

ADM-Aeolus Doppler Wind Lidar Observing System Simulation Experiment

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(Received 13 May 2005; revised 31 March 2006)

SUMMARY

Within the Atmospheric Dynamics Mission Aeolus (ADM-Aeolus) the European Space Agency (ESA) has approved a Doppler Wind Lidar (DWL) to fly on a dedicated platform orbiting dawn-dusk at 400 km altitude, planned for launch in 2008. Rigorous design trade-offs have resulted in a lidar concept capable of delivering high-quality wind component profiles, but with a limited coverage. A companion paper describes the realistic simulation of this DWL, whereas this paper sets out to assess the impact of such lidar in meteorological analyses and forecasts. To this end an Observing System Simulation Experiment (OSSE) is run. The superior conventional observation coverage of 1993 is used to simulate all conventional observations, whereas, on the other hand, a limited set of satellite observations is simulated. As a consequence, only the northern hemisphere DWL impact in the OSSE is assumed realistic. Here, in a 15-day period with variable weather, out of 15 daily forecasts, 14 show beneficial impact of the DWL. Although the experiment is limited, it corroborates other practical and theoretical evidence that the ADM DWL will demonstrate a beneficial impact in meteorological analyses and forecasts.

KEYWORDS: Atmospheric Dynamics Mission - Aeolus OSSE Data assimilation

1. INTRODUCTION

The quality of state-of-the-art Numerical Weather Prediction (NWP) is among other factors determined by the availability and quality of meteorological observations. However, conventional wind profile data lack coverage and a uniform distribution over the globe. On the other hand, NWP models have improved much over the last decades, and advanced 4D-var techniques are now being used for the analysis. The spatial resolution of global circulation models has improved as well, which leads to a need for more observations to initialise the sub-synoptic scales. On these scales the wind field, rather than the atmospheric temperature field determines the atmospheric dynamics. Furthermore, a prime factor determining meteorological instability is vertical wind shear.

For the study of climate processes extensive re-analysis experiments are being conducted. These experiments use the technique of data assimilation, as used for NWP, to establish long time series of the weather in support of climate studies. However, 3D wind information has been lacking in the tropics for an accurate definition of the Hadley circulation.

To fill in the gap in the global observing system, ESA has selected ADM-Aeolus as an Earth Explorer core mission to provide wind profile observations globally. This is achieved by flying a Doppler wind lidar on a free-flyer platform in a dawn-dusk polar orbit and measuring in the ultra-violet (UV) part of the electromagnetic spectrum at 355 nm. The instrument is non-scanning with a fixed scan angle perpendicular to the direction of satellite propagation. Profiles of wind components at about 1 km vertical resolution, ranging from the earth surface up to 26 km, are retrieved from received light backscattered from clouds, aerosol and molecules. The ADM wind requirements have been focussing on quality (error reduction) rather than quantity (coverage), in

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accordance with the WMO requirements. Moreover, past experience in data assimilation shows that quality can usually not be traded off against quantity without a degrading effect (e.g., Butterworth and Ingleby 2000; Rohn *et al.* 2000). To yield wind observation quality comparable to radiosondes the instrument is operated at 100 Hz during 7 seconds so that measured wind profiles are representative for a 50 km atmospheric track. Moreover the instrument is operated in burst mode with a 25% duty cycle, meaning that a wind profile is observed every 200 kilometres (see also ESA 1996; 1999; Stoffelen *et al.* 2005).

The ADM requirements focus on the spatial representativeness and accuracy of the wind profiles obtained, rather than on the number of wind profiles. Since good-quality conventional wind profiles are known to have large analysis impact this choice is based on practical experience. The potential detrimental effects of poor quality observations are also well known from Observing System Experiments (OSE). To achieve spatially representative and accurate observations, the 50-km-size wind profile cells are sampled by multiple shots. If these shots were spread over a larger domain one would get (i) fewer shots in a cell and therefore a lower number of photons returned, resulting in a poorer assessment of the wind conditions in the cell and (ii) a poorer sampling of the subcell wind variability and therefore an increased representativeness error. Both work in the same direction and favour accuracy rather than coverage as a wind profile mission driver. It is this choice that makes the ADM a feasible space-borne DWL demonstration mission. Furthermore, multiple shots in a cell allow the use of signal and wind variability measures for quality control purposes.

OSEs by the European Centre for Medium-range Weather Forecasts (ECMWF) (Kelly 1996) have confirmed the value of tropospheric wind profile data for NWP. ECMWF tested this in a series of experiments where they excluded conventional wind profile observations (TEMP/PILOT), or parts thereof in the free troposphere, and compare to experiments where conventional (TEMP/PILOT), or satellite (TOVS) temperature or humidity profile data, or single level observations, were excluded. In more recent experiments (Kelly 2004) satellite soundings play an increasingly important role and show clear positive impact in the northern hemisphere (NH). There are two probable causes for this: (i) satellite soundings have improved and are better exploited in more recent data assimilation systems, as may be inferred from the rapidly improving forecast skill in the southern hemisphere (SH); (ii) the conventional wind sounding network has been decaying in important parts of the NH, i.e., from 1993 to 1999 the number of TEMP/PILOT wind profiles has halved.

Complementary experimentation has been performed at the Deutscher Wetterdienst (DWD) to test the impact of continental North American wind profile observations (Cress 2001). From these experiments, a few points are noteworthy: (i) these experiments confirm the importance of wind profile data, compared to the importance of temperature/humidity data (Baker *et al.* 1995; ESA 1996; 1999); (ii) near-surface wind observations (Planetary Boundary Layer (PBL) winds) seem less important than winds in the middle and upper troposphere; (iii) in the OSE experiments, a small number of (good quality) wind profiles already show a positive impact on the quality of NWP.

The results and conclusions of OSEs give an insight into the effect of a particular existing observation type in an existing data assimilation system. However, it is difficult to draw conclusions from this on the added value of supplementary measurements for future meteorological analyses and forecasts. Such added value may be investigated through OSSEs. Météo France has made a first step in assessing the value of ADM. The work involved running OSSE experiments with the French Arpege NWP model, in order to test the impact of the OSSE database DWL wind profiles from a 10 micron laser

on a free-flyer satellite in a polar orbit (Cardinali *et al.* 1998). This scenario provided a wind profile density over the oceans comparable to the current conventional wind profile density over land in the NH. The assimilation experiments were performed with a low-resolution version of the NWP model (T42 spectral resolution, i.e. ~ 500 km horizontal resolution), and the DWL impact could be well demonstrated, even though the subsynoptic scales where wind observations become most relevant are not well resolved at this resolution.

DWL OSSEs performed in the United States indicate an impact even for low measurement accuracy (Atlas *et al.* 2003). However, the forecast quality was almost exclusively based on DWL information from the SH and therefore was bound to show an improvement against the control analysis which did not contain relevant observations in this area. More recent OSSE work (so called bracketing OSSEs) with the US National Center for Environmental Prediction (NCEP) NWP model aims to explore the bounds of the potential impact of DWL by considering various DWL concepts each focussing on particular atmospheric regions and based on scanning and non-scanning (ADM-type) instruments. Significant DWL impact has been demonstrated, e.g. larger than TOVS in the tropics and SH for all considered DWL scenarios (Masutani 2002; 2004).

For an operational system, the impact on NWP often depends on the capability of the data assimilation system used. Therefore it is worthwhile to perform an OSSE with the state-of-the-art ECMWF 4D-var system (Tan and Andersson 2004) in order to consolidate the requirements for an operational mission. Section 2 discusses the general OSSE setup and required attributes. Section 3 discusses results of the OSSEs performed to demonstrate the impact of ADM on atmospheric circulation analyses and NWP. For a correct interpretation of the results and to verify the realism of the OSSE method results were validated against the 1999 operational model in section 4. Section 5 provides a summary of the main conclusions.

2. OBSERVING SYSTEM SIMULATION EXPERIMENTS

OSSEs can be used to assess the potential impact of any new observing system, provided that the error properties of the system are well understood. The basic elements of an OSSE are a state-of-the-art data assimilation system, a nature run "truth" and a corresponding database of simulated observations (Atlas 1997; 2003). The latter includes both simulated observations of conventional meteorological systems, covering a network similar to the operational network, and simulated observations of the new instrument to be assessed. Generation of the nature run and database for conventional observation systems has been reported extensively in the past (Stoffelen *et al.* 1994; Becker *et al.* 1996).

