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The impact of Doppler lidar wind observations on a single-level meteorological analysis

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ABSTRACT

Through the use of observation operators, modern data assimilation systems have the capability to ingest observations of quantities that are not themselves model variables, but are mathematically related to those variables. An example of this are the so-called LOS (line of sight) winds that a Doppler wind Lidar can provide. The model - or data assimilation system - needs information about both components of the horizontal wind vectors, whereas the observations in this case only provide the projection of the wind vector onto a given direction. The analyzed value is then calculated essentially based on a comparison between the observation itself and the model-simulated value of the observed quantity. However, in order to assess the expected impact of such an observing system, it is important to examine the extent to which a meteorological analysis can be constrained by the LOS winds. The answer to this question depends on the fundamental character of the atmospheric flow fields that are analyzed, but more importantly it also depends on the real and assumed error covariance characteristics of these fields. A single-level wind analysis system designed to explore these issues has been built at the NASA Data Assimilation Office. In this system, simulated wind observations can be evaluated in terms of their impact on the analysis quality under various assumptions about their spatial distribution and error characteristics and about the error covariance of the background fields. The basic design of the system will be presented along with experimental results obtained with it. In particular, the value of simultaneously measuring LOS winds along two different directions for a given location will be discussed.

Keywords: Satellite observations, Doppler Lidar, meteorology, data assimilation

1. INTRODUCTION

In spite of tremendous progress in numerical weather prediction and analysis systems over the last several decades, operational forecasts still occasionally go seriously wrong. At a recent WMO workshop,[1] the lack of independent knowledge about the wind profile in the free troposphere over the oceans was cited as the single most important cause of sporadic, abnormally large forecast errors in the northern hemisphere extratropics.

Currently, much of the knowledge about the wind profile in these areas comes from the multivariate assimilation of satellite temperature soundings, in which temperature information is translated into information about the atmospheric flow under some assumptions about the nature of the prevailing balance. An additional important source of information is the set of wind observations calculated by tracking features in the cloud and water vapor images obtained by the geostationary satellites[2,3]

However, both these sources of information are incomplete. The information embedded in the temperature field is indirect, and it is only used correctly when the balance of the real atmosphere corresponds to what is assumed in the analysis system. The geostationary wind data are of a less indirect nature, but coverage is limited to where features can be detected and tracked, the motion of the selected features may not always correctly reflect the mean flow field in their area, and the correct assignment of altitude level to the derived winds remains problematic. Latitudes beyond 60° in either hemisphere are unobservable from geostationary orbit, and in practice the amount and the quality of wind observations both decrease markedly beyond 50° of latitude.

Direct measurement of winds away from the areas of relatively good radiosonde coverage therefore remains a high priority for the global observing system. Such observations are expected to be especially beneficial in situations where the balance assumptions used for assimilation of satellite sounding data are invalid, and in regions where the geostationary wind observations are either poor or missing altogether. A space-borne Doppler Wind Lidar (DWL) is one of the candidate systems for providing these data.It is a direct wind measurement with an accurate height assignment, and it can provide relatively uniform horizontal coverage. Several concepts for such wind instruments have been studied in the past[4,5,6] and the European Space Agency recently selected the Atmospheric Dynamics Mission (ADM) as one of its two Earth Explorer Core Missions[7] for a projected 2006 launch.

Both the ADM and some of the concepts studied earlier are single-perspective instruments, i.e. the orientation of the LOS with respect to the flight direction of the spacecraft is fixed, and the observations therefore consist of a series of projections of the local horizontal wind vector onto essentially parallel lines. This eliminates the need for a scanning mechanism, and it therefore simplifies the instrument design. Since raw line of sight winds have little direct value for the user, the main target application for these observations is data assimilation for numerical weather prediction (NWP) purposes. The underlying assumption is that the data assimilation system will be able to correctly infer the unobserved wind component orthogonal to the instrument LOS from a combination of the data themselves, the background field, and the background error covariance.

