

15B.7 A SEQUENTIAL VARIATIONAL ANALYSIS APPROACH FOR MESOSCALE DATA ASSIMILATION

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1. INTRODUCTION

A Space and Time Mesoscale Analysis System (STMAS) has been developed at Forecast Systems Laboratory (FSL) to generate a grid analysis of surface observations. It is a three-dimensional variational analysis (3DVAR) of horizontal space and time instead of pressure or height levels. It is used to detect boundary layer phenomena, frontal zones, and various nonlinear phenomena, and has been used in the DTC Weather Forecast Experiments (Koch et al. 2005) to verify 5-km resolution WRF model forecasts.

Surface observations are usually inhomogeneous in time. For example, the FSL Meteorological Assimilation Data Ingest System (MADIS) provides hourly data, 15-minute data, and 5-minute data, depending upon the networks and instruments. A single time frame analysis could result in some discontinuity in time because observations are available at different time frequencies. An analysis could provide better continuity both in space and time if it could include the time information. The time information has been used in a modification of the customary Barnes objective analysis scheme that assumed gravity wave behavior (Koch and O'Handley 1997). STMAS uses the time information under a much more generally applicable variational framework and potentially could handle non-conventional data, like radar and satellite radiance. This space and time analysis not only fills in the observation gaps in time, but also helps the analysis over data sparse region. Therefore,

STMAS provides time continuous analyses compared to the conventional, single time frame analysis scheme.

To handle nonlinearity of different weather conditions, a sequential 3DVAR approach is adopted in STMAS to make the analysis gradually approximate the nonlinearity of the analyzed fields, which cannot be done by one single 3DVAR. Similar to a single Barnes iteration, a single 3DVAR analysis can only represent the atmospheric field over scales determined by the length scale of its covariance. Without an accurate error covariance, a 3DVAR system may not provide good analyses, particularly a 3DVAR using simple recursive filter (Hayden and Purser 1995) approximating the covariance. For conventional observation datasets, a 3DVAR analysis can be worse than a Barnes analysis. Figure 1 shows the increments of the analyses from a single 3DVAR using a recursive filter, a two-correction Barnes (Koch et al. 1983), and STMAS. This test employs an analytic observation innovation dataset derived from a highly nonlinear function over the real observation sites of MADIS. A larger influence radius of the covariance for this single 3DVAR analysis can only produce a smoother field, but remove the smaller scales from its analysis.

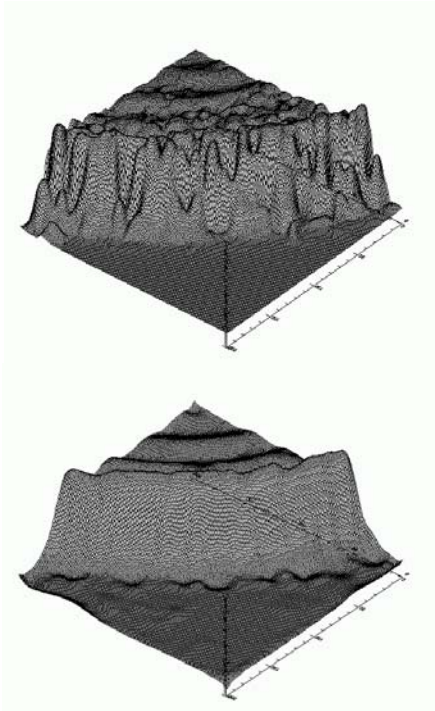
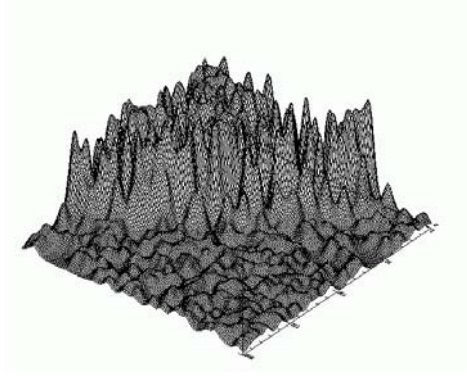


Figure 1. Comparison of single 3DVAR scheme using a recursive filter, a two-pass Barnes scheme and STMAS analyses.

In a highly nonlinear and inhomogeneous data assimilation situation, STMAS is a better variational analysis system, handling not only conventional data as good as a Barnes analysis, but also more complex data (radar and satellite data) like a 3DVAR system.