To build up a database of simulated observations one needs a description of the atmosphere over a certain time period. For this purpose, a synthetic "true" atmosphere is generated through a long period integration of a forecast model. This is called the "nature run". The nature run that we use in this study was the result of a 30-day integration, initiated on 5 February 1993 00 UTC and ended on 7 March 1993 00 UTC. Integration was performed with the operational forecast model at ECMWF in 1993, i.e. T213 (~ 100 km) horizontal and 31 levels vertical resolution (Stoffelen *et al.* 1994). An extensive evaluation of the nature run cloud cover has been performed at the National Centre for Environmental Prediction (NCEP) within the National Oceanic and Atmospheric Administration (NOAA) (Masutani *et al.* 1999). The nature run cloud cover was compared to available data sets from space-borne and surface-based observation systems in February 1993. From this study it was concluded that nature

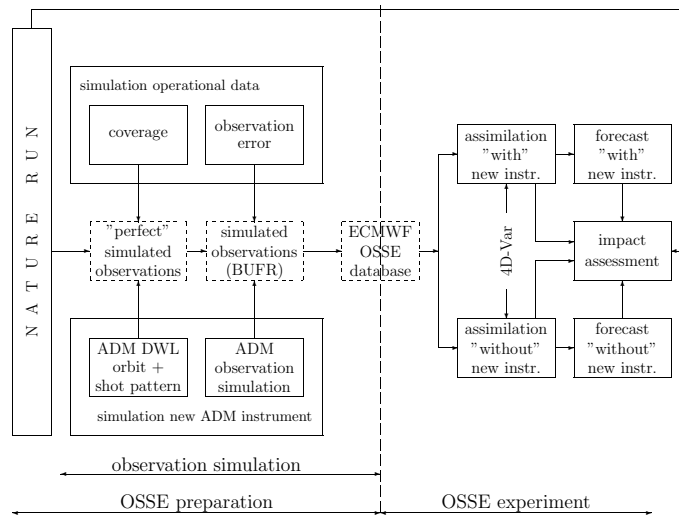


Figure 1. OSSE setup. Data assimilation "with" ("without") includes (excludes) the simulated observations of the new instrument.

run clouds generally agree well with observations. Main differences are found over both the North pole and South pole which show much more cloud cover in the nature run. In addition, the nature run generally overestimates high-level cloud cover and underestimates low-level cloud cover. On the other hand, high-level nature run cloud optical depth showed good agreement with observations. For low-level cloud cover it appeared that the nature run underestimates marine stratocumulus. Later on we show that DWL data are most important in the free troposphere in regions of atmospheric activity, so lack of marine stratocumulus is probably not serious in assessing lidar data impact through the OSSE study. Moreover, the winds in the PBL of the atmosphere below the stratocumulus clouds are relatively well sampled by the (simulated) ASCAT scatterometer in our experiments. In summary, it is concluded that nature run cloudiness is sufficiently representative of the real atmosphere.

Simulated observations for the OSSE are obtained through interpolation of the nature run fields to observation locations. This results in so-called "perfect" observations. For conventional observations, the locations are extracted from a real observation database to produce a representative sampling. Observation coverage charts can be found in (Stoffelen *et al.* 1994). The data coverage for new observation instruments such as a DWL needs to be simulated based on expected orbit characteristics and shot pattern. Finally, realistic stochastic observation errors, including instrument error and a representativeness error that accounts for the variability of the observed parameter on scales that cannot be resolved by the NWP model, are added to the perfect observations to simulate real observations, see figure 1. The result is a database with simulated observations of conventional meteorological observation systems, three earlier infrared lidar concepts and the ESA selected UV concept, denoted ADM_UV (Stoffelen *et al.* 2005).

To assess the impact of a simulated new observation system, two assimilation runs need to be performed; one excluding and one including the new system, see figure 1. For each run, we performed fifteen days of data assimilation, with an interval of six hours, starting at 5 February 1993, 12 UTC and finishing at 20 February 1993, 12 UTC. On each of these 15 days, one 10-day forecast was run from the corresponding analysis at 12 UTC. Differences in the forecasts from the two parallel runs are only due to

the impact of the simulated new observation system, hence their respective quality is a measure of observation impact.

(a) *Fraternal twin problem*

To be a useful tool for impact assessment of new instruments in NWP, OSSEs must represent meteorological practice as closely as possible. In meteorological practice, NWP model runs and nature truth diverge with time. In the OSSE the model run should also diverge from the truth, represented by the nature run. This divergence may not be completely realistic since error growth can be different in a genuine NWP system on the one hand, and between the model runs involved in an OSSE. In practice, the models used for the OSSE nature run and the experiments may be different, but nevertheless exhibit related flaws. When that happens, the differences between short range forecasts initiated from the data assimilation, and the nature run, may be smaller than genuine forecast errors. This problem, called the 'fraternal twin' problem, will bias the interpretation of results from the OSSE experimentation.

In this study the nature run was generated using the 1994 ECMWF operational forecast model, cycle 12r1. The OSSE has been conducted in 1999 with the 1999 operational ECMWF forecast model, cycle 21r1. Potentially this incurs the possibility of two similar or fraternal twin models, depending on model evolution in the period 1994 to 1999. The most significant model changes in this period may be obtained from the ECMWF webpages[†], but in summary show substantial changes in model dynamics, radiation and cloud parameterizations, and ancillary codes. Based on these changes, we expect the nature run atmospheric model and the OSSE model to be as different as any two other realistic models of the atmosphere. The experimental divergence of the nature run and OSSE model run is checked in section 3.

3. LIDAR IMPACT ASSESSMENT

This section discusses the use of OSSEs to demonstrate the impact of the DWL profiles on the atmospheric analyses and forecasts. The analysis step of the data assimilation cycle combines the knowledge on the atmospheric state from observations and a short range forecast, called background. The resulting most likely atmospheric state constitutes a compromise between the observations and the background based on their respective estimated errors (Lorenç 1986; Courtier *et al.* 1998). So, if at a particular location the observation and the background disagree, then the model state is modified, such that a more likely state results. The amplitude of the modification depends on the estimated error covariance of the observation relative to the estimated error covariance of the model (Derber and Bouttier 1999). The lower the estimated observation error is, the more impact it has. The errors of the observations and the background are assumed uncorrelated in the analysis.

(a) *OSSE database extension*

The operational ECMWF 4D-var assimilation system has been extended to enable the proper assimilation of lidar data. This requires the modification of the existing observation operator that relates observed variables to the model state vector for the assimilation of lidar data. The lidar observation operator includes the interpolation of model state parameters to locations of lidar observation and conversion of horizontal

[†] http://www.ecmwf.int/products/data/technical/model_id/index.html

wind components to Horizontal Line-Of-Sight, HLOS, wind components (see Marseille and Stoffelen (2003), in the remainder also denoted M&S).

M&S report results on a pre-OSSE analysis to assess profile quality in clear air, i.e. without clouds, and on the impact of clouds on atmospheric penetration. Moreover, wind shear and humidity flux visibility are assessed in relation to clouds. A recent study (Tan and Andersson 2005) simulates the performance of ADM in aerosol-rich atmospheres including realistic cloud scenes as measured by the Lidar In-space Technology Experiment (LITE) in 1994 (Winker *et al.* 1996). In both studies it was found that more than 90% of all Aeolus wind observations fulfil the WMO requirements for wind quality. Here we note that optically thin clouds (such as cirrus) in the upper troposphere return a strong signal that provide good-quality winds and generally have very limited (negative) influence on the quality of underlying measured winds. In the lower atmosphere data coverage is reduced by about 25% due to opaque clouds such as stratus. In the simulation of lidar observations we assumed uncorrelated errors both in the horizontal and the vertical. Lidar observation errors are further assumed unbiased and have a Gaussian probability density function with known but variable standard deviation (see M&S). In the assimilation of lidar HLOS wind components, we assume perfect knowledge of observation uncertainty.

(b) *Experimental setup*

We define two experiments to assess the potential impact of the ADM UV concept on NWP analysis and forecasts: (i) NoDWL (control) and (ii) DWL (control + DWL). The NoDWL experiment includes the assimilation of conventional observations as generated by (Stoffelen *et al.* 1994), i.e., TEMP, PILOT, AIREP, DRIBU, SYNOP, and SHIP, and the satellite-inferred data from PAOB, SATOB and ASCAT. Scatterometer winds are thinned resulting in a message structure containing nodes at 100-km sampling in both directions of the swath as is normal practise for using ERS scatterometer data. Cloud motion wind (SATOB) measurements were used at the spatial and temporal density as available in February 1993. High density winds are available nowadays, but do not provide substantially larger impacts in the ECMWF data assimilation system and are thinned prior to use (Rohn *et al.* 2000). Again, only in the NH the results obtained with this OSSE are representative of the complete observing system. We assessed the possibility to assimilate (A)TOVS radiances. Issues of concern were, among others: (i) incompatibility of the simulated TOVS radiances and the operational weather model, because of the use of a now obsolete stratospheric extrapolation to simulate radiances, and because of the OSSE NWP model to include the stratosphere, and (ii) lack of calibration of a bias correction scheme for OSSE TOVS data.