The purpose of this article is to examine this assumption in some detail. This is done through a series of analysis experiments based on simulated observations obtained from simple, idealized random observation networks. Before any experiments can be meaningfully interpreted, a metric of information content for the different kinds of wind observations needs to be defined. Since the target application for these particular observations is data assimilation, we have chosen to use the analysis error variance as the main metric. In other words, the sole criterion for success of a given observing system is the extent to which it contributes towards producing an analysis with a low expected error. Issues such as measurement error and density of horizontal coverage are considered irrelevant by themselves, and important only insofar as they contribute to achieving this goal.

In the following section, the experimental setup will be reviewed. Next a series of analysis experiments will be presented. The main issues addressed are: (i) one vs. two perspectives, (ii) separate vs. collocated dual perspectives, and (iii) dependency on the angle between the two perspectives.

2. THE EXPERIMENTAL SETUP

In order to explore some of the basic configuration issues for a space-borne Doppler Wind Lidar (DWL), a simple analysis system for simulated wind observations was developed at the NASA Data Assimilation Office (DAO). The system takes user-specified "true" and background states as input, simulates a set of observations of the true state with the required coverage and error characteristics, and produces an analysis based on the background and the simulated observations as output.

Both the analysis equation and the background error covariance models are similar to what is used in the DAO's operational PSAS system (Physical-space statistical analysis system[8]). The most important differences with respect to the full data assimilation system are that (i) the DWL analysis domain consists of a limited area on a single level, and (ii) the system does not include a forecast model. The system is thus easy and inexpensive to set up and run, and it is therefore very well suited to test how observations with different coverage and error characteristics propagate through the analysis equation, and ultimately how successful they are in reducing the analysis error.

The analyzed state w^a is found by solving the analysis equation

$$w^a = w^b + K(w^o - Hw^f). \tag{1}$$

In this equation, w^b is the prior, or background, state (in an operational context generally coming from a short-range forecast), K is the gain matrix, w^o is the vector of the observations, and H is the observation operator that translates information from the background state into a vector of simulated observations. For n state variables and p observations, both w^a and w^b are $n-$ vectors, w^o is a $p-$vector, and H is a $p \times n$ matrix. The optimal gain matrix – in the sense that the resulting analysis has the smallest expected error – is given by

$$K = P^b H^T (HP^b H^T + R)^{-1}, \tag{2}$$

where P^b is the background error covariance matrix, and R is the observation error covariance matrix. From eqs. (1) and (2) it is evident that the analysis depends not only on the background field and the observations, but also on the assumed error covariance characteristics of the observations and of the background. Roughly speaking, the diagonal elements of the background and observation error covariance matrices determine the relative weights assigned to the background and observations in the analysis, whereas the off-diagonal elements of the background error covariance matrix in particular define the impact of the observations on the analysis at the unobserved locations and on the unobserved variables.

The length of the state vector for a typical global meteorological forecast model is currently on the order of 10^7. Nominally, the background error covariance matrix P^b contains $n^2/2$, i.e. on the order of 10^{14}, elements. Since there is no known way of reliably specifying this many independent parameters describing the error statistics for a given forecast system, this matrix is normally modeled using rather crude assumptions. It is important to keep in mind that any conclusions regarding the impact of a given type of observation on an analysis system depend critically on the assumptions used in modeling the covariance matrix of that system.

Generally, the univariate background error covariance P_{ij}^b between the values of a given state variable at two different locations with indices i and j is given by

$$P_{ij}^b = \sigma_i \sigma_j \rho_{ij} \tag{3}$$

where σ_i is the background error standard deviation at point i, and ρ_{ij} is the background error correlation between points i and j. In actual implementations, this is often simplified by assuming e.g. that the forecast error correlations only depend on the distance between i and j and that the forecast error standard deviations are constant on a given vertical level.

