4D.5

ASSIMILATION OF GPS DROPWINDSONDE DATA USING A VICBAR ENSEMBLE

Brian J. Etherton[1] and Sim D. Aberson[2]
[1]-*University of Miami,* [2]-*NOAA-AOML*

1 -- INTRODUCTION

In recent years, the routine observational network has been augmented by GPS dropwindsondes released from aircraft, improving forecasts of tropical cyclones (Tuleya and Lord 1997, Aberson and Franklin 1999). However, operational data assimilation schemes may only be realizing limited benefit from the targeted observations. Etherton and Bishop (2002) showed that in a simple system the inclusion of ensemble based error statistics in the data assimilation scheme resulted in smaller analysis and forecast errors. In this extended abstract, we outline results from using ensemble based error statistics for the assimilation of GPS dropwindsonde data into the VICBAR model.

2 -- METHODS

The Hybrid analysis scheme approximates the forecast error covariance matrix $\mathbf{P}^f$ with a mix of the conventional, NCEP-like, parameterized 3D-Var covariances, $\mathbf{B}^f$, with flow dependent, ensemble-based covariances, $\mathbf{F}^f$. Following from Hamill and Snyder (2000), the forecast error covariance matrix $\mathbf{P}^f$ from Etherton and Bishop (2002) is given by

$$\mathbf{P}^f = (1-\alpha)\lambda\mathbf{F}^f + \alpha\rho\mathbf{B}^f, \qquad (1)$$

The parameters λ and ρ, calculated using the maximal likelihood approach of Dee (1995), are used to rescale $\mathbf{P}^f$ and $\mathbf{B}^f$ such that the traces of $\lambda\mathbf{F}^f$ and $\rho\mathbf{B}^f$ are the same, and both roughly equal to the magnitude of the first guess error. The matrix $\mathbf{F}^f$ is:

$$\mathbf{F}^f = \mathbf{Z}^f\mathbf{Z}^{f\mathrm{T}}, \qquad (2)$$

where each column of the matrix $\mathbf{Z}^f$, is proportional to the difference between an ensemble member forecast and a reference forecast at the time at which observations are to be assimilated. For the matrix $\mathbf{B}^f$, a simple correlation function, was used.

$$f(r) = \exp[\ln(0.1)(r/D)2] \qquad (3)$$

In (3), r is the distance away from an observation site, and D was chosen to be 5 degrees. Using $\mathbf{P}^f$, the increment equation ,

$$\mathbf{x}^a - \mathbf{x}^f = \mathbf{P}^f\mathbf{H}^\mathrm{T}(\mathbf{H}\mathbf{P}^f\mathbf{H}^\mathrm{T}+\mathbf{R})^{-1}(\mathbf{y}-\mathbf{H}\mathbf{x}^f), \qquad (4)$$

that minimizes analysis error variance is used to combine observations with the first guess field to produce a new analysis. The first guess field, $\mathbf{x}^f$, is the mass-weighted 850 to 200 mb winds from 1-degree AVN analysis data. Observations, $\mathbf{y}$, were deep layer mean wind values from GPS dropwindsondes. Observational error was assumed to be 0.5 m/s.

3 – A SAMPLE CASE

Hurricane aircraft were deployed to observe the early stages of Michelle on November 1, 2001. Figure 1a shows the deep layer mean wind observations from a flight which occurred around 00Z on November 1st. The general flow field is shown in figure 1b, mass averaged 850-200mb wind from the AVN analysis.

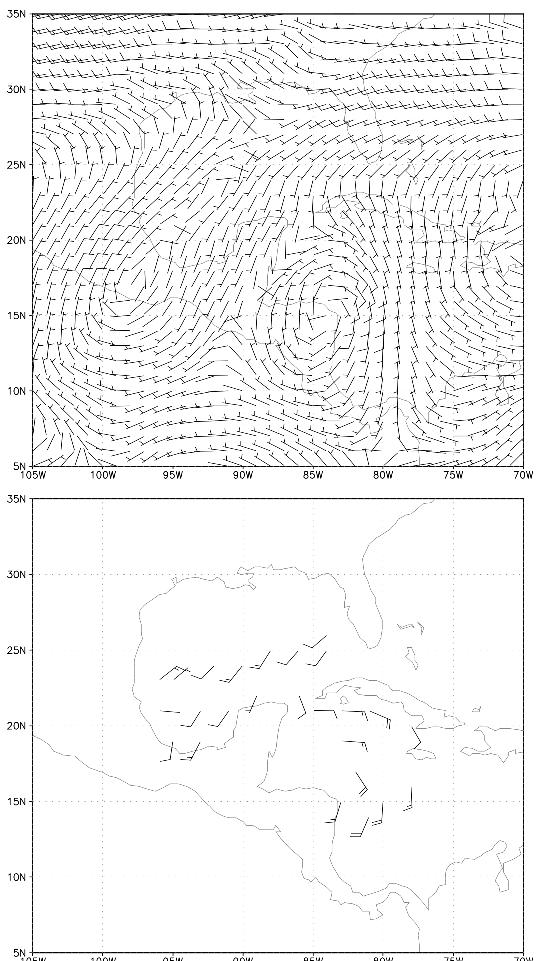

Figure 1, The AVN deep-layer mean wind (a) and GPS dropwindsonde DLM winds (b) in knots.