As mentioned in the introduction, the 1993 OSSE database contains more than twice as many conventional wind profile data than available in 1999 or nowadays. On the other hand, the number of SATOB, aircraft winds, and the exploitation of passive radiometer data, has improved over the last decade. Moreover, sounder data are missing. Given the demonstrated importance of wind profile data in the ECMWF data assimilation system, and based on OSE work at ECMWF (Kelly 1996; 2004) and the more general experience at other meteorological centres we assume over all that the 1993 OSSE data base is comparable in NWP information content to the current observing system in the NH. As such we expect a noticeable but limited effect on the lidar impact assessment in the northern hemisphere. However in the tropics and southern hemisphere OSSE impact results are not representative of the impact expected in the presence of today's GOS because of the generally dominating effect of satellite data here.

The second experiment contains the same data as the control experiment, but in addition the simulated lidar measurements of ADM_UV. When forecasts and analyses from this experiment compare better to the nature run than those of the control, then we have demonstrated positive impact of the ADM in the data assimilation system as used.

The 4D-var incremental analysis is performed at T63 (~300 km) resolution in the horizontal and 31 levels in the vertical. The ECMWF 4D-var data assimilation system contains several switches to include features of the model that are used operationally, but are not really required to obtain representative results on DWL impact. The features that are not used include coupling of the ocean wave model (WAM) to the atmosphere model, and variable land surface fields, such as snow cover; these fields were fixed.

(c) *Theoretical Assessment of Lidar Observation Impact*

The impact of lidar data on NWP and climate studies is determined by the effectiveness of the 4D-var system to assimilate lidar data. In an idealized situation all data contain information and have a positive impact on the analysis quality. Meteorological practice however is more complex as discussed in this section.

In variational assimilation the aim is to minimize a cost function that optimally combines information from a short-term forecast and observations in a statistical manner to arrive at a consistent description of the atmosphere. The incremental formulation of the cost function J is as follows (e.g. Courtier 1997; Courtier *et al.* 1998)

$$J(\delta x) = \frac{1}{2} \delta x^T \mathbf{B}^{-1} \delta x + \frac{1}{2} v^T \mathbf{R}^{-1} v \quad (1)$$

with,

$$v = \mathbf{H} \delta x - d, \quad \text{and} \quad d = y - \mathbf{H} x_b \quad (2)$$

where δx is the increment from the background (background), x_b , that is obtained from a forward model integration initialized with the analysis in the previous time window. \mathbf{B} is the estimated background error covariance matrix, v and d are called innovation vectors, \mathbf{H} is the linearized observation operator, y is the observation vector and \mathbf{R} the observation error covariance matrix. The optimal solution δx^a of Eq. (1), also denoted analysis increment, is added to the background x_b to arrive at the analysis x_a . The solution can formally be written

$$x_a = x_b + \mathbf{K}[y - \mathbf{H}x_b], \quad \text{with} \quad \mathbf{K} = \mathbf{B}\mathbf{H}^T(\mathbf{H}\mathbf{B}\mathbf{H}^T + \mathbf{R})^{-1} \quad (3)$$

Here, \mathbf{K} is the Kalman gain matrix. Assuming that \mathbf{B} and \mathbf{R} are perfect estimates of the error covariances it can be shown that for the analysis error covariance matrix \mathbf{A} we then have

$$\mathbf{A}^{-1} = \mathbf{B}^{-1} + \mathbf{H}^T \mathbf{R}^{-1} \mathbf{H} \quad (4)$$

Since \mathbf{R} is positive definite Eq. (4) states that each observation adds information (for non-zero \mathbf{H}) and thus contributes to a reduction of the analysis error covariance, \mathbf{A} . One of the fundamental limitations of variational data assimilation is the lack of exact knowledge of the background and observational error structures. In operational practice one uses (imperfect) estimates of the \mathbf{B} and \mathbf{R} matrices. As a consequence, the gain matrix \mathbf{K} is generally not optimal, meaning that the information content of new observations is not optimally exploited and might locally even result in mean negative impact.

The discussion above implies that in an optimal 4D-Var, where the innovation covariance matrix is correctly specified, all observations are useful and contribute to

a reduction of the analysis error. In the operational ECMWF 4D-Var, the usefulness of an observation will depend on the accuracy of the assumed covariance matrices. Hence, an observation is likely to be useful if

1. the observation error characteristics are sufficiently well known;
2. its assimilation is not affected by wrong model error assumptions;
3. its errors are uncorrelated with the background and other observations;
4. it is accurately characterized by its forward observation operator;
5. \mathbf{B} accurately transforms to observed quantities at observation points, i.e. matrix \mathbf{HBH}^T is accurately known.

In the OSSE, all conditions except (2) are fulfilled.

To determine lidar data impact on analyses we define x_a^c and x_a^l that denote the analysed state vector for the control (NoDWL) and lidar (DWL) experiment respectively, x_t denotes the nature truth. The analysis error covariance matrices of the NoDWL and DWL experiment, denoted with \mathbf{A}_c and \mathbf{A}_l , respectively are defined by

$$\begin{aligned}\mathbf{A}_c &= \text{cov}[x_a^c - x_t] = \text{E}[(x_a^c - x_t)(x_a^c - x_t)^T] \\ \mathbf{A}_l &= \text{cov}[x_a^l - x_t] = \text{E}[(x_a^l - x_t)(x_a^l - x_t)^T]\end{aligned}\quad (5)$$

with E denoting the expectation operator. For the first analysis cycle of using DWL data, it can be shown relatively easily that the inverses of both matrices are related through

$$\mathbf{A}_l^{-1} = \mathbf{A}_c^{-1} + \mathbf{H}_l^T \mathbf{R}_l^{-1} \mathbf{H}_l \quad (6)$$

with \mathbf{R}_l the covariance matrix of lidar observation errors and \mathbf{H}_l the lidar observation operator. Eq. (6) shows that, in theory, all lidar data add information to the analysis in addition to the conventional data, since \mathbf{R}_l is positive definite. As outlined in the beginning of this section, meteorological practice is less straightforward. This is clearly illustrated in the next example.

(i) *Single case example: 5 February 1993, 18 UTC.* The analyses of the NoDWL and DWL experiment are identical only at the beginning of the experiment at 5 February 1993, 12 UTC. The difference in the analyzed fields of both experiments at 18 UTC is due to the addition of 6 hours of lidar data in the DWL experiment. To visualize the impact of lidar data on the analysis we plot the differences of the root mean squared errors (RMSE) of the analyzed fields of the NoDWL and DWL experiments, both verified against the nature run, i.e. $\text{RMS}(x_a^c - x_t) - \text{RMS}(x_a^l - x_t)$. For a single case this reduces to $|x_a^c - x_t| - |x_a^l - x_t|$. Negative/positive values correspond to negative/positive impact of lidar data on the analysis. Figure 2 displays the lidar impact for the 5 February 18 UTC analysis. Not surprisingly, the impact of the lidar data on the wind field is concentrated near the measurement locations, indicated with crosses. However, adjustment of the wind field is not isolated to lidar locations. The assimilation system spreads the added information. Beside the positive regions, other places show negative impact, which is caused mainly by the stochastic properties of the observation and background errors. Here it is important to note that observations do not everywhere yield a positive impact as suggested by Eq. (4). First of all, in real life the forecast model is not perfect and model and observation errors (e.g. spatial representativeness) tend to depend on the meteorological situation, and can even be systematic (bias). Furthermore, the response of the model is non-linear, making background error covariance estimates difficult to assess and inaccurate, and therefore contribute to a wrong relative weight of observations. However, in line with Eq. (6), a positive impact on the RMS average is obtained when the random errors are averaged over large areas.