Since the wind is a vector quantity rather than a scalar, the problem of specifying background error covariances for winds is slightly more complicated. Disregarding the vertical component of the wind, it involves specifying the covariances for a set of two scalars as well as the possible cross-covariances between them. The two scalars can be e.g. orthogonal wind components, vorticity and divergence, or velocity potential and streamfunction. However, both the actual choice of scalars and the functional form of the covariance can have a profound impact on the quality of the wind analysis. This is particularly evident in the case of incomplete observations such as wind measurements taken along parallel lines of sight. Here all the observational information pertains to one of the two scalars involved, and any innovation added to the analyzed state about the wind component orthogonal to the observed direction comes entirely from the assumptions built into the forecast error covariance matrix.

The assumption of nondivergence which is frequently used in atmospheric modeling and analysis can be used to illustrate this last point. Assume that both the truth and the background states are nondivergent. Also the background error will then be nondivergent. Let now the two-dimensional wind field $\vec{u} = (u, v)$ be defined in terms of a streamfunction ψ with a known error covariance matrix P_ψ^b through the following relationship

$$\vec{u} = \vec{k} \times \nabla\psi. \tag{4}$$

For a discretized numerical applications, it is convenient to express this in operator form:

$$\vec{u} = A\psi, \tag{5}$$

where

$$A = \begin{pmatrix} -\frac{\partial\psi}{\partial y} \\ \frac{\partial\psi}{\partial x} \end{pmatrix}. \tag{6}$$

Using this operator, the wind error covariance matrix $P_{\vec{u}}^b$ is easily obtained from the streamfunction error covariance:

$$P_{\vec{u}}^b = AP_\psi^b A^T, \tag{7}$$

where A^T is the transpose of A. The matrix $P_{\vec{u}}^b$ will generally speaking be full, i.e. there will be terms in it linking the error of one wind component to the error of the other. Thus even if observations of only , say, the u-component are provided, the analysis system would still update both the $u-$ and $v-$components based on the assumption of nondivergence that links the two errors. One might even expect that observations of just a single wind component to

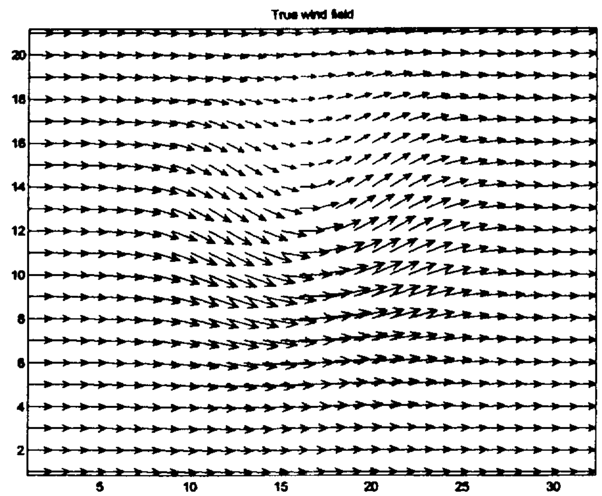

Figure 1. Vector winds plotted for the "true" state.

contain enough information to effectively constrain the analysis in such a case, since the assumption of nondivergence reduces the number of degrees of freedom per grid point from two to one. However, it is easy to see from eq. (4) that even full knowledge of one wind component mathematically only allows determination of the other component to within a constant of integration. The experiments discussed in the next sections were set up to test whether this theoretical limitations can be expected to pose real problems for the single-perspective observations.

3. EXPERIMENTAL RESULTS

For the experiments described in this section, the true state w^t is a nondivergent zonal flow with a single eddy, as shown in Fig. 1. The analysis domain is a rectangular array of regularly spaced grid points defined at a single vertical level, 31 in the zonal direction by 21 in the meridional. The grid spacing is fixed at 100 km. The extent of the domain is thus 2000 by 3000 km, and the dimension of the state vector is 1302 ($31 \times 21 \times 2$).