2. RESPONSE ANALYSIS

To demonstrate the necessity of solving a sequence of 3DVAR analyses for an

STMAS analysis, a response function analysis of a single 3DVAR system using a recursive filter and a Barnes system is presented. A recursive filter has the following form (see Hayden and Purser 1995),

$$u'_i = \alpha u'_{i-1} + (1 - \alpha)u_i \quad \text{left pass}$$

$$u''_i = \alpha u''_{i+1} + (1 - \alpha)u'_i \quad \text{right pass}$$

A Fourier transformation into wavenumber space yields,

$$(1 - \alpha Z^{-1})\bar{u}' = (1 - \alpha)\bar{u}$$

$$(1 - \alpha Z)\bar{u}'' = (1 - \alpha)\bar{u}'$$

or

$$\bar{u}'' = \frac{(1 - \alpha)^2}{1 - \alpha(Z^{-1} + Z) + \alpha^2} \bar{u}$$

for a single pass of a combination of the left and right filters, where Z is a unit complex number. Using this response function, we can find a response function of a single Barnes iteration. Figure 2 shows the response functions of the recursive filter with $\alpha = 0.5, 0.7,$ and 0.9 and the corresponding responses of a Barnes iteration, respectively, where the responses are plotted as functions of dimensionless wavelength $\lambda^* = \lambda/L$, where L is an arbitrary scale length (see Koch et al. 1983 for details).

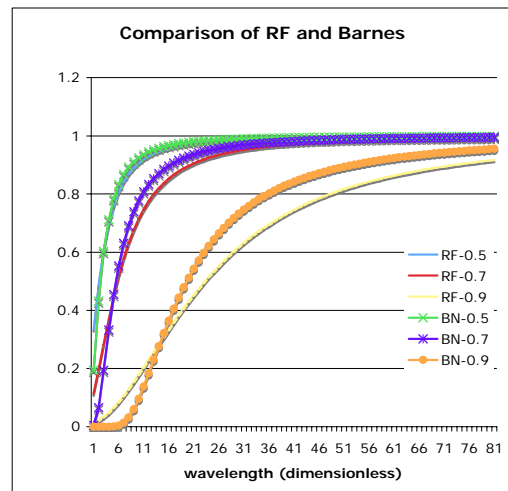


Figure 2. Response functions of single 3DVAR recursive filter (RF) and single-pass Barnes filter (BN) for various values of the weighting coefficient α .

It is known that a single iteration is not enough for a good Barnes analysis (Koch et al. 1983), and successive corrections are necessary. This figure shows that a single Barnes analysis can achieve the similar analysis from a 3DVAR using a given recursive filter. Two successive corrections using RF-0.9 and RF-0.7 can obtain essentially the same analysis as a two-correction Barnes analysis (see Fig. 3).

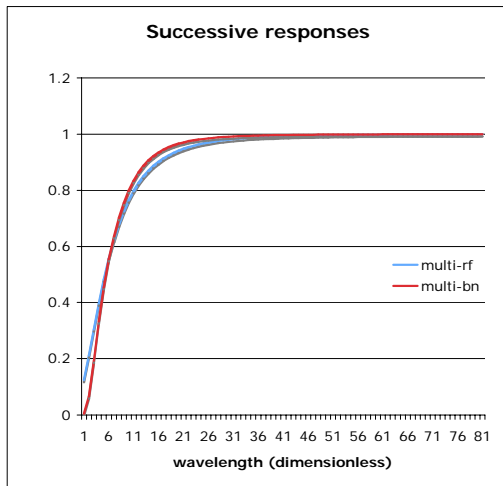


Figure 3. Response function of multi-iteration of 3DVAR and Barnes.

Thus, a sequential 3DVAR method is necessary in a multi-scale analysis. For conventional data, a Barnes analysis can match any 3DVAR analysis if the same error distribution can be used. This response function analysis explains why 3DVAR analyses cannot be as good as a Barnes analyses for conventional data. Instead, a sequential 3DVAR, as used in the STMAS, can obtain analyses like Barnes. While extending the benefits to include off-map time temporal weighting in a general sense and non-conventional data with their particular attributable error characteristics (not handled by a Barnes analysis).

3. STMAS: A SEQUENTIAL 3DVAR

STMAS uses a sequence of 3DVARs to derive its final analysis. For each 3DVAR, the current implementation is to use a grid analysis with the above one-dimensional recursive filter applied sequentially to x , y and t . With this recursive filter approximating the background covariance, B , a single 3DVAR is:

$$\min \frac{1}{2}(x - x^b)^T B^{-1}(x - x^b) + \frac{1}{2}(Hx - y)^T O^{-1}(Hx - y)$$

where x^b is the background field, y is observation, O is the observation error covariance, and H is the operator mapping grid values to observations.