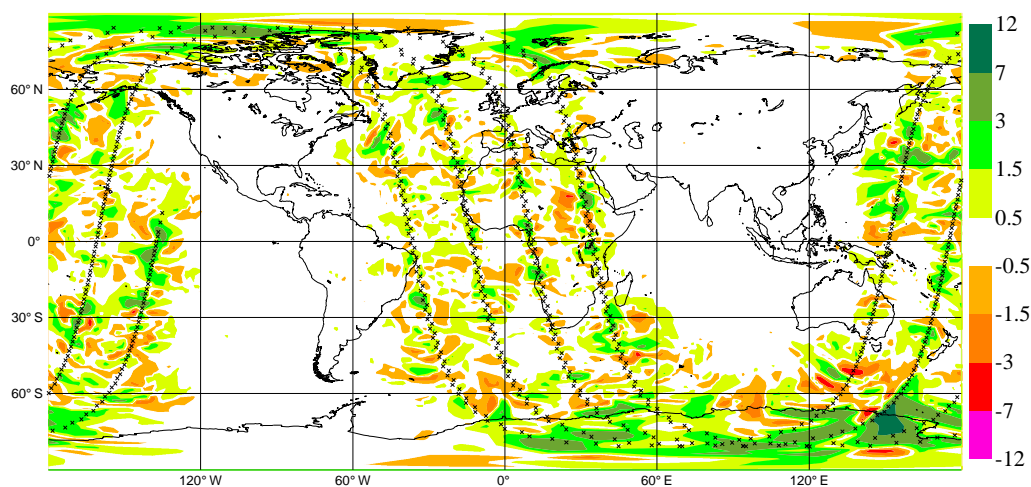


Figure 2. 500 hPa Wind field RMSE difference at 5 February 1993 18 UTC of NoDWL and DWL experiment, both verified against the nature run. Red denotes negative impact, green denotes positive impact, white denotes no significant impact. Black crosses indicate the lidar profile locations. The differences are due to 6 hours of lidar data only

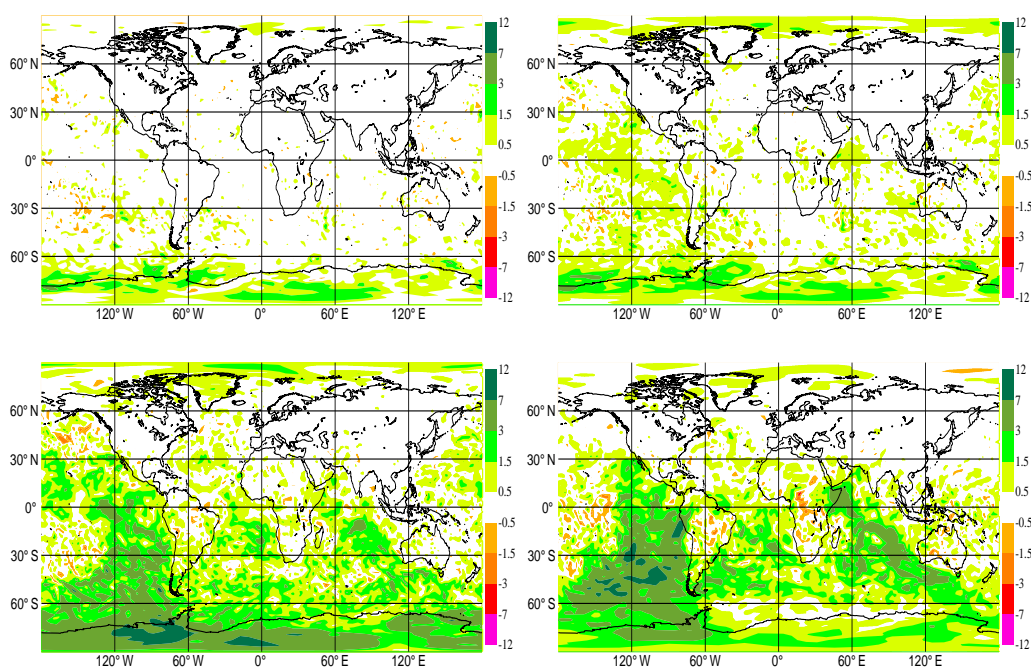


Figure 3. Mean lidar observations impact on vector wind analyses over the complete assimilation period at 1000 hPa (upper left), 850 hPa (upper right), 500 hPa (lower left) and 200 hPa (lower right). Impact is visualised by the difference of the RMSE of the NoDWL and the DWL run i.e. $\text{RMS}(\text{NoDWL-NR}) - \text{RMS}(\text{DWL-NR})$. The mean is taken over 15 cases. White areas denote a negligible lidar impact, green areas a positive impact, red denotes a negative impact.

(d) *Results of the 15-day assimilation period*

Subsection (i) discusses the impact of DWL on analyses for the complete 15-day assimilation period. Subsection (ii) discusses data usage in the OSSEs and relates this to the 1999 operational ECMWF 4D-var system to indicate how well the OSSE observational network relates to the 1999 operational network, with respect to observation coverage and quality. Analyses serve as the forecasts initial state. The impact of lidar data on forecasts is assessed based on the scheme of figure 1 and using some objective measures to verify forecasts initialized with (DWL) and without (NoDWL) lidar data. This is discussed in subsection (iii).

(i) *Lidar impact on analyses.* We compare the analyses of both experiments with the nature run every day at 12 UTC, starting at 6 February 1993 and finishing at 20 February 1993, i.e. for 15 days. The mean squared errors (MSE) of the analyses wind vector fields (verified against the nature run) are displayed in table 1 for different pressure levels and regions of the globe. Here, the MSE is used rather than variances to take into account possible biases. Table 1 shows a positive impact of lidar data on the analysis

TABLE 1. RMSE of analysis wind fields (m s^{-1}) for the NoDWL and DWL experiments verified against the nature run, i.e. \mathbf{A}_c and \mathbf{A}_l respectively. The mean is taken over 15 cases, i.e. analyses at 12 UTC from 6 February 1993 until 20 February 1993.

	domain boundaries				1000 hPa		850 hPa		500 hPa		200 hPa	
	N	S	W	E	NoDWL	DWL	NoDWL	DWL	NoDWL	DWL	NoDWL	DWL
Globe	90	-90	-180	180	2.30	2.18	2.82	2.55	4.58	3.54	5.28	3.97
N.Hemis	90	20	-180	180	2.27	2.24	2.50	2.39	3.33	3.06	2.76	2.54
S.Hemis	-20	-90	-180	180	2.57	2.30	3.12	2.70	5.63	3.84	6.37	4.08
Tropics	20	-20	-180	180	2.06	2.01	2.81	2.54	4.49	3.66	5.91	4.88
Europe	75	35	-12	42	1.53	1.52	1.62	1.59	1.77	1.73	1.71	1.68
N.Atlantic	75	20	-75	-5	2.50	2.49	2.63	2.53	3.46	3.15	3.14	2.88
N.America	75	30	-130	-75	1.63	1.57	2.08	1.91	3.04	2.69	2.92	2.45

at all considered pressure levels and regions. The impact increases with decreasing pressure. Despite the generally high quality lidar data at 1000 hPa, their mean impact is modest in all regions. This can be understood from the high-quality simulated ASCAT scatterometer winds that have good coverage over the ocean surface.

Not surprisingly, a large impact is found in the tropics and southern hemisphere, because of the reduced coverage of satellite data (no AMSU or TOVS). A smaller but consistently beneficial impact is found over all areas in the northern hemisphere.

Figure 3 shows the mean global impact of lidar data on analyses averaged over the assimilation period. Again, large impact is seen in the tropics and southern hemisphere especially over the oceans. Positive impact is also seen over the North Atlantic and Europe. We note a correlation between regions of negative lidar impact and regions of low quality lidar data in figure 7 of M&S, in particular in the tropics. This indicates that low-quality observations can on average deteriorate the analysis.

In particular, the a priori background error covariance estimate, whose evolution in time is estimated from heuristic relationships, is uncertain in the OSSE. On the other hand, the observation error structure is perfectly known. Let us elaborate on this. Equation (4) provides the analysis error covariance as a function of background and observation error covariances. We identify two cases

1. Observations have relatively low quality, in which case the estimated analysis quality is entirely determined by the uncertain background error.

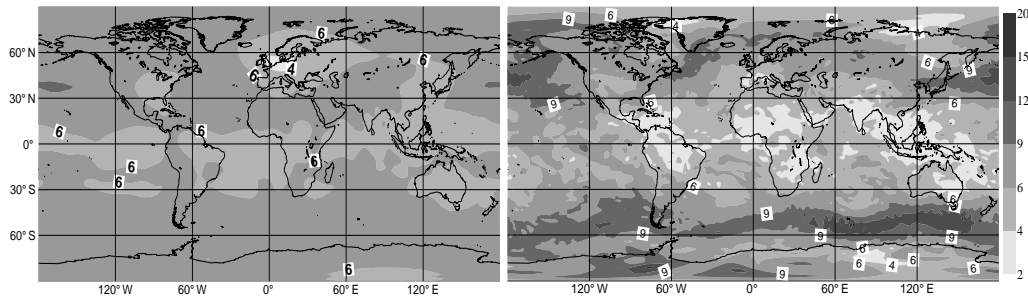


Figure 4. 500 hPa standard deviation of wind vector background error (m s^{-1}) estimated over the period 6 February 1993 00 UTC until 19 February 1993 18 UTC. Left, a priori estimate as used in 4D-Var. Right, from background minus nature run field statistics.

2. The background is of relatively low quality, in which case the estimated analysis quality is determined by the well-known observation error.

Case 1 appears the most problematic; in particular, when the estimated background error is wrong and too high. In this case the poor observations are assigned too much weight and are overfitted. This obviously could be harmful to the extent that the analysis is deteriorated with respect to the background. On the other hand, if the background error is too low, then the poor observations have too little impact, which is not optimal, but probably only to the extent that the improvement upon the background by the analysis is too small. So, low quality observations in the presence of overestimated background errors appear most detrimental.

