Simple Doppler Wind Lidar adaptive observation experiments with 3D-Var and an ensemble Kalman filter in a global primitive equations model

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Abstract

Through simple Observing System Simulation Experiments, we compare several adaptive observation strategies designed to subsample Doppler Wind Lidar (DWL) observations along satellite tracks, and examine the effectiveness of two data assimilation schemes, 3D-Var and the Local Ensemble Transform Kalman Filter (LETKF). With respect to sampling strategies, our results show that the LETKF-based ensemble spread method is superior to the other strategies tested, namely, use of a uniform distribution, the climatological spread strategy, or use of a random distribution, and is close to the ideal result obtained assuming that the true forecast error is known. With 10% DWL observations from the ensemble spread strategy, both 3D-Var and LETKF attain about 90% of the impact that 100% DWL wind profile coverage would provide. However, when the adaptive DWL observations coverage is reduced to 2%, 3D-Var becomes less effective than the more advanced LETKF assimilation scheme.
11. **Introduction**

Within the next few years, the first Doppler Wind Lidar (DWL) will be deployed in space by the European Space Agency (ESA, see, [http://www.congrex.nl/06c05/](http://www.congrex.nl/06c05/)). In addition, in its recent Decadal Survey Report, the National Research Council recommended a US global winds mission in the coming decade. Because the operation of DWL is strongly constrained by energy resources (Rishojgaard and Atlas, 2004), a frequently stated qualitative goal is to get about 90% of the total effectiveness from just 10% coverage with adaptive observations. Here, 10% coverage means making measurements in only 10% of the total footprints that the DWL can possibly scan in a certain interval such as 6 hours. Unlike the applications of adaptive dropsonde observing in field experiments (FASTEX, NORPEX, Joly et al., 1997; Bergot, 1999; Langland et al., 1999a; Langland et al., 1999b; Pu and Kalnay, 1999; Szunyogh et al., 1999; Majumdar et al., 2002; Toth et al., 2002; Langland 2005), which attempt to optimize the 2-3 days forecast within a specified verification region (e.g., Europe, or North America), the goal in our study is to optimize the 6-hour global analysis by optimally distributing the limited DWL observation resources. As pointed out by Lorenz and Emanuel (1998), if adaptive observations are made at the locations with largest background uncertainty, the global analysis error will be most reduced as compared to other locations. The question we address is how to represent the background dynamical uncertainty and choose adaptive observation locations accordingly.

The Ensemble Kalman Filter (EnKF) (Evensen, 1994; Anderson, 2001; Houtekamer and Mitchell, 2001; Bishop et al., 2001; Whitaker and Hamill, 2002; Ott et al., 2004; Hunt et al., 2007), a relatively new data assimilation approach, provides an estimate of the background dynamical uncertainty. We call the diagonal value of an EnKF-computed background error
covariance matrix for a given variable the ensemble spread for that variable. Locations with large ensemble spread are those in which dynamical instabilities of the evolving flow will result in large background (forecast) error and therefore where observations can be most useful. The different observation location selection strategies that we compare are (a) one based on the LETKF ensemble spread, (b) a uniform observation distribution, (c) one based on the climatological background uncertainty, (d) random locations, and (e) an “ideal” strategy based on assumed knowledge of the true forecast error. We compare the impacts of adaptive observations selected with these different methods by assimilating them with two different data assimilation schemes, 3D-Var and Local Ensemble Transform Kalman Filter (LETKF). We test both 10% and 2% adaptive observations coverage, allowing for relatively dense and sparse adaptive observation scenarios. Comparison of these two scenarios will show the sensitivity of data assimilation schemes to the amount of adaptive observations.

2. Model, observations, and data assimilation schemes

In this study, we use the Simplified Parameterizations, primitive Equation DYnamics (SPEEDY) model, developed by Molteni (2003) and adapted for data assimilation by Miyoshi (2005). It has a simplified but complete set of physical processes, seven vertical levels, 96 longitudinal grid points, and 48 latitudinal grid points. We follow a “perfect model” Observing System Simulation Experiments (OSSEs) setup, in which the simulated “truth” (long model integration) is generated with the same atmospheric model as the one used in data assimilation. In such an experimental setup, we avoid the complications of model error, and the only source of forecast errors comes from the initial conditions. Observations are obtained from the “truth” with added Gaussian random perturbations. The observation error
standard deviations assumed for wind components (u, v), temperature (T), specific humidity (q) and surface pressure (p) are 1.0m/s, 1.0K, 0.1g/kg, and 1.0hPa, respectively.

