TN16

Advanced monitoring of Aeolus winds

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CHANGE LOG

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1.0	21 April 2015	Initial version
1.1	28 August 2015	Updates for the first draft done.
1.2	3 November 2015	Incorporate review by KNMI and Lars
1.3	23 Aug 2016	Incorporate review by Oliver Reitebuch and review by ESA (Anne Grete); plus some improvements in readability.

Contents

1 Introduction

This technical note discusses the need for the advanced monitoring of ADM-Aeolus observations by using the ECMWF weather model as the geophysical reference. The advanced monitoring will help significantly in the characterisation of the mission and in the detection of Aeolus data problems. As a new remote sensing technique in space, Aeolus will likely encounter data problems or unexpected behaviour, not only during the Commissioning Phase, but during the mission lifetime, hence a robust set of monitoring methods will be needed throughout the mission.

Such monitoring requires the NWP model winds to be sufficiently accurate in comparison to the Aeolus retrieved winds to allow Aeolus observation problems to be detectable. Therefore part of this technical note assesses the accuracy of the ECMWF NWP model, focussing on the model's systematic wind errors in relation to the detectability of Aeolus observation systematic error. These estimates suggest that if Aeolus observation systematic errors are persistent enough (i.e. vary in predictable ways), it should be possible to detect and estimate them using the ECMWF NWP model as a reference. However in certain conditions the model has much lower accuracy (such as the tropical upper troposphere and in/around jet streams) and here the model should be used with some caution when trying to estimate Aeolus' systematic errors.

A discussion of the generic operational ECMWF observation monitoring tools is presented. Justification is provided for the development of additional bespoke Aeolus monitoring tools which is what we refer to as "advanced monitoring". Based on for the expected Aeolus' error sources, we suggest ways of presenting the Aeolus versus ECMWF model differences (also known as observation minus background (O-B) departure statistics), to aid the detection of and to determine the causes of the observation errors.

This document is an output of work package 2370 of CCN5 (Change Request No: 5, Aeolus Level 2B/C Enhancements and Launch Extension of ESA Contract No: 4200018555/04/NL/MM Development and Production of Aeolus Wind Data Products). WP2370 concerns "implementation: advanced monitoring of L2B/C processing". In particular the proposal stated that the following work shall be done:

As part of preparations for Aeolus phase E product monitoring at ECMWF:

- *A review of the current possibilities for the L2/Met PF monitoring will be undertaken.*
- *A plan will be devised regarding which parameters should be monitored and technically what is the best way to achieve the desired outcome.*
- *The plan will be formulated in consultation with the L1B and L2B project teams.*
- *Following this, advanced monitoring software for the L2B/C processing will be developed, to be integrated at ECMWF during phase E.*

The monitoring software shall (with the aid of ECMWF forecasts) be able to:

- *Monitor L2B input calibration file inputs e.g. changes in Rayleigh response curves (via AUX_RBC), changes in Mie response (MRC) curves (via L1B files). Detecting when problems occur in the weekly updates to calibration, by comparing fields to previous files, expected ranges.*
- *Monitoring of input L1B data and comparing L2B wind results to the L1B*
- *Monitoring of L2B processing parameters and products with the aid of NWP data. For example:*
    - *PDFs of background and analysis departures. Statistics to show dependence upon altitude (or possibly range), geographical location, time, ascending/descending orbit, NWP background HLOS wind and NWP cloud conditions should be considered.*
    - *Plots to help diagnose biases, e.g. slope error, time-varying biases (e.g. along-orbit biases)*
    - *Time-trends of QC flag counts*

    - *Production of automatic warnings when threshold criteria are exceeded e.g. automatic emails sent*
- *Part of the work will investigate whether it is suitable to use the AUX_MET files to provide the required NWP data; therefore allowing such monitoring to be implemented at any location with access to appropriate AUX_MET files.*
- *ECMWF will execute the Aeolus L2B advanced product monitoring software during the commissioning phase and report the outcomes to ESA and the Aeolus CAL/VAL team and will perform updates when thought appropriate*

Since the proposal was written in 2013, the actual implementation deviates slightly from the original plan as new ideas and a deeper knowledge about expected Aeolus systematic errors has been obtained in the past two years.

Note that the monitoring tools discussed in this TN focus on Aeolus winds and not explicitly on the instrument characterization, such as e.g. Rayleigh channel expected photon counts given AUX_MET input temperature and pressure, changes of these signals after introducing new calibration files, etc. Currently, there are no tools in place for the latter by the L2B team, however monitoring instrument and first calibrations is a L1B team task based on some of the experience gained with A2D data.