Corresponding author address: Brian J. Etherton, University of Miami, Rosenstiel School of Marine and Atmospheric Science, Department of Meteorology and Physical Oceanography, 4600 Rickenbacker Causeway, Miami FL, 33149-1098

Three features are evident in figure 1b: a sharp trough over Mexico, the signature of Michelle, and an anticyclone at 20N, 70W. Data collected from the flight of November 1st were combined with the first guess data shown in figure 1b using the error statistics in equation (4). Figure 2 shows the increments produced using purely isotropic covariances (top) and purely flow dependent covariances (bottom).

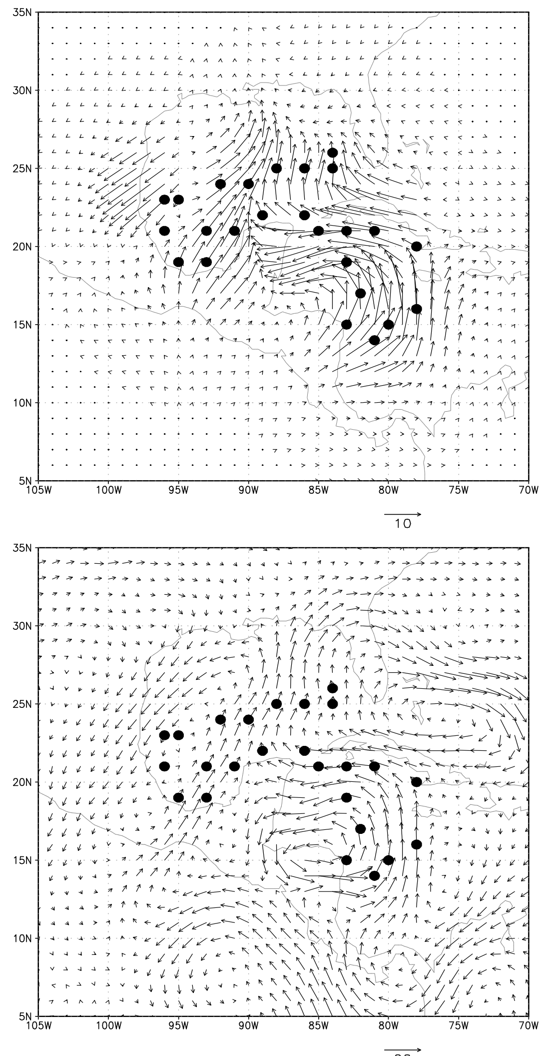

Figure 2, The deep-layer mean wind increment to the AVN wind field using (a) 3D-Var or (b) the ETKF from GPS dropwindsondes data. Winds speeds in knots.

It is clear that the ETKF allows for longer distance correlations that 3D-Var does, maximizing the impact of data on an analysis. Note that, regarding the trough centered in Mexico, the impact of the observations extends much further to the south when the Hybrid is used than when 3D-Var is used. Note also that there is an anticyclone to the east of the Bahamas in the Hybrid increment, which does not exist when 3D-Var is used. Lastly, note that the wind speeds of the increment are larger then the hybrid is used, closer to the actual observed values.

The extra information resultant from using the ensemble based error statistics does not guarantee a better analysis, as the correlations could be spurious, the result of too few ensemble perturbations to make a robust $\mathbf{F}^f$ matrix.

Having formed increments to the first guess field, the next step in this research is to add these increments to the AVN field, import these fields in to VICBAR, and generate track forecasts. We will compare the skill of the VICBAR forecast initialized with a Hybrid increment to one initialized with 3D-Var. We hope to show that the analysis which uses flow dependent error statistics produces a better forecast.

In addition to the case of Michelle, several runs will be done between now and the time of the conference, with a collection of results to draw from. We will look at more storms, and hope to show that from this larger sample, whether or not using ensemble based error statistics to assimilate omega dropwindsondes data consistently improves VICBAR track forecasts. If this is shown to be so, it suggests that additional gain from observations than is currently being realized is possible, that VICBAR forecasts can be improved by assimilating GPS sonde data using flow dependent error statistics.

4 – REFERENCES

Aberson, S. D., J. L. Franklin, 1999: Impact on hurricane track and intensity forecasts of GPS dropwindsonde observations from the first-season flights of the NOAA Gulfstream-IV jet aircraft. *Bull. Amer. Meteor. Soc.*, **80**, 421–428.

Dee, D., 1995: On-line estimation of error covariance parameters for atmospheric data assimilation. *Mon. Wea. Rev.*, **123**, 1128-1145.

Etherton, B. J., and C. H. Bishop, 2002: The Resilience of hybrid ensemble/3D-Var analysis schemes to model error and ensemble covariance error. *Mon. Wea. Rev.*, submitted.

Hamill, T. M., and C. Snyder, 2000: A hybrid ensemble Kalman Filter / 3D-variational analysis scheme. *Mon. Wea. Rev.*, **128**, 2905-2919.

Tuleya R. E., and S. J. Lord, 1997: The impact of dropwindsonde data on GFDL hurricane model forecasts using global analyses. *Wea. Forecasting*, **12**, 307-320.