To test the sensitivity of the impacts of adaptive observations to data assimilation methods, we use both 3D-Var (Parrish and Derber, 1998, Miyoshi, 2005) and LETKF (Ott et al., 2004; Hunt et al., 2007). 3D-Var uses a constant background error covariance, which is calculated as in Parrish and Derber (1998). LETKF, a newly developed scheme belonging to EnKF family, employs the time evolving error covariance estimated from the forecast ensemble. It automatically gives the estimation of the forecast uncertainty. The application of LETKF on the SPEEDY model follows Hunt et al. (2007).

3. Adaptive strategies and the distribution of simulated adaptive DWL observations

We mimic satellite tracks and DWL observations assuming that the satellite scans half hemisphere “orbits” in each 6- hour analysis cycle. The basic observations (u, v, T, q, p) assimilated in all our experiments are simulated rawinsondes, shown as closed circles in Figure 1 (6 hr “orbits” are shown separated by vertical dashed lines). Figure 1 also shows an example of the distribution of 10% adaptive observations (crosses) from the ensemble spread strategy (defined below) at 1200 UTC. At 0000 UTC, the satellite scans the same half hemisphere orbit as at 1200 UTC, and the other half hemisphere orbit is scanned at 0600 UTC and 1800 UTC. Thus, we assume that each grid point can be observed twice a day (this is too optimistic because we neglect the impact of clouds). Since the characteristics of the forecast uncertainties are different in different regions (Kalnay, 2003), the adaptive DWL observations are distributed into seven subregions, the equatorial region, the northern and southern tropics, and northern and southern mid- and high-latitudes (separated by horizontal dashed lines in Fig. 1). Each subregion is allotted a number of adaptive observations
proportional to its area. At the selected adaptive DWL locations, both zonal wind and meridional wind are observed at all vertical levels, which is also over-optimistic because the lidar wind component that is actually observed is its projection on the line-of-sight direction (Stoffelen et al., 2005).

In all of the five adaptive observation strategies we tested, we impose a horizontal separation constraint to minimize possible observation redundancy, namely that the adaptive observations have to be at least two grid points apart in both longitude and latitude directions. Hamill and Snyder (2002) account for observation redundancy by selecting the observations serially in minimizing the analysis error variance. However, directly minimizing the analysis error variance is much more expensive than computing ensemble spread and applying the separation constraint, especially when selecting adaptive observations from a very large pool of observation locations. Moreover, by selecting adaptive observations at the locations with large ensemble spread in ensemble spread strategy, we indirectly minimize the analysis error variance. The separation constraint is done by first ordering the average 6-hour forecast ensemble spread of wind at 500hPa from largest to smallest in each region. Within each region, the location with largest ensemble spread is selected as the first adaptive observation location. Then, we delete the locations adjacent to the first adaptive observation location in both zonal and meridional direction from the potential adaptive observation queue. The second adaptive observation location is where ensemble spread in the remaining queue is largest. This process is repeated until all the adaptive observation locations are selected. If all the observations are either selected or deleted before the allotted number of adaptive observations are picked out, the remaining adaptive observations are the locations with largest ensemble spread that were deleted from the queue. A similar separation constraint is
applied in all of the other strategies. In the climatological spread method, the climatological background ensemble spread is obtained from LETKF analyses of rawinsondes observations, and the adaptive observations are at the locations with largest climatological ensemble spread. In the ideal strategy, the adaptive observations are located where the background error (i.e., the absolute difference between 6-hour forecasts of 500hPa wind and the true 500hPa wind field) is largest. Since this strategy requires knowing the “truth”, it cannot be implemented in practice. The adaptive observation locations from ensemble spread, random location and the ideal strategy change with time, whereas the locations are fixed for uniform distribution and climatological ensemble spread strategies. In order to test whether the forecast ensemble spread truly represents forecast uncertainty, we use the same adaptive observation locations for both 3D-Var and LETKF in the ensemble spread and climatological ensemble spread strategies, even though they are both derived from LETKF assimilations.

We examine the effectiveness of these five adaptive observation strategies by computing the analysis Root Mean Square (RMS) errors and comparing them to extremes of both 0% DWL coverage (i.e., rawinsondes only), and full (100%) DWL coverage. The percentage improvement for each strategy is defined as 

$$PI = \frac{RMS - RMS^{0\%}}{RMS^{100\%} - RMS^{0\%}} \times 100\%,$$

where $RMS$ is the time mean global average RMS error of the adaptive strategy, $RMS^{100\%}$ and $RMS^{0\%}$ are the time mean global average RMS error of full DWL coverage and no DWL coverage, respectively.