The background state is a zonal flow (not shown), and the experiments thus essentially test the ability of the analysis to correctly extract the information from the observations about the presence of a wave in the flow, and add it to the background state. The RMS difference between the true and background states is 2.4 m/s both for the zonal and meridional wind components. Since both the true state and the background are nondivergent, also the background error will be nondivergent in this framework. Real background errors on the other hand, are combinations of divergent and nondivergent errors, and the relative amounts in which the two types of errors are present in a given situation is generally unknown. The controlled framework of the experiments presented here has the advantage that the error is known, and the error covariance can therefore be specified correctly or incorrectly as desired.

3.1. One vs. two perspectives

In the first series of experiments, the impact on the analysis of having one vs. two perspectives on the flow at a given location is explored. The observations consist of samples of the true field at a set of locations that are randomly scattered over the domain. A simulated observation error in the form of uncorrelated Gaussian mean-zero noise with a standard deviation of 0.5 m/s is added to the samples. The number of observations, p, is set by the experimenter. For the one-perspective experiments, the samples are p projections of the true field onto this direction. For the two-perspective experiments, the samples are $p/2$ projections onto both this and the orthogonal direction. The two types of experiments thus contains the same amount of information, in the sense that the observational dataset contains the same number of scalar values. The purpose of the experiments is to examine whether they also contain the same amount of information in an analysis error reduction sense.

The background error is assumed to be nondivergent, and the background wind error covariance matrix is therefore derived from a streamfunction error covariance matrix using eq. (7). As already mentioned, the assumption of

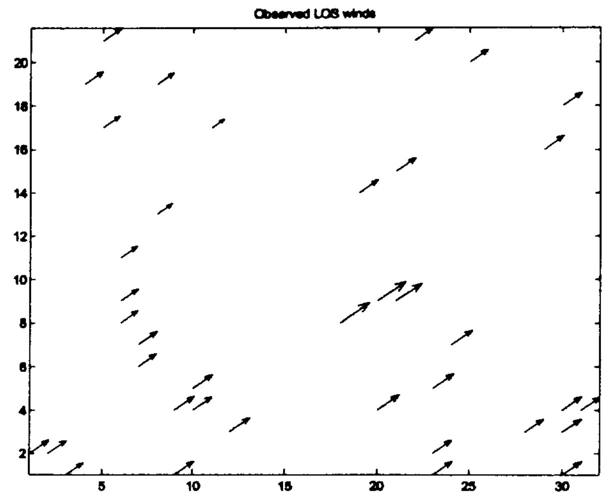

Figure 2. Single line-of-sight (LOS) observations of the state shown in Fig. (1)

nondivergence is expected to be useful for constraining the unobserved wind component orthogonal to the LOS. The disadvantage of using this assumption is that it excludes any potentially important divergent flows from the analysis. This problem may become more pronounced as the models and hence the analyses progress to smaller and smaller horizontal scales. We emphasize again that while the assumption of nondivergence is correct for this particular experiment, the amount of nondivergence in a given atmospheric situation is unknown. The background error covariance formulation used here, however, requires the user to explicitly specify the relative amounts of information about the rotational and divergent components of the flow that should be extracted from the observations. This is unfortunate, since ideally this information should come from the wind observations themselves.

In Fig. (2), a typical set of single-perspective observations is shown for $p = 40$, and a LOS azimuth angle of 60°.