1.1 *Documents*

1.1.1 Applicable documents

	Title	Ref	Ver.	Date
[AD1]	Change Request No: 5, Aeolus Level 2B/C Enhancements and Launch Extension of ESA Contract No: 4200018555/04/NL/MM Development and Production of Aeolus Wind Data Products	CR5	1.1	24/01/2014
[AD2]	Unknown bias budget	AE.TN.ASF.AL00584	2.0	20/12/2012
[AD3]	Aeolus Mission & Performance Budget Document	AE.RP.ASU.SY.128	6.0	22/02/2013
[AD4]	ADM-Aeolus Project Mission Requirements Document	AE-RP-ESA-SY-001	1.41	01/05/2015

1.1.2 Reference documents

	Title	Ref	Ver.	Date
[RD1]	The assimilation of horizontal line-of-sight wind information into the ECMWF data assimilation and forecasting system, part II: the impact of degraded wind observations. By András Horányi, Carla Cardinali, Michael Rennie and Lars Isaksen	Q.J.R. Meteorol. Soc., 141: 1233–1243. doi: 10.1002/qj.2551	N/A	2015
[RD2]	Dee, D. P., Bias and data assimilation.	Q.J.R. Meteorol. Soc., 131: 3323–3343. doi: 10.1256/qj.05.137	N/A	2005
[RD3]	Rodwell, M.J. and Palmer, T.N., Using numerical weather prediction to assess climate models.	Q. J. R. Meteorol. Soc. 2007, 133, 129–146.	N/A	2008
[RD4]	Anna Booton, Bill Bell, Nigel Atkinson, An improved bias correction for SSMIS	Proc. EUMETSAT Meteorological satellite Conference, Vienna		Sep 2013
[RD5]	Ad Stoffelen and Jur Vogelzang, Wind bias correction guide		1.0	2011
[RD6]	Quifeng Lu and William Bell. Characterizing Channel Center Frequencies in AMSU-A and MSU Microwave Sounding Instruments	Journal of Atmospheric and Ocean Technology, 31, 1713–1732.		Aug 2014
[RD7]	William Bell. Post-launch characterisation of satellite instruments	ECMWF 2014 seminar proceedings		8-12 Sep 2014
[RD8]	Analysis of enhanced noise in A2D observations	AE.FR.DLR.A2D.CN11.02 1014, version 1.1		20 April 2015
[RD9]	Podglajen, A., A. Hertzog, R. Plougonven, and N. Žagar (2014), Assessment of the accuracy of (re)analyses in the equatorial lower stratosphere,	J. Geophys. Res. Atmos., 119, 11,166–11,188,		2014
[RD10]	Žagar, N., Gustafsson, N. and Källén, E. (2004), Variational data assimilation in the tropics: The impact of a background-error constraint.	Q.J.R. Meteorol. Soc., 130: 103–125. doi: 10.1256/qj.03.13		2004
[RD11]	Harris BA, Kelly G. A satellite radiance-bias correction scheme for data assimilation.	Q. J. R. Meteorol. Soc. 127: 1453–1468.		2001
[RD12]	X. J. Sun, R. W. Zhang, G. J. Marseille, A. Stoffelen, D. Donovan, L. Liu, and J. Zhao, The performance of Aeolus in heterogeneous atmospheric conditions using high-resolution radiosonde data	Atmos. Meas. Tech., 7 , pp. 2695-2717 doi:10.5194/amt-7-2695		2014
[RD13]	Milan, M., and L. Haimberger (2015), Predictors and grouping for bias correction of radiosonde temperature observations	J. Geophys. Res. Atmos., 120, doi:10.1002/2015JD023635.		2015
[RD14]	TN15.3, End-to-end testing of the continuous mode L2B processor	AE-TN-ECMWF-153-v3.1_20140319_final		2014
[RD15]	Rodwell, M. J., et al. (2013), Characteristics of occasional poor medium-range weather forecasts for Europe	Bull. Am. Meteorol. Soc., 94(9), 1393–1405, doi:10.1175/BAMS-D-12-00099.1.		2013
[RD16]	Cardinali, C., and L. Rukhovets, and J. Tenenbaum, 2004: Jet Stream Analysis and Forecast Errors Using GADS Aircraft Observations in the DAO, ECMWF, and NCEP Models,	MWR, 132, 764-779 Drue, C., and W. Frey, and A. Hoff, and Th. Hauf, 2007:		2004

1.2 Acronyms

ACCD	Accumulation Charge Coupled Device
ADS	Airbus Defence and Space
AOCS	Attitude and Orbit Control System
ALADIN	Atmospheric Laser Doppler Instrument
ATBD	Algorithm Theoretical Baseline Document
A2D	ALADIN Airborne Demonstrator
BM	Burst mode
BRC	Basic Repeat Cycle
CM	Continuous mode
CoP	Chain-of-processors software
CP	Commissioning Phase
DA	Data assimilation
DCMZ	Dark Current in Memory Zone
DEM	Digital Elevation Model
DWL	Doppler Wind Lidar
ECMWF	European Centre for Medium-Range Weather Forecasts
EGM	Earth Gravitational Model
ESOC	European Space Operations Centre
ESTEC	European Space Research and Technology Centre (part of ESA)
GADS	Global Aircraft Data Set (GADS), comes from flight data recordings of British Airways Boeing 747-400 aircraft
HBE	Harmonic Bias Estimator
HK	Housekeeping data
HLOS	Horizontal Line Of Sight
IDL	Interactive Data Language
IODD	Processor Input/Output Data Definitions Interface Control Document
ITCZ	Inter Tropical Convergence Zone
KNMI	Royal Netherlands Meteorological Institute
LOS	Line of sight
L1B	Level-1B
L2B	Level-2B
L2Bp	L2B processor
LWDA	Long Window Data Assimilation cycle at ECMWF
N/A	Not applicable
NWP	Numerical weather prediction
QC	Quality control
RB	Rayleigh-Brillouin
RBC	RB Correction
RMA	Reference model atmosphere
RMS	Root mean square