4. Results

Figure 2 shows the time evolution of the global averaged zonal wind analysis RMS errors for 3D-Var (left) and LETKF (right) with 0% coverage (solid line with crosses) and 100% coverage (solid line), as well as the five adaptive strategies using 10% coverage. The
time averaged RMS error for the second month is presented in Table 1. Not surprisingly, the ideal strategy (dot dashed line) has the smallest errors, and is close to the 100% coverage. The LETKF-based ensemble spread strategy (solid line with open squares) is the best of the adaptive strategies that are feasible in practice, and is very close to the ideal strategy even for the 3D-Var analysis. The random location (dashed line) is better than the uniform distribution strategy (solid line with closed circles). The worst results are obtained from the climatological ensemble spread distribution (solid line with open circles) because there are no adaptive observations over vast areas (not shown). The adaptive strategies with time-changing locations (ensemble spread, random location, ideal strategy) are all better than the constant observation distributions (uniform distribution, climatological ensemble spread), a conclusion consistent with previous results (Lorenz and Emanuel, 1998; Hamill and Snyder, 2002).

Through the covariance between winds and the other variables in background error covariance, the wind observations improve the analysis of the other variables as well, such as temperature (not shown). The different adaptive observation strategies have the same ranking as for the wind analysis.

A striking result is that the RMS error of LETKF (Fig. 2b and Table 1) shows a much smaller difference among the adaptive strategies than that of 3D-Var, although their relative ranking is the same. This is because 3D-Var, with a constant background error covariance, is much more sensitive to the choice of observations. With less optimal adaptive strategies, such as uniform distribution, the large background errors are not effectively reduced due to lack of observations around some locations with large background error (left panel in Fig. 3). On the other hand, with the ensemble spread strategy, the adaptive observations are near the locations with large background errors (right panel in Fig. 3). Therefore, the assimilation of
these adaptive observations is equivalent to providing the information of the time-changing large background errors to 3D-Var. As a result, the analysis increments in 3D-Var have a shape more similar (but with opposite sign) to the background error (Fig. 3, right) than in any other feasible method. By contrast, LETKF, whose background error covariance already includes information on the “errors of the day”, is more efficient in extracting information from the observations even if their locations are not optimal, so that all the strategies give similarly small analysis errors.

It is clear from Figure 2a and Table 1 that 3D-Var attains more than 90% of the improvements between 0% and 100% coverage from just 10% adaptive observations determined with the ensemble spread strategy. The percentage improvement of ensemble spread strategy in LETKF is somewhat smaller than for 3D-Var, and, as discussed above, all adaptive strategies are similarly successful (Table 1). This seems to contradict the conclusions based on the previous adaptive observation field experiments that adaptive observations would be more effective with more advanced data assimilation schemes, such as 4D-Var or EnKF (Langland, 2005). However, we used relatively dense adaptive observation coverage in our experiments with 10% observed every 6 hours over half the globe. To make our results more compatible with previous field experiments, we now use the same adaptive observation strategies but substantially reduce the number of observation locations to only 2% of the full coverage (Table 2). With this small number of adaptive observations, the analysis errors of the adaptive strategies in 3D-Var are much larger, and even the most effective strategies, random location and ensemble spread, are only able to reduce the errors by less than 30%. By contrast, the LETKF still obtains 77% improvements from just 2% adaptive observations. The difference in performance among the five adaptive observation
strategies is much more evident, but with the same ranking as before. This result shows that with fewer adaptive observations, the data assimilation scheme plays a more important role in determining the effectiveness of adaptive observations. More advanced data assimilation schemes, such as the LETKF, use more efficiently of small amounts of observation information, which is consistent with previous field experiments (Langland, 2005). The small number of observations is not enough to provide enough global information on the “errors of the day” needed for the improvement of 3D-Var, while in the LETKF, it is possible to estimate the evolving error structures even with few observations.

5. Conclusions and discussion

In this study we showed the potential of a simple ensemble spread strategy for adaptive observations in the context of minimizing the energy required by DWL laser firings. The same adaptive strategy could be used for any satellite instrument designed to “dwell” in regions of high uncertainty rather than providing uniform coverage along the orbit as conventionally done.

We compared ensemble spread with several other adaptive observation strategies (uniform distribution, random distribution, climatological ensemble spread) and found that the 6-hour LETKF forecast ensemble spread gives a useful estimate of background uncertainty and dynamical instabilities. With 10% adaptive DWL observations, the ensemble spread sampling strategy gives the best result in both 3D-Var and LETKF, attaining more than 90% effectiveness of the full observation coverage. 3D-Var is more sensitive to adaptive strategies than the LETKF. Since the latter includes information on the “errors of the day”, different adaptive strategies have closer performances.
We found that the sensitivity of adaptive observation effectiveness to data assimilation schemes is related to the amount of adaptive observations to be determined. With a relatively dense number of adaptive wind observations, such as 10% of the maximum coverage, 3D-Var can be as effective as LETKF, a more advanced data assimilation schemes. With only 2% coverage, 3D-Var is not as effective as LETKF even when using the LETKF ensemble spread locations.