An analysis obtained from the observations in Fig. (2) is shown in Fig. (3). It is evident that – even in spite of the favorable specification of the background error – the analysis is only marginally capable of detecting the presence

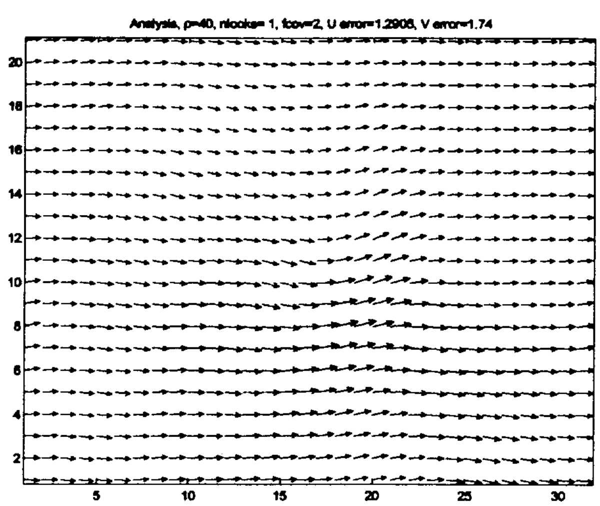

Figure 3. Analysis based on the observations shown in Fig. (2)

of the eddy from the observations. The analyzed structure lacks intensity, and non-zero V-components are evident throughout the meridional range of the plot.

The RMS differences for U and V between the true and analyzed states (Figs. 1 and 3) is 1.3 and 1.7 m/s, respectively. As one would expect, the error reduction is largest for the U-component, since the projection of this component on the LOS is the larger of the two.

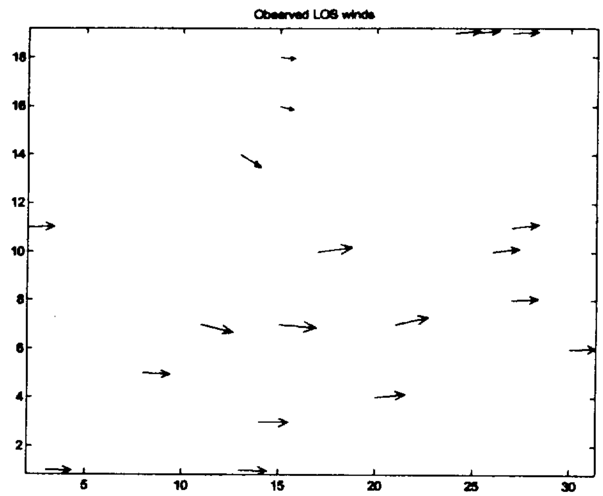

Figure 4. Orthogonal LOS observations of the state shown in Fig. (1)

In Fig. (4), a typical set of dual-perspective observations is shown for $p = 40$, and LOS azimuth angles of 60° and 150°. An analysis obtained from the observations in Fig. (4) is shown in Fig. (5). The analysis is based on the same background wind error covariance formulation as the one used for the single-perspective analysis in Fig. (3). It is clear that the dual-perspective analysis is superior to the single-perspective analysis for the flow configuration and the parameters shown here. The analyzed eddy has the correct location and horizontal extent, with the main shortcoming being a lack in intensity. The RMS analysis error with respect to the background field is now 0.8 and 1.3 m/s for U and V, respectively, which again indicates a substantial improvement over what was seen in the single-perspective analysis.

In order to examine the difference between the one vs. two perspective analyses more extensively, a series of experiments similar to the ones just described was carried out with values of p ranging from 10 to 320. For each value of p, 15 single-perspective and 15 dual-perspective experiments were carried out to generate reasonably robust statistics. In each individual single-perspective experiment, the azimuth LOS angle was randomly selected between 0° and 180°. The purpose of this was to obtain a representative sample of experimental results irrespective of any preferential direction present in the true and/or background states.

In Fig. (6), the mean and standard deviations of the RMS analysis errors for U and V are shown for both single and dual perspective experiments as a function of p. It is clear that the analyses based on dual perspective observations are superior to the ones based on the single LOS winds. The difference between the two increases with p, indicating that true vector information gets increasingly important at smaller scales, whereas the impact of the scalar single perspective observations saturates at a relatively coarse resolution of the observations. The analysis error of the dual perspective experiments is also more robust: lower error bars in the plot indicate relatively uniform analysis errors over the 15 experiment samples. This is probably mostly due to the fact that the impact of the single LOS observations on a given wind component is sensitive to the alignment between the LOS and that component.

