMSE, as well as RMSE of U and V wind components in the Tropics, for the experiments with HG.

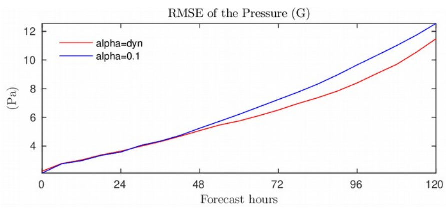

Fig 2. RMSE of pressure during 120 hour forecast.

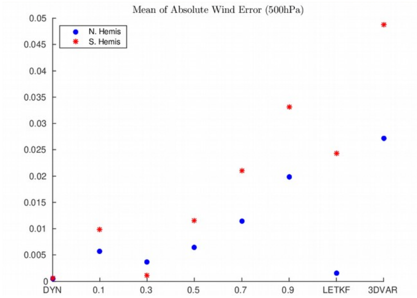

Fig 3. Mean Absolute Wind Error (500 hPa) in m/s for 8 experiments (with various alpha values shown on the x-axis) for the Southern (red) and Northern Hemispheres (blue).

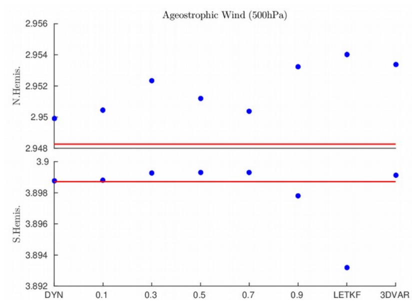

Fig 4. Mean Ageostrophic Wind (500hPa) in m/s for eight experiments for the Northern Hemisphere (top) and Southern Hemisphere (bottom). The blue points are the experimental values, and the red lines indicate the values for the Nature Run.

The Figures shown here come from a paper under review.

4. References:

Barker, D. M., W. Huang, Y.-R. Guo, A. J. Bourgeois, and Q. N. Xiao, 2004:A three-dimensional variational data assimilation system for MM5:Implementation and initial results. Mon. Wea. Rev., 132, 897–914, https://doi.org/10.1175/1520-0493(2004)132<0897:ATVDAS>2.0.CO;2.

Hunt, B. R., E. J. Kostelich, and I. Szunyogh, 2007: Objective weather-map analysis.Physica D Nonlinear Phenomena, 230 (1-2), 112–126, http://www.sciencedirect.com/science/article/B6TVK-4MNHXX0-3/2/43ec2cf5dffe5aacdf538cdeb90cd480.

Molteni, L., 2003: Atmospheric simulations using a GCM with simplified physical parametrizations. I: Model climatology and variability in multi-decadal experiments. Climate Dyn.,20,175–191

Penny, S. G., 2014: The hybrid local ensemble transform Kalman filter.Mon. Wea. Rev., 142, 2139–2149, http://dx.doi.org/10.1175/MWR-D-13-00131.1.

Wespetal, M. E., 2019: Advanced data assimilation for a Mars atmospheric reanalysis, thesis Prospectus, University of Maryland.