We checked the global distribution of a priori specified background error standard deviations with the a posteriori computed error variances to confirm the occurrence of case 1. Figure 4 shows that 4D-Var overestimates the background error over the tropical and subtropical continents. Consequently, the relatively poor lidar data in these regions, see M&S figure 7, are assigned too much weight resulting locally in negative impacts, see Fig. 3. Also, 4D-Var underestimates the background error in the North Atlantic, leaving good quality lidar data insufficient weight to correct the analysis. Further note the difference in spatial detail between the real and estimated error covariances, showing the uncertainty in the estimate of \mathbf{B} as used in 4D-Var.

In reality, we also expect that the observation error structure is generally better known than the background error structure, and as such an OSSE seems ideal to test data assimilation systems. A second conclusion from the above is obviously that observation quality control is critical for data assimilation, since it may reduce the negative consequences of case 1 above (Tan and Andersson 2004).

(ii) *Data Usage.* The operational assimilation system at ECMWF archives information on the usage of observations by the system. This includes information on whether the observations are used or rejected in the assimilation cycle. Rejection may be the result of quality control or data blacklisting. The difference of the used data with the background and analysis field is stored to check the performance of the system. After an experiment, fits of the observations to the background and analysis fields are generated and visualized by standard RMS plots, bias plots, and histograms (not shown). From these statistics it is concluded that the simulated lidar winds are unbiased and have overall a slightly lower quality than radiosonde (TEMP) winds ($3\text{--}5 \text{ m s}^{-1}$ vs. $2\text{--}4 \text{ m s}^{-1}$ RMS background departure) and highest values in the tropics ($3\text{--}7 \text{ m s}^{-1}$ vs. $3\text{--}5 \text{ m s}^{-1}$ RMS). We note that as expected the DWL data have more heterogeneous quality

TABLE 2. Global observation coverage and statistics of OSSE related to the operational ECMWF system in 1999 for the same period, i.e. 5 February 18UTC to 16 February 12UTC. (o-b) Denotes the background departure and (o-a) the analysis departure.

	OSSE experiment			Operations 1999		
	number of data	data RMS		number of data	data RMS	
		o - b	o - a		o - b	o - a
TEMP-wind [m s^{-1}]	830,118	3.2	2.8	307,301	3.7	3.0
TEMP-T [K]	400,290	3.8	3.7	402,404	3.0	2.8
TEMP-q [kg/kg]	264,425	0.16e-2	0.15e-2	215,811	0.24e-2	0.23e-2
PILOT [m s^{-1}]	328,870	3.2	2.8	241,334	3.7	3.0
AIREP-wind [m s^{-1}]	100,060	5.8	5.3	920,698	4.3	4.0
AIREP-T [K]	66,774	2.6	2.5	407,484	2.2	2.2
TOVS [K]	0	-	-	2,347,298	6.5	5.0
LIDAR [m s^{-1}]	532,992	4.2	3.4	0	-	-
SYNOPship-10U [m s^{-1}]	49,794	3.0	2.8	67,754	3.9	3.8
DRIBU-10U [m s^{-1}]	2,618	5.1	4.9	11,712	3.3	3.0
SCAT-10U [m s^{-1}]	99,685	2.7	2.1	114,756	1.7	1.2
SYNOPland-2RH [%]	24,727	14.0	14.0	282,571	14.0	14.0
SYNOPship-2RH [%]	16,960	15.0	13.0	33,948	16.0	15.0
SATOB-wind [m s^{-1}]	37,576	4.3	4.1	981,886	5.3	5.2
PAOB (Pa)	3,255	229	207	3,353	307	273
RAOB-wind [m s^{-1}]	1,183,830	3.9	3.5	855,975	5.2	4.6

For instruments measuring profiles, the number of data equals the sum of data at all levels. The data RMS is an average over all levels. For SCAT sea-surface winds only the closest 10m u-wind vector of the two available ambiguities is considered.

than radiosonde data, but that high-quality DWL winds are given more weight in the data assimilation than lower quality DWL winds. RMS fits to other data types were generally improved when DWL data were used. Very few HLOS winds were rejected by the variational quality control, consistent with the use of Gaussian errors.

Interpreting results from the DWL OSSE in terms of expected impact of DWL observations in 2008, when ADM will fly, is not trivial since it requires a comparison of the 1993 and the (yet unknown) 2008 observational network. As a first approach we compared the observational network as generated in Stoffelen *et al.* (1994) with the 1999 operational network, i.e. at the time the OSSE was conducted. To this end we compared the observation statistics of the OSSE with the operational observation statistics in the February period of 1999. The results are summarized in Table 2 and show that the OSSE uses more radiosondes (TEMPS), less AIREPs, less SATOBs and less DRIBUs.

Besides their relative abundance in 1993, the simulated data quality of the network of wind sounders (TEMP, PILOT) is overestimated as compared to reality in 1999. Since the wind sounding network is the backbone for NWP (e.g., WMO 2004), one would thus expect that the impact of real lidar data would be more significant in the operational system than the simulated data in the OSSE. The effect of reduced wind profile information available to NWP, currently, is however compensated by the abundance of other data types (see introduction).

(iii) *Lidar impact on forecasts.* To assess the impact of lidar data on forecasting, 10-day forecasts are produced, initiated with the 15 analyses at 12 UTC, i.e. from day 6 to 20 February 1993. Several objective statistical measures to verify forecast quality are proposed in the literature. Most popular among these are the root-mean-square error (RMSE) and anomaly correlation coefficient of forecasts against the analyses. In the special case of an OSSE we verify forecasts against the nature run. Figure 5 shows the wind vector RMSE of the forecasts with respect to the nature run at 500 hPa for the

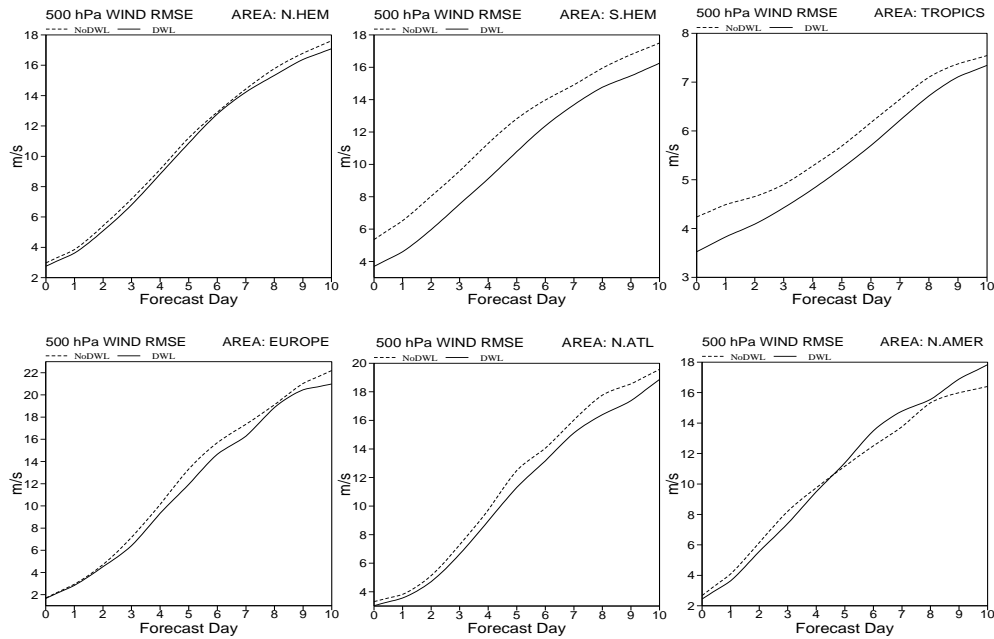


Figure 5. Forecast skill; 500 hPa wind vector RMSE of forecast (w.r.t. nature run) field for NoDWL (dashed) and DWL (solid) experiment as a function of forecast range and for six global regions. The top row shows the forecast skill for the northern hemisphere (left), southern hemisphere (center) and tropics (right), the bottom row for Europe, the North Atlantic and North America. Forecasts are initialised with analyses at 12 UTC in the period 6 until 20 February 1993. The mean is taken over all 15 cases.

NoDWL and DWL experiments for different global regions. The mean is taken over all 15 cases. Forecast day 0 corresponds with the analysis. The northern hemisphere regions show forecast improvements up to half a day. Similar results are found at other pressure levels (not shown). Anomaly correlation computations (see also section 4) for geopotential height show similar improvements. Values remain above 60% up to forecast day 7-8 for the northern and up to day 5-7 for the southern hemisphere (not shown). The small positive impact over Europe after 2 days originates from the positive impact of lidar data on the analysis over the North Atlantic as depicted in Fig. 6.