Note that the analysis error for the dual-perspective experiments seems to saturate at around 0.25 m/s, well below both observation and background errors. This is consistent with what one would expect from estimation theory, assuming that the error covariances are correctly specified. The analysis error in for the single-perspective experiments, on the other hand, seems to saturate at around 0.7 m/s which is well above the size of the observation

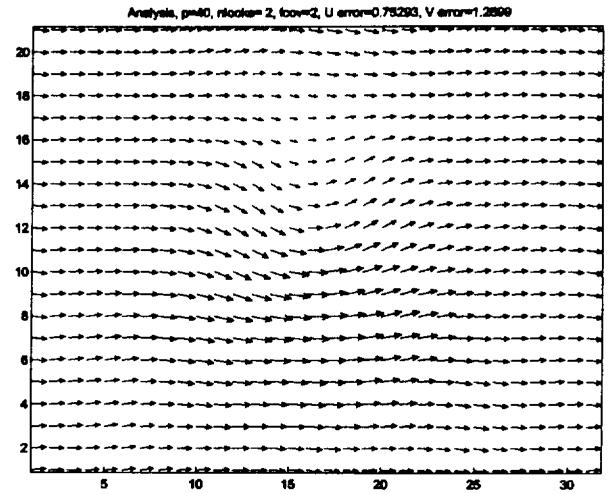

Figure 5. Analysis based on the observations shown in Fig. (4)

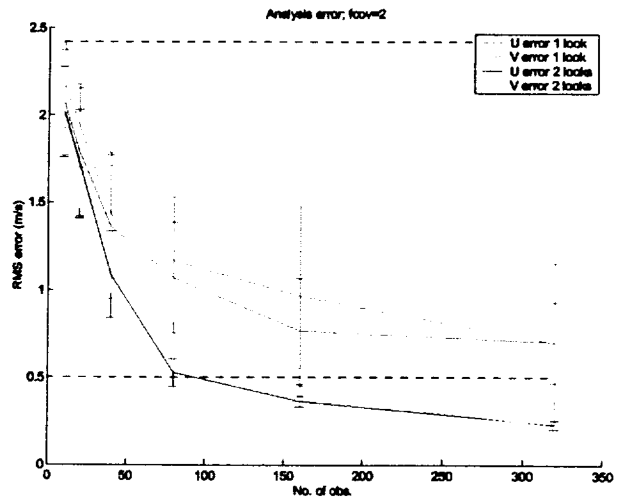

Figure 6. Analysis errors for U and V for one and two perspectives vs. the number of observations, p. The solid lines show the mean error over 15 independent experiments for each value of p, and the error bars show the standard deviation of the errors.

error. This supports the notion discussed in the previous section that even the simple nondivergent flow configuration tested here cannot be fully determined from observations along a single direction, even though it only contains one degree of freedom per grid point.

3.2. Coincident vs. separated perspectives

In the previous section it was shown that dual-perspective observations are much more useful than single-perspective observations for reducing the analysis error in the simple test case explored here. One of the issues that would need to be addressed before one can specify the user requirements for dual-perspective observations is the level of spatial and temporal coincidence that is needed between the two perspectives. It is likely that a fairly relaxed requirements on this will provide added degrees of freedom in the design and/or the operations phase of a given instrument. We do not here explore the issue of temporal coincidence beyond simply noting that if the two perspectives of a given atmospheric situation are obtained during one overflight (same orbit), the time difference would at most be on the order of a few minutes. This would seem to be insignificant compared to the temporal resolution of the analyses and of most other observing systems.

In order to test the performance of observations with a low degree of spatial coincidence, a series of experiments was carried out with observations taken along two orthogonal directions, but at random, separate locations. The overall flow is thus sampled along two independent directions, but any individual location is likely to be sampled along just one of these. An example of such observations for $p = 40$ is shown in Fig. (7).