ROM SAF	The Radio Occultation Meteorology Satellite Application Facility
RR	Rayleigh response
RRC	Rayleigh response calibration
SI	The International System of Units
SP	Spectrometer
SNR	Signal to noise ratio
SRD	System requirements document
TBD	To be determined
TN	Technical note
VHAMP	Vertical and Horizontal Aeolus Measurement Positioning
WGS	World Geodetic System
WP	Work package
XML	Extensible Markup Language
ZWC	Zero wind correction

2 Advanced monitoring concept

2.1 The need for advanced monitoring

The ADM-Aeolus Mission Requirements [AD4] defines an upper limit for unknown ADM-Aeolus HLOS wind observation biases to be less than 0.7 m/s. Such biases have been shown to be acceptable for Numerical Weather Prediction models, but clearly lead to less observation impact compared to bias-free observations. It is therefore of great importance to monitor and correct potential product biases in order to maximize the mission impact.

For example [AD2] states that the unknown bias budget for the Rayleigh channel is 1.7 MHz, which corresponds to 0.5 m/s HLOS wind. This bias budget has been calculated assuming a successful Harmonic Bias Estimator (HBE) correction. The Aeolus HBE correction scheme makes use of ground return speed estimates, which by definition are a zero wind reference (assuming the ground is fixed relative to the rotating earth reference frame). LOS speed retrieved from the ground returns are called ZWC (Zero Wind Correction) values and can be used to correct wind errors which are a constant offset for a given section of the orbit. The ZWCs over many orbits are planned to be processed by the Harmonic Bias Estimation tool to determine biases which vary harmonically with the orbit phase. However it is unclear whether there will be enough good quality ZWC data for this form of calibration to work, because the ground returns: (i) are noisy (particularly for the Rayleigh channel); (ii) can be contaminated with near-surface winds (from drifting snow and/or sand); and (iii) the global sampling will be limited (to land surfaces with large albedo values) — hence there will be residual unknown biases.

Without the application of the HBE correction the unknown bias budget is 1.6 m/s HLOS wind. Note that these budget values are RMS values, because the bias is expected to vary continuously along the orbit, hence the bias could peak at $\sqrt{2}$ times these values i.e. up to 2.25 m/s HLOS assuming a sinuosoidally varying unknown bias.

A further Aeolus product bias correction scheme which is currently being implemented concerns range-dependent wind errors. Due to the satellite (circular) orbital motion, the telescope angle of incidence of the backscattered light from different ranges along the instrument line-of-sight (LOS) vary, causing different interferometer instrument responses for an equivalent LOS motion. These range-dependent biases need to be characterized and removed by the so-called Range Dependent Bias (RDB) correction scheme. Special measurement campaigns will have to be defined and implemented to allow for an accurate correction of this effect.

A further systematic error source for the ALADIN lidar detection system is imperfect detector response calibrations. The detector response as a function of frequency (the so-called response slope) needs to be accurately known for the Aeolus Doppler wind calculations. The response slope accuracy is estimated by industry to ~0.5%, i.e. a 100 m/s wind may have a 0.5 m/s systematic error due to slope error.

In comparison to the magnitude of the NWP forecast errors being corrected in the ECMWF analysis through data assimilation (1-4 m/s standard deviation of short-range forecast error for HLOS wind), these biases may be unacceptably large if uncorrected.

The DLR A2D Noise Study, [RD8], found noise levels in excess of Poisson noise due to variations in laser frequency, laser energy and RSP temperature. Although it has been shown that these errors are smaller for the ALADIN space-based operations and design (quiet operation environment without pressure modulations, fully monostatic system, better RSP thermal control etc.), it needs to be confirmed how large such error sources are for ALADIN. Furthermore, although some of the errors may not affect the Aeolus satellite wind mode due to the normalization of the atmospheric signal with the internal reference, they may still affect the response calibration and hence could lead to larger systematic errors than predicted by the ADS report; this emphasises the need to monitor Aeolus biases.

An ECMWF impact study, see [RD1], using real conventional wind observations demonstrated that bias in the range of 1-2 m/s for HLOS wind observations (for which the assigned standard deviation of error, random component of error, is ~2 m/s) significantly reduces the impact of the observations (see [RD1]). With 2 m/s constant bias (which was the worst case, compared to e.g. slope error percentage) this produced an overall negative impact, meaning the observations would not be used in operational data assimilation. A potential solution is for the observations to be bias corrected prior to or in the data assimilation system (such bias correction techniques will be briefly discussed later). To do so we need to estimate the bias, hence the need for advanced monitoring methods.

Given that systematic errors may compromise the usefulness of Aeolus observations, it is sensible to make preparations to mitigate them. A first step in such a procedure is to detect the observation systematic errors. This can be done by monitoring the observations against an independent reference that is known to be less biased than the observations or biased in different ways i.e. bias depends on different variables.