The positive impact over Europe and the North Atlantic is clear, evolving into half a day forecast gain after 6 days. Local negative impact is observed as well in the northern hemisphere. Negative forecast impacts seem associated with the locally negative analysis impacts as described in the previous section. This confirms again the relevance of a well-tuned data assimilation system and a careful observation quality control that rejects or downweights relatively inaccurate observations in the analysis.

The total northern hemisphere impact is positive after averaging the local realizations of the impact scores. We note again, that due to the random noise in the observations and the chaotic behaviour of the atmosphere a stochastic behaviour of the scores is expected. As such, it is an important result that the forecast scores vary considerably from one day to the next, see for example the left figure in Fig. 7, nevertheless for the northern hemisphere 14 out of 15 forecasts have improved, as shown in the right figure of Fig. 7, providing convincing evidence of the future benefit of ADM to NWP.

4. OSSE CALIBRATION

An important aspect for the interpretation of OSSE results is to validate the realism of the experimental setup. A common approach is to conduct a series of OSEs for existing observing systems in the OSSE system (Atlas 1997, Masutani *et al.* 2004). Ideally, the OSSE impact of simulated observations should agree with the OSE impact of the corresponding real observations. Calibration of the OSSE results is required for a realistic assessment of the expected impact of the new observing system in the operational NWP system. Any changes in data coverage between OSE and OSSE would have to be accounted for (see table 2). We adopt an alternative approach, where we compared the distributions of background and analysis departures for the various observation types used in the OSSE experiments with those in the ECMWF operational system. We show that the impact of observations in the OSSE analysis is similar to that in 1999 operations. In addition we show that the forecast anomaly correlation coefficient, which is a measure of forecast skill, for the OSSE fits well with operations

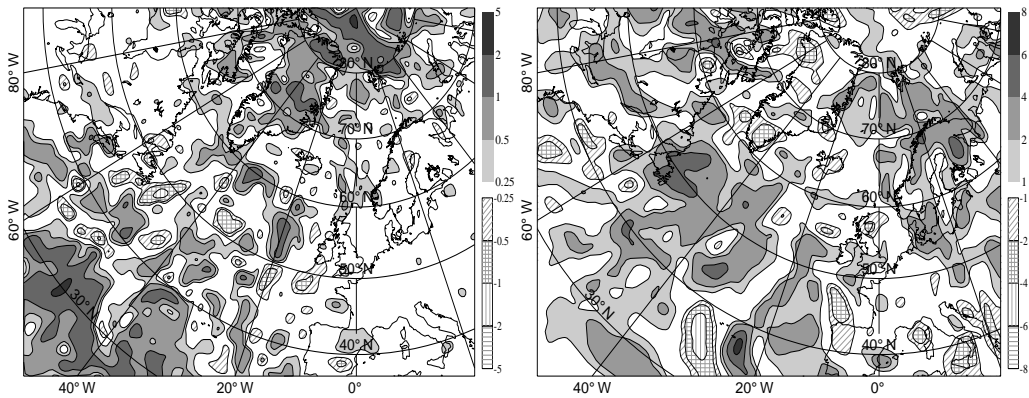


Figure 6. 500 hPa lidar observations impact on the wind field (m s^{-1}) over Europe and the North Atlantic for the analysis (left) and 4-day forecast (right), averaged over 15 cases. The difference of the RMSE of the NoDWL run and the DWL run is plotted. White areas denote a negligible lidar impact and filled/dashed areas a positive/negative impact. Lidar data have a positive impact on the 4-day forecast over Europe and the North Atlantic.

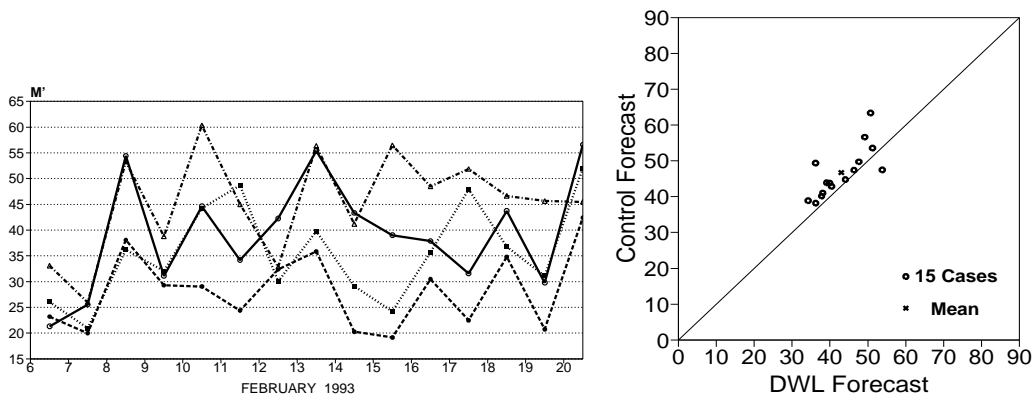


Figure 7. Left, forecast verification. RMS error of the forecasts of 500 hPa geopotential height (m) over North America for three (dashed)- and four (solid)-day DWL forecasts and three (dot)- and four (dash-dot)-day NoDWL forecasts. Right, 500 hPa geopotential height RMS error (m) of the DWL and NoDWL four-day forecasts north of 20N. Circles indicate the 15 individual forecasts. The cross represents the mean over the 15 cases.

over the 1993-1999 time period. Both results confirm the absence of a fraternal twin problem as was anticipated in section 2(a).

(i) *Observation Impact.* The divergence of the OSSE forecast model from nature truth is compensated through the input of observed meteorological data in the assimilation cycle. Hence, observation impact is related to the extent to which the weather model diverges from the true atmospheric evolution. For small divergence, the background fields after six hours of forward integration and the corresponding nature run fields will be very similar, hence underestimating the impact of additional observations. This so-called fraternal twin problem was investigated by comparing the observation minus background differences and observation minus analysis differences of the OSSE in February 1993 and the operational system at ECMWF in February 1999. Background (analysis) departure is defined as the departure ($y - \mathbf{H}x$) between the background $x = x_b$ (respectively the analysis $x = x_a$) and observations y with \mathbf{H} the observation operator that relates model fields to observations. Introducing the "true" nature run fields, x_t , the departure expression can be written as follows

$$\begin{aligned} y - \mathbf{H}x &= y - \mathbf{H}(x_t + x - x_t) \\ &= y - \mathbf{H}x_t + \mathbf{H}(x_t - x) \\ &= r + \mathbf{H}(x_t - x) \end{aligned} \quad (7)$$

with r the observation error. Assuming no correlation between observation and background field errors, the covariance matrix of the background departures equals $\mathbf{D}_b = \mathbf{R} + \mathbf{H}\mathbf{B}_t\mathbf{H}^T$, with \mathbf{R} the observation covariance matrix and \mathbf{B}_t the true background error covariance matrix defined by

$$\begin{aligned} \mathbf{R} &= \mathbf{E}[(y - \mathbf{E}[y])(y - \mathbf{E}[y])^T] \\ \mathbf{B}_t &= \mathbf{E}[(x_b - x_t)(x_b - x_t)^T] \end{aligned} \quad (8)$$

Using Eq. (3) we may write for the analysis departure $y - \mathbf{H}x_a = [\mathbf{I} - \mathbf{H}\mathbf{K}](y - \mathbf{H}x_b)$. Note that the analysis error and observation error are correlated. For the covariance matrix of the analysis departures, \mathbf{D}_a , we then have $\mathbf{D}_a = [\mathbf{I} - \mathbf{H}\mathbf{K}]\mathbf{D}_b[\mathbf{I} - \mathbf{H}\mathbf{K}]^T$. For the unlikely event of having perfect knowledge of the background error covariance matrix the Kalman gain from Eq. (3) is optimal in minimizing the analysis departure and \mathbf{D}_a simplifies to $\mathbf{D}_a = [\mathbf{I} - \mathbf{H}\mathbf{K}]\mathbf{R}$.