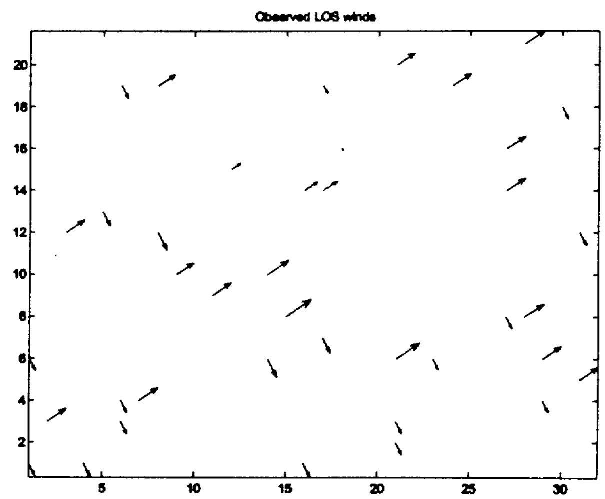

Figure 7. Orthogonal LOS observations at separate horizontal locations of the state shown in Fig.(1)

The resulting analysis errors with uncertainty estimates from a series of experiments is shown in Fig. (8) as functions of p. Even though the collocated perspectives experiments tend to outperform the separate perspectives experiments in the middle range of p-values, the two sets of curves are much closer together for all values of p than what was seen in Fig. (6). The two sets of experiments are similar also in their level of consistency over the 15-experiment samples (roughly similar error bars). Overall, the results indicate that from an analysis point of view getting independent information about the two wind components is of paramount importance, while it seems to be considerably less important that these two pieces of information be obtained at the exact same geographical locations. In particular, we note that for the single-perspective observations, the analysis error seems to saturate at the 0.7 m/s level (Fig. 6), with no apparent benefit to be expected from increasing the number of observations beyond the maximum value of 320. In the dual-perspective, separate locations experiments shown in Fig. (8), the mean analysis error has fallen below 0.7 m/s already at $p = 80$.

3.3. Angle between perspectives

The experiments described thus far were all based on either orthogonal or parallel perspectives. The evidence is that there are substantial benefits to be had from obtaining orthogonal perspectives. Some proposed instrument configurations fall in between these two extremes in providing intersecting but non-orthogonal perspectives. It is therefore of interest to study also the impact of dual-perspective observations as a function of the angle between the lines of sight.

In Fig. (9), the mean analysis error and uncertainty is shown for a series of experiments in which the angle α between the two lines of sight was varied from 0° to 90°. For each value of α, 15 experiments were run, and the overall orientation in space of the two LOS was selected randomly for each experiment in order to generate reliable statistics for both wind components. It is seen that the analysis skill improves dramatically when α increases from 0° to 30°. From 30° to 60° there is a modest improvement, and beyond 60° the analysis error is nearly constant.

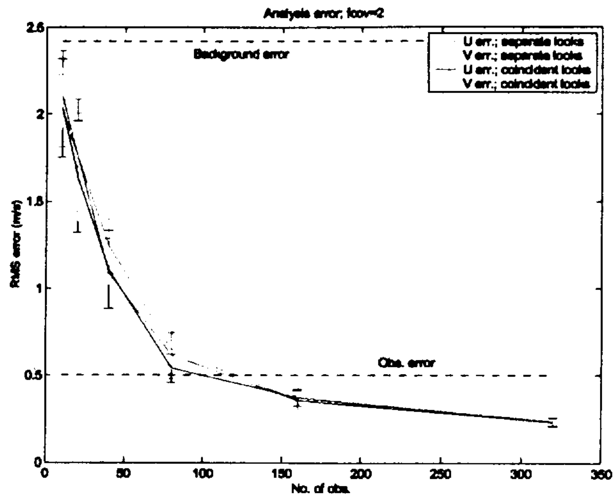

Figure 8. Mean analysis errors with error bars, similar to Fig. (1), but for two orthogonal perspectives obtained at either separate or coincident locations.