Ideally systematic observation errors are removed by applying instrument calibrations in the observation processing stage (L1B, L2B processing). However if a bias source was unknown at the instrument design stage and hence calibration procedures are absent, then such corrections may not be possible; this is particularly true for a new mission concept like Aeolus DWL. It is also true if the bias source is known but cannot be fully characterized and corrected though the envisioned calibration procedures. In this situation, the only option is to calibrate the observations using an independent reference dataset as a proxy for the truth. **Such a reference could be either other available observations of the same geophysical variable (i.e. wind) that are sufficiently close in space and time, and/or NWP model analyses or forecasts. We will explain later why the NWP model winds can be used as geophysical reference.**

It is also informative to monitor the behaviour of the Aeolus observation random errors. For example: do the Aeolus random errors agree with the L2B processor generated standard error estimates (propagated from signal levels), do the observation error standard deviations vary significantly with orbit argument of latitude due to varying solar background noise ionospheric emissions, or noise at detector level due to variable cosmic radiation levels (e.g. in the South Atlantic Anomaly)? The standard deviation of departures (relative to NWP) will perhaps highlight areas with non-zero vertical winds or strong turbulence. Also, the instrument transmission will degrade during mission lifetime due to aging of the various optical elements and the detectors. These degradations are normally expected to be slow, but could be accelerated in case of coating damage, radiation damage or contamination of the telescope etc.

It might be possible to assess, via monitoring against the NWP model, what the correlations in Aeolus random errors are (an effect which must be considered in DA for good impact). It should also be possible to show if Aeolus observation errors are performing better or worse than the MRD [AD4].

By monitoring against an independent reference we expect to:

- Perform a post-launch characterisation of the Aeolus wind observations, in particular determining the presence of any Aeolus observation systematic error and the level of random error
- Analyse and detect the source of the bias i.e. upon which variables does it depend. Ideally providing evidence of its physical origin.

- Report calibration, operation and data quality issues to the Aeolus Mission management
- Inform the decision regarding the operational data assimilation at ECMWF of the observations
- Provide guidance for the specification and design of any future DWL satellite instruments

2.2 Data assimilation and systematic observation errors

The NWP data assimilation analysis systems used by many NWP centres have difficulties handling biased observations as the fundamental DA methods assume unbiased observations (e.g. the variational method). Therefore a lot of work is done at NWP centres to remove bias prior to use in data assimilation. Ideally biases should be removed in the observation processing. However not all observation biases are detectable, which limit their positive impact in data assimilation.

Standard data assimilation theory shows that observation bias becomes increasingly problematic for observations with relatively small error variance in combination with larger background forecast error variance i.e. in such conditions the biased observation is given large weight in the analysis and hence the observation bias is propagated into the analysis. The derivation in Appendix 9.2 shows this.

How the resultant mean analysis error then degrades the NWP forecasts can only be assessed by running cycling DA experiments from the biased analyses. This has been investigated for the ECMWF system in [RD1], which showed that assimilating real HLOS wind observations with bias of 2 m/s in combination with random error of 2 m/s led to a large degradation in forecast skill, compared to not assimilating the HLOS winds. Hence the only way to benefit from such observations in NWP would be to correct the bias and bring the observations closer to the truth (or often in practice closer to the NWP model climatology). If the bias is constant i.e. not varying in space and time, then it should be easy to detect and hence correct, however if it is varying as a complicated function (as it might be the case for Aeolus based on our later assessment of possible sources of bias), then it is not such a trivial exercise.

2.3 Reference datasets for monitoring Aeolus

As Aeolus will be the only Doppler wind lidar in space during its lifetime, there will not be any opportunities to compare to other similar satellite observations i.e. inter-satellite calibration. However there will be airborne validation campaigns during the Aeolus CAL/VAL period with DWL payloads; but the quantity of data for direct comparison with Aeolus will be rather limited, and hence there will be a limited range of atmospheric conditions that are sampled. An advantage of assessing against aircraft DWL data (in particular the A2D campaigns) is that comparisons can be made at lower processing levels (e.g. comparisons of useful signals and calibrations), rather than just comparisons at the retrieved wind level; this may help to find the source of possible errors.

It might be useful to compare Aeolus raw data (e.g. spectrometer counts) with the result of Aeolus simulations using NWP meteorological fields as input. This can be done by using ECMWF meteorological fields (along the Aeolus track) as input to the Aeolus End-to-end Simulator (E2S) tool. However, it is unclear at this stage how accurate E2S's assumptions on the Aeolus instrument characteristics are (e.g. transmissions through spectrometers) and hence how comparable it can be with real Aeolus data. This can be gradually validated and established when on-ground and in-orbit observations by Aeolus becomes available.

Other possible reference datasets include existing wind observations in the global Observing System (GOS). Commercial aircraft winds are densely sampled horizontally at cruise levels (~200 hPa), especially over North America and Europe. These have been verified to be accurate wind observations. However the vertical distribution is limited, and given the sparse temporal and horizontal sampling of Aeolus winds per day, the observation datasets may not be well collocated. Radiosondes and wind profilers are useful references also, due to the accuracy and good vertical sampling, but are rather limited in horizontal sampling for co-locations with Aeolus. AMVs have very good horizontal sampling (but poorer vertically), but are known to have quality issues (e.g. vertical geolocation, and if the tracked features are being advected with the wind) and therefore QC is critical prior to making comparisons with Aeolus.

The ECMWF NWP global model analysis (and short range forecasts, initialised from the analysis state) of the wind field are world leading in terms of accuracy i.e. verification statistics place ECMWF ahead of other NWP centres in terms of errors statistics (the case for many years). The NWP fields are available globally with excellent spatio-temporal coverage. This is a major advantage for their use as a reference wind dataset, compared to using sparsely available independent observations for assessing the quality of Aeolus. Also, several different NWP models can be compared to Aeolus, to try to distinguish if NWP model error is the source of discrepancy rather than Aeolus observation error.