We compared the RMS of background and analysis departures for the various observation types used in the OSSE experiments and in the ECMWF operational system respectively. The RMS is equal to the square root of the diagonal elements of the covariance matrices \mathbf{D}_a and \mathbf{D}_b . In fraternal twin experiments, the background will be much closer to the truth than in operations. Then, the true background errors (\mathbf{B}_t) are much smaller than observation errors (\mathbf{R}). Additional data thus would have minimal impact or may even be detrimental for the analysis. The latter is understood by the fact that the analysis, observation and background weights are pre-determined with anticipated deviations of the background from truth (based on experience in operations). The a priori background error covariance (\mathbf{B}) is much larger than it truly should be, resulting in modifications of an accurate background on the basis of relatively inaccurate observations. In other words, since the true gain matrix \mathbf{K}_t is unrealistically smaller than the estimated \mathbf{K} (for \mathbf{B} is larger than \mathbf{B}_t), observation increments are overestimated by the assimilation system. Thus fraternal twin experiments generate small and often negative impact of observations and this results in almost similar background and analysis departure statistics. However, the RMS differences of background and analysis

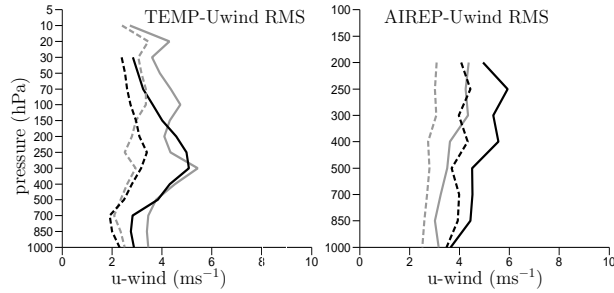


Figure 8. Statistics of TEMP u-wind component (left) and AIREP u-wind components (right) in OSSE (black) and the operational ECMWF system (grey) for the period 5 February 1999 12 UTC until 8 February 1999 06 UTC. Solid/dashed lines denote background/analysis departures, i.e. (o-b)/(o-a).

departures of the OSSE and those from operations are quite similar (Fig. 8). This implies realistic impact of observations in our OSSE and thus realistic divergence of the OSSE NWP model from the (nature run) truth.

(ii) *Anomaly correlation of OSSE versus operational system.* Anomaly correlation coefficients provide an indication of the forecast skill. Anomaly correlation is defined as the correlation between the forecast and analyzed deviations (anomalies) from climatology (Holton 1992; Wilks 1995). The anomaly correlation for a particular forecast variable is defined as follows

$$\text{acc}(i) = \frac{\sum_m \delta F_m(i) \delta A_m(i)}{\sqrt{\sum_m \delta F_m^2(i) \sum_m \delta A_m^2(i)}}, \quad \text{with } \delta F_m(i) = (F_m(i) - C_m) - \overline{(F_m(i) - C_m)} \quad (9)$$

and similar for $\delta A_m(i)$. Here $F_m(i)$ is the i -day forecast field variable at grid point m , and A_m and C_m the corresponding verifying analysis and climatology field variables. The summation is over an area of interest and the overbar denotes the area mean value. Values for the anomaly correlation are between -1 and 1, with 1 implying a perfect forecast. A value larger than 0.6 is generally regarded as an indication of a useful forecast (e.g. Krishnamurti *et al.* 2003).

For fraternal twin nature run and operational forecast models one would expect a much better skill compared to the operational system, since fraternal twin NWP models would exhibit a more similar time evolution. In fig. 9 we compare the OSSE forecast skill with the skill of the operational system in the years 1993 until 1999 by computing anomaly correlations computed from ten 5-day forecasts in the OSSE assimilation period (i.e. 6 February until 20 February). We concentrated on the northern hemisphere, more specifically the North Atlantic and Europe, where the OSSE observing system is representative of the 1999 operational observing system. Forecast skill difference of the operational system for different years is related to different meteorological situations and evolution of the forecast model.

The forecast skill of the OSSE is better than for the operational system in 1993 by roughly half a day on the short-term, but almost similar in the mid-term. Note however that the OSSE weather is different from the real weather of February 1993, and half a day of shift in the scores is well within the year-to-year variations and improvement of the skill of the operational system in the month of February from 1993 to 1999. We conclude that the forecast skill performance in the OSSE is not significantly better than in the operational system.

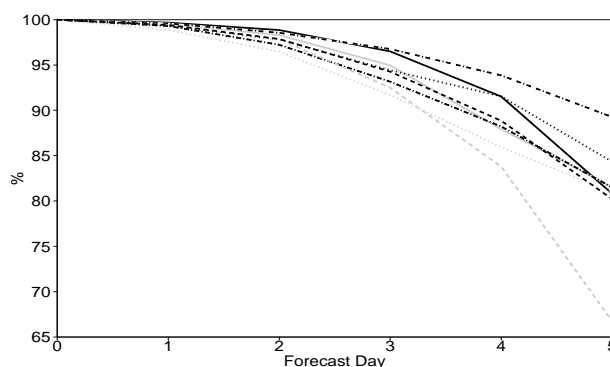


Figure 9. 500 hPa geopotential height anomaly correlation coefficients for the OSSE related to the ECMWF operational system (OPER) for the North Atlantic and European region in the period 1993-1999. The black solid line corresponds to the OSSE, black-dash (OPER 1993), light-grey-dash (OPER 1994), dark-grey-dot (OPER 1995), light-grey-dot (OPER 1996), black-dot (OPER 1997), dark-grey-solid (OPER 1998) and light-grey-solid (OPER 1999).

We conclude that assessment of the potential impact of lidar data on NWP through OSSEs is not significantly affected by the fraternal twin problem in this study.

5. CONCLUSIONS

In this study we realistically simulated the meteorological impact of the UV Doppler Wind Lidar as proposed for the ESA Core Earth Explorer Atmospheric Dynamics Mission, ADM_UV. ADM_UV has a clear and demonstrable positive impact on the analyses and forecasts in the northern hemisphere. In the tropics and southern hemisphere the impact is overwhelmingly positive, but here the OSSE observing system is not representative of the real-world observing system. In particular in the southern hemisphere, the satellite temperature soundings could unfortunately not be used. However, based on current operational experience, this is supposedly of little limitation in the northern hemisphere in the presence of the extended radiosonde coverage as available in 1993.

The average benefit of lidar data on medium-range (5-day) 500 (200, not shown) hPa wind forecast in the OSSE was about 0.25 (0.4) days in the northern hemisphere (above 20N). Local impacts varied and were up to 0.5 (0.8) days, for example for Europe. To test the significance of our results we verified that time series of forecast impact showed sufficient day-to-day variability. At the same time, in a clear majority of cases the DWL forecast was better than the control, indicating that our results are significant, even though obtained over a limited period of 15 days.

Good quality ADM_UV wind observations have a clear and beneficial impact on the analyses. Some large and beneficial forecast impacts of ADM_UV can be traced back to areas with large analysis impact. Wind profile observations are of key importance to the GOS, as demonstrated here again. However, the operational wind profile network is expected to further decrease in the future. As an illustration of this fact we note that the conventional wind profile network in operations is much smaller than that used in the OSSE. This will result in a larger impact of satellite data in the future in the northern hemisphere, both for mass and wind observations. Moreover, the simulated quality in the OSSE database was somewhat overestimated for the conventional wind profiles. This reduces the improvements brought by ADM_UV in the OSSE. On the other hand,

more AIREP and wind sounders are available nowadays, mainly resulting in tropopause flight level observations, but also some profiles over land.

Moreover, a closer look was given to the nature run clouds, but no serious deficiencies were found. The relative lack of PBL clouds over the oceans as compared to satellite observations may be improved. However, we found that in the PBL over the ocean, the DWL impact is limited due to the presence of the ASCAT scatterometer. On the other hand, inaccurate ADM_UV data cause negative impacts locally. This occurs probably because those observations are not properly weighted against the background model fields in the analysis. The background error estimates are locally poor, probably frequently resulting in detrimental observation impacts in the analysis. Excessive weight given to low-quality observations cause detrimental impact. Underweighted high-quality ones are usually beneficial. In areas with extensive high-level cloud cover negative impacts were most frequent. We may conclude from this that (i) tuning of data assimilation systems is very important for achieving beneficial observation impact (Tan and Andersson 2004) and OSSE could be used for this, (ii) good accuracy and representativeness of observations is a prime requirement for their impact and (iii) quality control on real observations is very important in cloudy regions (Tan and Andersson 2004).

We rigorously tested the presence of a so-called fraternal twin problem, but found no substantial evidence of such a problem. Although we have verified in this study that ADM_UV is indeed capable of demonstrating the potential value of space-borne wind profile observations for improving atmospheric analyses and NWP, this study was of limited extent and more experimentation is desirable as outlined in the following recommendations:

- OSSEs for other and more periods would reveal more about the significance of the results that we have found here. A two-week assimilation period is generally thought of as the minimum to be able to demonstrate impact with an OSE or OSSE.
- OSSEs can be used to tune data assimilation systems.
- Quality control is very important. In the OSSE low-quality ADM_UV observations show often detrimental impact. Observations from LITE (Winker *et al.* 1996) have shown their usefulness to investigate the interaction of a lidar with a cloudy atmosphere and to study quality control issues (Tan and Andersson 2004; 2005). Also the ICESat mission (Spinhirne 2005) and air and ground measurements may help to verify processing schemes.
- Where ADM_UV is designed to demonstrate the capability of a space-borne DWL, OSSE-like studies may be used to study scenarios for an operational meteorological mission to be implemented when ADM_UV has successfully flown. Options for targeting LOS profiles, multiple LOS or even multiple satellites could be tested (Marseille *et al.* 2005).
- To entirely avoid the fraternal twin problem we recommend the use of a foreign model for the production of the nature run. These fields can then be interpolated and processed at any location to provide an OSSE database in standard meteorological format. The ECMWF has a great capability to run OSSEs on such input.
- OSSEs including (A)TOVS and AMSU data would be better capable of assessing the relative benefit of temperature and wind sounding in the southern hemisphere and tropics. Simulation of AIRS or IASI or other new observation systems is also worthwhile. However, we note that for these observations, cloud clearing is a major issue and consequently error properties are complex and more difficult to simulate realistically.