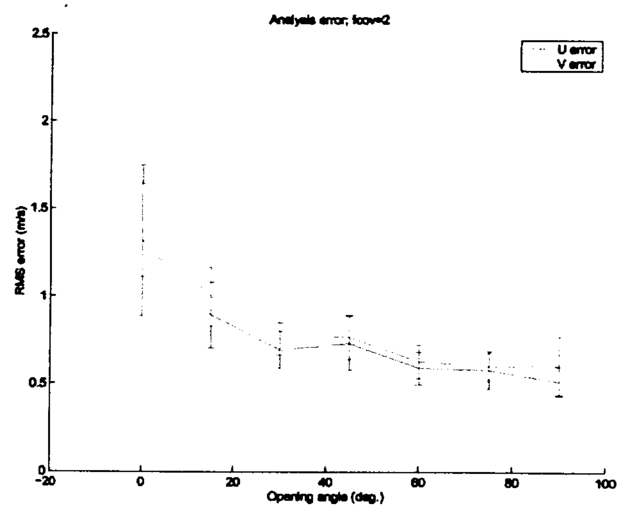

Figure 9. Mean U and V analysis errors with error bars for dual perspective observations, $p = 80$, as a function of the angle between the two wind observations

4. DISCUSSION

The results shown in the previous section provide a very strong indication that it would be preferable to obtain LOS wind observations along two independent directions rather than one. Both the analysis system, the simulated observations, and the flow configurations studied here are gross simplifications of the corresponding real-world systems, and one might therefore be concerned whether the findings on one vs. two perspectives do indeed carry over to real NWP applications and real observing systems. It is worth emphasizing again that the experiments described here actually tend to favor the single-perspective experiments. The basic test that the observations are subjected to here is to help the analysis recover from a nondivergent error that is correctly specified in the sense that it uses a background error covariance matrix that is derived under the assumption of nondivergence. This is a much easier test to pass than the more realistic one of correcting an error with an unknown mix of rotational and divergent components, to which real-world analysis systems are subjected. An incomplete observing system such as a single-perspective wind instrument will thus get a substantial amount of help from the correctly specified background error covariance matrix in our experiments, whereas a real-world observing system would have to overcome not only an erroneous background field, but also an incorrectly specified background error covariance.

Providing only single-component wind observations thus puts a large part of the burden of getting a correct analysis on the first guess and on the assumptions underlying the error covariance model. This is likely to work quite well whenever the background field is reasonable and the balance assumptions built into the covariance matrix are valid. However, if the purpose of flying a satellite Doppler Wind Lidar is to specifically reduce the frequency of abnormally large forecast errors, it is clear that the observations would be particularly valuable when and where new and unexpected developments occur i.e. precisely in those situations where the background field by definition is in error. One might fear that these could also be situations where the normal assumptions about geostrophy and hence nondivergence could be violated.

5. SUMMARY AND CONCLUSIONS

The question of information content in wind observations obtained along one vs. two directions has been examined in the context of a simple analysis system. Information content is defined here as the ability to reduce the analysis error. It was shown that dual perspective observations are much more efficient at doing this for an equal number of measurements. It was further shown that the two perspectives need not be strictly collocated, as long as the flow field is sampled sufficiently along two independent directions. The two perspectives need not be orthogonal. Most of the benefit from having dual perspectives is realized when the angle between the lines of sight is larger than 60°. The quality of the analysis decreases with the angle when this is less than 30°.

Concerning the applicability of these findings to real observing systems, it was argued that the results may tend to be too positive towards the single LOS observations. It is therefore likely that the difference between analyses of single vs. dual perspective wind observations would be even larger in a more complete analysis system.

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