The NWP model analysis combines the true state of the atmosphere, as measured by the global observing system, with the previous short-range forecast of the atmosphere (determined by previous observations and the NWP model) in a statistically optimum way. Therefore (at least according to theory) to NWP analysis state should be the most accurate estimate of the atmosphere available at the resolution of the model.

Therefore NWP model forecasts are suggested as a reference dataset for the Aeolus advanced monitoring.

An investigation into the quality of NWP model winds is given in section 3 for assessing the accuracy of NWP global model winds as a reference dataset.

A potential advantage to using the ECMWF global model as the geophysical reference, is that with an effective horizontal resolution estimated to be around 4-8 times the grid scale (at sea level but lower effective resolution in the free-troposphere, therefore on the order of 100 km in the ECMWF operational T1279 high resolution model in 2015), it should match the nominal averaging length scales of Aeolus Rayleigh winds reasonably well and hence the model may, in this respect, be a more appropriate reference than point-like wind observations from radiosondes and aircraft (i.e. ECMWF model has very small representativeness error for Aeolus compared to radiosonde winds). Figure 1 shows an example of the relative smoothness of the ECMWF model winds compared to point winds is illustrated by the comparison of a high vertical resolution radiosonde profile to the T1279 (~16 km horizontal grid) L137 ECMWF model.

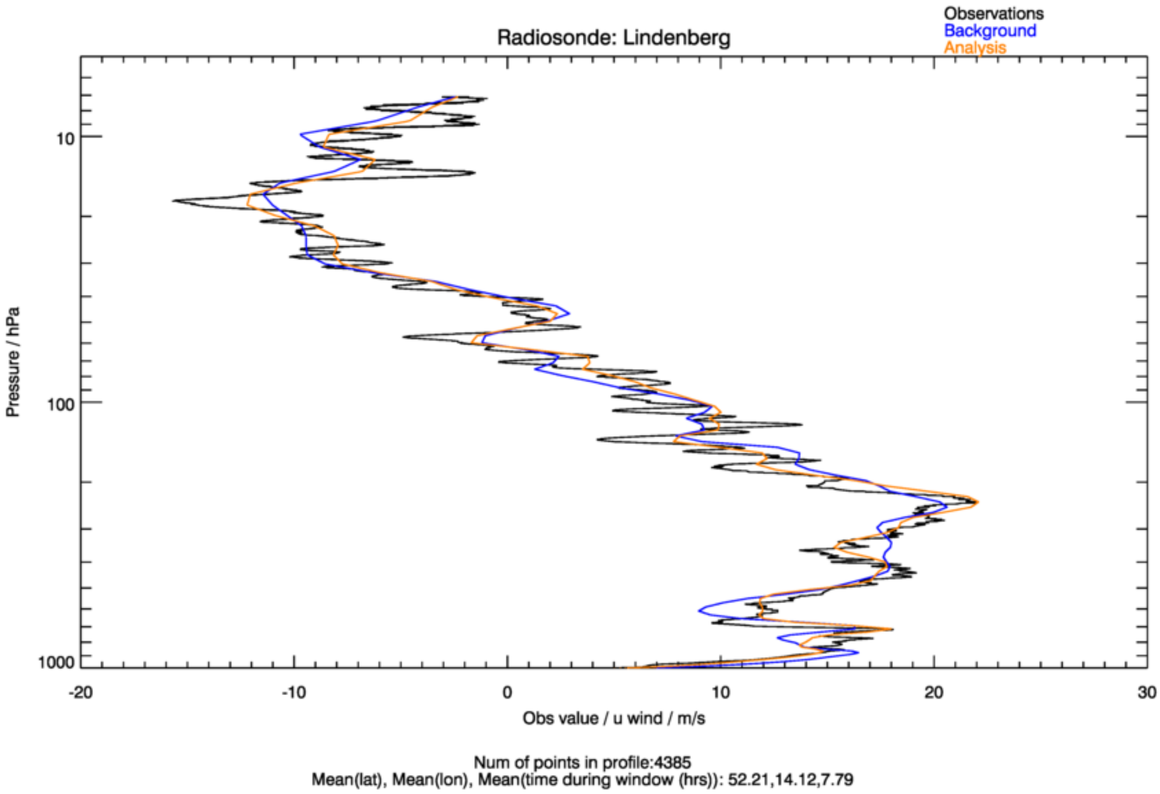


Figure 1. A comparison of a highly vertically sampled, high vertical radiosonde wind profile to the equivalent ECMWF model winds. A zonal-component wind profile from the: radiosonde (black line), the ECMWF background forecast (blue line) and the ECMWF analysis (orange line). Example from April 2015 at Lindenberg, Germany.

Figure 1 shows that radiosonde winds have larger variability at small vertical scales compared to the ECMWF model i.e. ECMWF model is a spatially and temporally averaged estimate of reality. The radiosonde data is transmitted using a BUFR radiosonde format which provides many vertical levels: 4385 points in this case. Such variability is typical for high-res radiosondes and the fluctuations are realistic i.e. not instrument noise, because this radiosonde (Vaisala RS) derives the wind from the instantaneous Doppler shift of on-board measured GPS signals with wind random error < 0.15 m/s (1σ). Also, there is an algorithm to remove the pendulum motion of the sensor below the balloon.