STMAS starts its sequence of 3DVARs with a large α value, say 0.999. It solves the above 3DVAR problem with the observation dataset and obtains an initial solution. This is similar to what a single 3DVAR does. In its subsequent sequence of 3DVAR analyses, STMAS reduces the value of α from the previous 3DVAR step by τ , where $\tau \in (0.5, 1)$ is a constant, and solves the 3DVAR problem with a new set of observations. This set is always generated by subtracting the previous 3DVAR analysis values at the observation sites from the observation values (i.e., calculation of innovation) used by the previous 3DVAR analysis just like a Barnes analysis. This sequence of 3DVARs is repeatedly solved until the α value is small enough, where its corresponding influence radius is smaller than the scales that can be resolved by the observation network (Koch et al. 1983). The final STMAS analysis will be the summation of all of the previous analyses.

From the definition of the algorithm, it can be seen that STMAS is a variational extension of Barnes scheme that successively corrects the analysis over difference scales as these recursive filters progress through smaller and smaller scales. Comparing to Barnes, since STMAS is a

variational analysis, it can handle radar, satellite, and other complex data type naturally. STMAS is also an extension of the standard 3DVAR in handling non-conventional data and the nonlinearity of the analysis. However, without a perfect covariance, a single 3DVAR cannot yield the same results as STMAS. This is shown in our analytic tests and real time data analysis.

4. A REAL TIME ANALYSIS

STMAS is currently running every half hour to provide fifteen-minute analysis in real time. Using dense surface observation data from MADIS, STMAS analysis provides a good verification tool for high resolution model forecasts. The surface data mainly comes from MADIS-MESONET through the Local Analysis and Prediction System (LAPS). Selecting “dwf1” as the domain name, though, can access a real time STMAS analysis instead of a conventional LAPS analysis from this website: <http://laps.fsl.noaa.gov/>. An example of STMAS analysis is presented here for April 7, 2005 at 1645UTC.

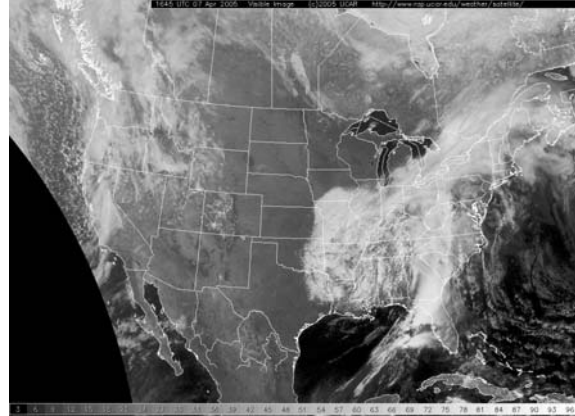
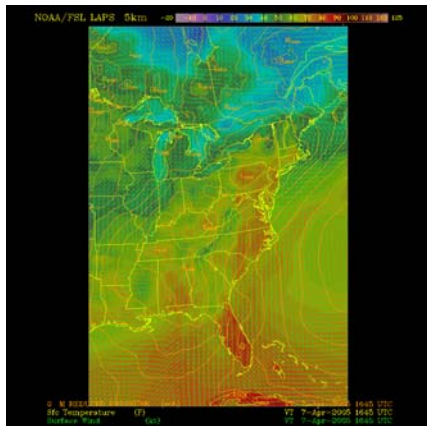


Figure 4. Top: STMAS analysis; Bottom: satellite image.

5. SUMMARY

To analyze various nonlinear weather phenomena, STMAS uses a sequence of 3DVARs in both the space and time domains to obtain multi-scale grid analysis, which as shown cannot be done through a single 3DVAR analysis. Just like a single iteration of Barnes, it is impossible to achieve an accurate analysis without a perfect error covariance for a single 3DVAR. The sequence of 3DVARs makes STMAS analysis inhomogeneous and anisotropic, even though it is currently implemented using a simple filter. Based on our experiments and analysis, STMAS is competitive to a two-pass Barnes scheme using surface meso-network observation data. However, STMAS is a natural extension of the conventional Barnes. Its ability to incorporate the time variability in a flexible, general, and continuous fashion, and non-conventional data may make STMAS a better and more robust nonlinear analysis tool.

6. REFERENCES

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