- OSSE are costly and alternative impact simulation experiments may be developed such as in (Marseille et al. 2005) that include the nowadays operational network of satellite sounders.

ACKNOWLEDGEMENT

We thank ESA for their support of the project under Contract No. 13018/98/NL/GD. Siebren de Haan did a great job in interfacing the OSSE observation data base to the ECMWF system. We acknowledge staff at ECMWF and Météo France for supporting this study, in particular Drasko Vasiljević and Carla Cardinali. Special acknowledgement goes to ECMWF for maintaining the OSSE database and nature run in their archives. We appreciate the motivating interests of Joachim Fuchs (ESTEC), Paul Ingmann (ESTEC), and Uwe Kummer (Astrium) in this study.

REFERENCES

- Atlas, R. 1997 Observing System Simulation Experiments: Methodology, Examples and Limitations. In proceedings of CGC/WMO Workshop Impact of various observing systems on Numerical Weather Prediction, Geneva, 7–9 April, World Weather Watch Technical Report No 18, WMO/TD No. 868, pp 155–163.
- Atlas, R., Emmitt, G. D., Terry, J., Brin, E., Ardizzone, J., Jusem, J. C., and Bungato, D. 2003 Recent observing system simulation experiments at the NASA DAO. In proceedings of The Seventh Symposium on Integrated Observing Systems: The Water Cycle
- Baker, W., Emmitt, G. D., Robertson, F., Atlas, R., Molinari, J. E., Bowdle, D. A., Peagle, J., Hardesty, R. M., Menzies, R. T., Krishnamurti, T. N., Brown, R. A., Post, M. J., Anderson, J. R., Lorenc, A. C., McElroy, J. 1995 Lidar-Measured Winds from Space: A Key Component for weather and Climate Prediction, *Bull. Am. Meteorol. Soc.*, **76**, 869–888
- Becker, B. D., Roquet, H., Stoffelen, A. 1996 A simulated data base including ATOVS, ASCAT and Doppler Wind Lidar data, *Bull. Am. Meteorol. Soc.*, **77**, 2279–2294
- Butterworth, P. and Ingleby, N. B. 2000 Recent Developments in the use of Satellite Winds at the UK Met. Office. In proceedings of the Fifth Int. Winds Workshop, 28/2-3/3/, Lorne, Australia, EUMETSAT, Darmstadt, Germany
- Cardinali, C., Pailleux J., Thépaut J. N. 1998 Use of simulated Doppler Wind Lidar data in NWP: an impact study, CNRS, Météo France.
- Courtier, P. 1997 Variational methods, *J. Meteorol. Soc. Jpn.*, **75**, 211–218
- Courtier, P., Andersson, E., Heckley, W., Pailleux, J., Vasiljevic, D., Hamrud, M., Hollingsworth, A., Rabier, F., Fisher, M. 1998 The ECMWF implementation of three dimensional variational assimilation (3D-Var). Part I: Formulation, *Q. J. R. Meteorol. Soc.*, **124**, 1783–1808
- Cress, A. and Wergen, W. 2001 Impact of profile observations on the German Weather Service's NWP system. *Meteor. Zeitschrift*, **10**, 91–101
- Derber, J., Bouttier, F., 1999 A reformulation of the background error covariance in the ECMWF global data assimilation system, *Tellus*, **51A**, 195–221
- European Space Agency 1996 The nine-candidate earth-explorer missions-Atmospheric Dynamics Mission. ESA Report ESA-SP-1196(4), European Space Agency, Noordwijk, The Netherlands
- European Space Agency 1999 Atmospheric Dynamics Mission. The four-candidate earth-explorer missions. Report for mission selection. ESA Report ESA-SP-1233(4), European Space Agency, Noordwijk, the Netherlands.
- Holton, J. R. 1992 *An introduction to Dynamic Meteorology*. third edition, Academic Press

- Kelly, G. 1996 Influence of observations on the operational ECMWF system, *WMO Bulletin Vol. 46, No. 4*, October, pp. 336–342 (in the English version).
- Kelly, G. 2004 OSEs of all main data types in the ECMWF operational system. In proceedings of the Third WMO Workshop on the Impact of Various Observing Systems on NWP, Alpbach.
- Krishnamurti, T. N., Rajendran, K., Vijaya Kumar, T. S. V., Lord, S., Toth, Z., Zou, X., Cocke, S., Ahlquist, J. E., Navon, I. M. 2003 Improved Skill for the Anomaly Correlation of Geopotential Heights at 500 hPa, *Mon. Weather Rev.*, **131**, 1082–1102
- Lorenc, A. C. 1986 Analysis methods for numerical weather prediction. *Q. J. R. Meteorol. Soc.*, **112**, 1177–1194
- Marseille, G. J., Stoffelen, A. 2003 Simulation of wind profiles from a space-borne Doppler wind lidar. *Q. J. R. Meteorol. Soc.*, **129**, 3079–3098
- Marseille, G. J., Stoffelen, A., Barkmeijer, J. 2005 PIEW - Prediction Improvement of Extreme Weather, study report available from KNMI
- Masutani, M., Woollen, J. S., Lord, S. J., Derber, J. C., Emmitt, G. D., Wood, S. A., Greco, S., Atlas, R., Terry, J., Kleespies, T. J., Sun, H. 2002 Impact assessment of a doppler wind lidar for NPSS/OSSE. AMS preprint volume for 15th Conference on Numerical Weather Prediction 12–16 August 2002 in San Antonio, TX. 346-349.
- Masutani, M., Campana K. A., Lord, S., Yang, S. K. 1999 Note on Cloud Cover of the ECMWF Nature run used for OSSE/NPOESS project, NCEP Office note No. 427.
- Masutani, M., Lord, S. J., Woollen, J. S., Yang, W., Sun, H., Kleespies, T. J., Emmitt, G. D., Wood, S. A., Katz, B., Treadon, R., Derber, J. C., Greco, S., Terry, J. 2004 Global OSSE at NCEP. In proceedings of the Eighth Symposium on Integrated Observing and Assimilation Systems for Atmosphere, Oceans, and Land Surface
- Rohn, M., Kelly G. 2000 The use of the MPEF quality indicator, In Proceedings of the ECMWF seminar: Exploitation of the New Generation of Satellite Instruments for Numerical Weather Prediction, 4–8 September, available at ECMWF, Reading, UK.
- Spinhirne, J. D. 2005 Aerosol and Cloud Observations and Data Products by The GLAS Polar Orbiting Lidar Instrument, Invited Paper in proceedings AMS Symposium on Lidar Atmospheric Applications, San Diego.
- Stoffelen, A., Becker, B., Eyre, J., Roguet, H. 1994 Theoretical Studies of the Impact of Doppler Wind Lidar Data - Preparation of a database, ESA-CR(P)-3943.
- Stoffelen, A., Pailleux, J., Källén, E., Vaughan, J. M., Isaksen, I., Flamant, P., Wergen, W., Andersson, E., Schyberg, H., Culoma, A., Meynard, R., Endemann, M., Ingmann, P. 2005 The Atmospheric Dynamics Mission for Global Wind Field Measurement, *Bull. Am. Meteorol. Soc.*, **86**, 73–87
- Tan, D., Andersson, E. 2004 Expected Benefit of Wind Profiles from the ADM-Aeolus in a Data Assimilation System, ESA contract report 15342/01/NL/MM.
- Tan, D., Andersson, E. 2005 Simulation of the yield and accuracy of wind profile measurements from the Atmospheric Dynamics Mission (ADM-Aeolus) *Q. J. R. Meteorol. Soc.*, **131**, 1737–1757
- Wilks, D. S. 1995 *Statistical Methods in the Atmospheric Sciences*, Academic Press
- Winker, D. M., Couch, R. H., McCormick, M. P. 1996 An Overview of LITE: NASA's Lidar In-Space Technology Experiment, Proc. of the IEEE, vol. 84, no. 2
- WMO 2004 Current Statement of Guidance Regarding How Well Satellite Capabilities Meet WMO User Requirements in Ten Application Areas. WMO satellite reports.