A particularly turbulent case of GADS aircraft wind observations (same observation method as AMDAR, but sampled every 4 seconds) was found on 17th January 2011. A comparison of this data to the ECMWF model equivalent is shown in Figure 2 (for measurements in the north Atlantic region). This is for wind observations at cruise level (around 250 hPa) on long-haul flights. It is clear that the ECMWF model zonal wind is often smooth in the horizontal dimension also compared to point measurements.

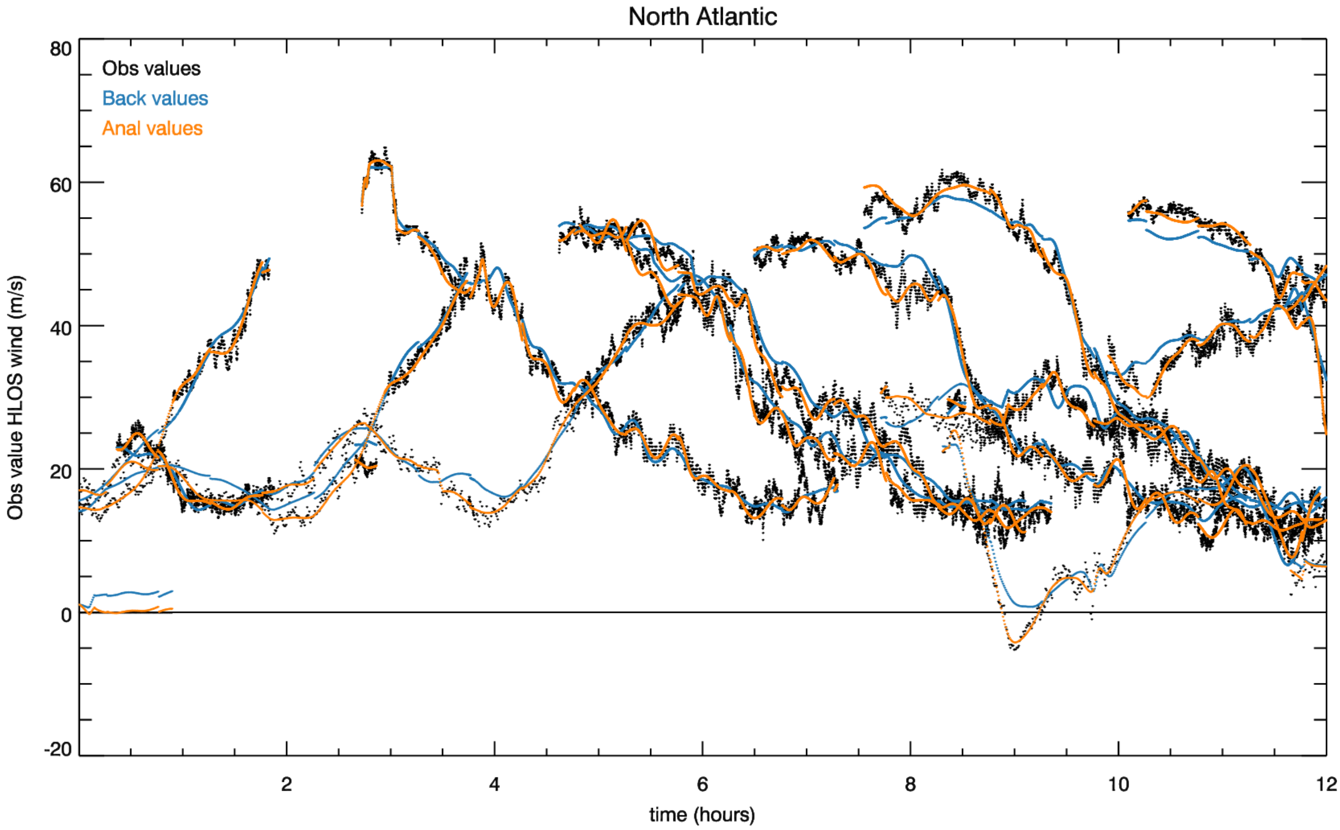


Figure 2. GADS aircraft zonal-component wind observations (black points) with (for comparison) the ECMWF model (T511) background (blue points) and analysis (orange points, when the GADS has been assimilated). Behaviour during a 12 hour DA window for data in the North Atlantic region on 17/01/2011 00 UTC LWDA cycle. Assuming a cruise speed of 260 m/s, then on hour corresponds to roughly 930 km horizontal distance.

2.4 Using NWP forecasts as a reference dataset

2.4.1 Monitoring observation departures

The key method at ECMWF for investigating the error properties of observations, and hence the main focus of advanced monitoring, is to compare them to the short-range NWP model forecast equivalent. That is, is to produce **O-B (observation minus background) statistics**. This technique is standard practice at NWP centres, and is done for all observation types which are assimilated or being considered for assimilation. An O-B value (also known as an innovation or observation departure) is calculated as:

$$\mathrm{dy} = \mathrm{y} - H(\mathbf{x}_{\mathrm{b}})$$

Where y = observed value (scalar value)

$\mathbf{x}_b$ = vector of model generated meteorological state estimate (known as the background)

$H(.)$ = the observation operator or forward model. This converts a model state vector to an observation space scalar; e.g. this could be simply an interpolation of discretised model fields to the observation location, in 4D-Var this involves the integration of the model (in time, to the observation time). For complex observations the geophysical model variables have to be transformed to the observation space e.g. from temperature, pressure and humidity to GPS Radio Occultation (GPSRO) bending angles or to satellite radiance observations. For Aeolus, this is a HLOS wind operator, which is a simple linear equation (a function of the laser azimuth angle and the model horizontal wind components)