Although our results are indicative of the potential for adaptive observations in remote sensing, we made several simplifying assumptions, using a perfect model scenario, a low resolution global model, an extreme simplification of satellite orbits and DWL observations, assuming uncorrelated Gaussian observation errors, and neglecting the effect of clouds. As a result, the actual percentage improvements from assimilating DWL adaptive observations may be overoptimistic. Experiments with state-of-the-art OSSE systems should be carried out to verify whether our results are valid in a more realistic setup. We believe that the main results (that the EnKF-based uncertainty estimation gives valuable guidance to allocate limited observation resources along the satellite track, and that the effectiveness of data assimilation schemes is sensitive to the amount of adaptive observations) would be valid even in a realistic experimental setup.
Acknowledgements

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References


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Fig. 1 Example of the distribution of adaptive observations (crosses) from the ensemble spread sampling strategy at 1200 UTC February 03. The closed circles represent rawinsonde observation locations. Shades represent the average ensemble spread of zonal and meridional wind at 500hPa at that time. Horizontal dashed lines divide the whole globe into seven latitude bands. Vertical dashed lines separate the globe into four sub-regions representing two “orbits”.

Fig. 2 2-month evolution of 500hPa globally averaged zonal wind analysis RMS errors for 3D-Var (left panel) and LETKF (right panel) from 10% adaptive observations assimilation. From top to bottom their order is solid line with crosses: rawinsonde observation (0% DWL) assimilation; solid line with open circles: climatological spread; solid line with closed circles: uniform distribution; dashed line: random locations; solid line with open squares: ensemble spread adaptive strategy; dot dashed line: ideal sampling; solid line without marks: 100% adaptive observation coverage over half hemisphere.

Fig. 3 3D-Var zonal wind analysis increments (contour interval 0.3m/s), background error (shaded) and adaptive observation distribution (crosses) from uniform distribution (left panel) and from ensemble spread sampling strategy (right panel) at 1200 UTC February 03. The closed circles are rawinsonde observation locations.
Table 1 500hPa zonal wind time average (over February) of global mean RMS errors and percentage improvement (PI) of 10% adaptive observations for both 3D-Var and LETKF.

<table>
<thead>
<tr>
<th>Data assimilation</th>
<th>Experiment</th>
<th>Rawinsonde (0%)</th>
<th>Climatology (10%)</th>
<th>Uniform (10%)</th>
<th>Random (10%)</th>
<th>Spread (10%)</th>
<th>Ideal (10%)</th>
<th>100%</th>
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<tr>
<td>3D-Var</td>
<td>RMS error (m/s)</td>
<td>4.04</td>
<td>2.36</td>
<td>0.92</td>
<td>0.74</td>
<td>0.43</td>
<td>0.36</td>
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<td></td>
<td>PI</td>
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<td>83%</td>
<td>88%</td>
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<td>98%</td>
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<td>LETKF</td>
<td>RMS error (m/s)</td>
<td>1.18</td>
<td>0.38</td>
<td>0.36</td>
<td>0.33</td>
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<td>PI</td>
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<td>84%</td>
<td>89%</td>
<td>91%</td>
<td>94%</td>
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Table 2 500hPa zonal wind time average (over February) of global mean RMS errors and percentage improvement (PI) of 2% adaptive observations for both 3D-Var and LETKF.

<table>
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<th>Data assimilation</th>
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<th>Rawinsonde (0%)</th>
<th>Climatology (2%)</th>
<th>Uniform (2%)</th>
<th>Random (2%)</th>
<th>Spread (2%)</th>
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<td>3D-Var</td>
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<td>4.04</td>
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<td>3.11</td>
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<tr>
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<td>28%</td>
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<tr>
<td>LETKF</td>
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<td>62%</td>
<td>71%</td>
<td>77%</td>
<td>81%</td>
<td>N/A</td>
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Fig. 1 Example of the distribution of adaptive observations (crosses) from the ensemble spread sampling strategy at 1200 UTC February 03. The closed circles represent rawinsonde observation locations. Shades represent the average ensemble spread of zonal and meridional wind at 500hPa at that time. Horizontal dashed lines divide the whole globe into seven latitude bands. Vertical dashed lines separate the globe into four sub-regions representing two “orbits”.


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