Observation departures are the most important input to the data assimilation process to produce an analysis ($\mathbf{x}_a$). In the BLUE (Best Linear Unbiased Estimator) analysis equation, the analysis increment (for a given cycle) is:

$$\mathbf{dx} = \mathrm{x_a} - \mathrm{x_b} = \mathbf{Kdy}$$

Where **K** is the Kalman gain matrix:

$$\mathbf{K} = \mathbf{BH^T}(\mathbf{HBH^T} + \mathbf{R})^{-1}$$

B (**R**) is the background (observation) error covariance matrix and $\mathbf{H} = \frac{\partial H(\boldsymbol{x})}{\partial \boldsymbol{x}}$ is the linearized observation operator:

Statistics of O-B values provides information on the quality of the observation and model. Assuming that the observation and background errors are uncorrelated then the expectation value of a sample of O-B departures is (assuming linearity in *H*(.) operator):

$$\langle \mathbf{dy} \rangle = \langle \mathbf{y} - H(\mathrm{x_b}) \rangle = \langle \boldsymbol{y} - \boldsymbol{y_t} - \mathbf{H}\boldsymbol{x_b} + \boldsymbol{y_t} \rangle = \langle \boldsymbol{y} - \boldsymbol{y_t} - \mathbf{H}\boldsymbol{x_b} + \mathbf{H}\boldsymbol{x_t}) \rangle$$
$$= \langle \boldsymbol{y} - \boldsymbol{y_t} \rangle - \langle \mathbf{H}(\boldsymbol{x_b} - \boldsymbol{x_t}) \rangle = \langle \boldsymbol{\varepsilon_o} \rangle - \langle \mathbf{H}\boldsymbol{\varepsilon_b} \rangle$$

Where subscript t = true value, ε_o = y-y_t is observation error and $\boldsymbol{\varepsilon_b}$ = x_b-x_t is background error. The expectation of O-B (a scalar) is the difference between bias (mean error) in the observation and bias (mean error) in the forward modelled observation (assuming the forward model is perfect). Hence, if we have an estimate of the mean model error (e.g. assume it is negligible) then we can estimate the mean observation error.

The covariance of a set of O-B departures is (again assuming observation and background errors are uncorrelated):

$$covar(\mathbf{dy}) = covar\big(\mathbf{y} - \boldsymbol{y_t} - \mathbf{H}(\boldsymbol{x_b} - \boldsymbol{x_t})\big) = covar(\mathbf{y} - \boldsymbol{y_t}) + covar(\mathbf{H}(\boldsymbol{x_b} - \boldsymbol{x_t}))$$
$$= \mathbf{R} + \mathbf{HBH^T}$$

If we have an estimate of the background error covariance then we can estimate the observation error covariance. There are caveats regarding which sample of O-B to use when trying to estimate the error properties of the observation and background components that will be discussed later.

Advanced monitoring of Aeolus O-B statistics will be useful to:

- Detect degradations in the quality of the observations or the NWP model
- Detect, and help to understand observation systematic errors which can have complex structure in time and space:
  - Help determine whether the source of an observation bias is instrumental or geophysical (i.e. related to meteorological state). If an instrumental source of the bias is found, then hopefully it can be corrected without using NWP information, but instead using instrumental calibration information. If NWP model information is needed for calibration, then various methods exist (see section 5.1.3)
- Help to determine an estimate of the observation error variance (or verify if the L2Bp values are appropriate) for optimal data assimilation. These can be compared to the L2Bp generated observation error variance estimates.

A technique to help partition the sources of non-zero mean (O-B) statistics is to compare the statistics of different NWP centres for the same observations; differences are then attributable to the differences in the mean model states. This method is commonly used by EUMETSAT SAF monitoring. An example of the monitoring is provided in Figure 3 below from the ROM SAF website (http://www.romsaf.org/monitoring/index.php). There are notable mean differences between ECMWF and the Met Office background forecast forward modelled GPSRO bending angles at higher than 30 km altitude, which is due to forecast model or forward model (observation operator) differences.

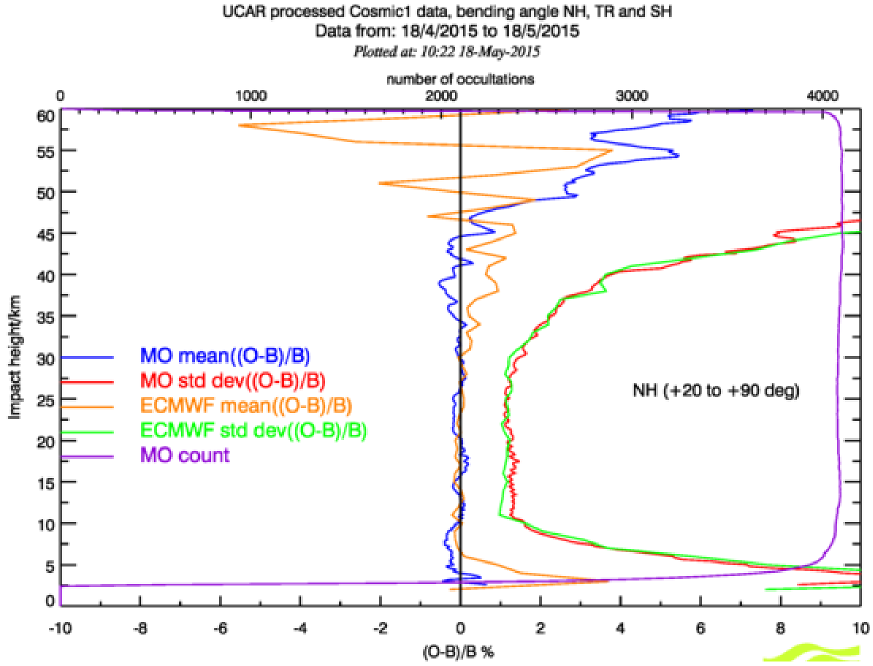


Figure 3. Comparison of normalized (O-B) statistics from the Met Office and ECMWF for GPS radio occultation observations (COSMIC 1) in the northern hemisphere. Courtesy of ROM SAF: http://www.romsaf.org/monitoring/

In practice, observation and background error statistics vary with space and time. A sample of many independent draws of the random variable O-B from identical conditions i.e. as if a fixed laboratory, is generally not possible for meteorological observations. Therefore in practice if we want to assess the observation and background error statistics we make the assumption that a set of O-B values from non-identical conditions are actually independent draws of the same random variable. Statistics based on such a sample will give some form of average estimate of the combined observation and background error statistics. This is mitigated to some extent by binning the O-B statistics into similar conditions e.g. restricted to observations over Europe, between 200 and 300 hPa, etc. we get closer to the ideal situation of having repeat measurements of the same random variable, and hence can learn more useful information about the error statistics.

For Aeolus (O-B) datasets it will be necessary to partition into L2B winds types: e.g. Mie-cloudy, Rayleigh-clear observations, because of the rather different error characteristics i.e. they are effectively different observation types. O-B can be further binned into different meteorological conditions, by e.g. partitioning into geographical areas/times/altitude ranges. Binning according to various parameters for which we hypothesise observation (or background) errors may depend upon will also be useful.

However such binning leads to smaller samples, and hence increased sampling errors if interested in determining confident estimates of bias. A sufficiently large sample of O-B values will be needed to accurately detect a bias given the observation and background error variance. This is investigated in the Appendix 9.3, the conclusion of which is that **a confident estimate of mean(O-B) should be possible with a sample of ~1000 values if the bias is truly constant and observation errors are uncorrelated.**

The Aeolus wind observation random error distribution varies with the scene being measured, since there is a strong dependence upon the number of backscattered photons used for the derivation of wind. This is more variable for Mie winds than for Rayleigh, since the levels of backscatter (and hence photon counts) from clouds/aerosol is more variable than that from the exponentially decreasing atmospheric density with altitude (however, density profiles do vary around the globe of course). Perhaps Aeolus is an unusual observation in regard to the variability of observation error statistics e.g. this is not the case for Vaisala radiosonde winds where the errors depend on GPS Doppler signals which are very stable.

To allow many different Aeolus O-B values to be accumulated and to test the Gaussianity of the error statistics (another assumption often employed in DA) it may be useful to normalise the O-B values by their expected standard error i.e.

$$\frac{\mathbf{dy}}{\mathrm{E}(\mathbf{dy})} = \frac{\mathbf{y} - H(\mathbf{x}_\mathrm{b})}{\sqrt{\mathbf{R} + \mathbf{HBH^T}}}$$

The estimated instrumental observation error variance is provided with each Aeolus L2B wind result (a propagation of error from Poisson noise on photon counts to the wind result). The estimated background error variance (forward modelled to HLOS wind) is available from the ECMWF Ensemble of Data Assimilations (EDA) spread mapped into observation space.

An important practical point is that O-B statistics can be monitored at ECMWF without operationally assimilating the data i.e. the departures are calculated but the observations have no influence on the analysis, which will be necessary in the early phase of the Aeolus mission.

2.4.2 Analysis departures

The observations can also be compared to the analysis state (O-A statistics). A small improvement in the fit to accurate observations is expected for the analysis state compared to the background state, assuming the said observations are not being assimilated. If the observations are assimilated then the analysis will be a substantially closer fit than the background (depending on the weight given to the observations).

2.4.3 A practical example of detecting instrument problems using observation departures

An example of the use of NWP model fields to determine a source of instrument error is that of [RD6]. Lu et al. found evidence that the channel centre frequencies in Microwave sounding instruments can differ from the assumed value (measured on ground). Based on their physical intuition for this being the cause of large deviations between observation and background brightness temperatures, they determined frequency shift values for each channel such that the O-B variance is minimised relative to the NWP forward modelled brightness temperatures. The procedure found similar frequency shifts using many NWP models, adding credence to the fact that is not simply interpreting NWP model bias as a bias in the channel centre frequency.

An error in the assumed frequency leads to an error in the radiative transfer model (observation operator) which means the vertical weighting functions (i.e. the vertical sensitivity of the observation to temperature through a column of the model) are misplaced vertically which in turn leads to O-B differences which vary strongly with the mass field of the atmosphere (in particular the temperature lapse rate). By using a more correct frequency much of the complex geographical structure to the O-B mean differences was eliminated.

This error was due to a lack of the knowledge of what the instrument is measuring (characterisation). One could imagine a similar type of error occurring for Aeolus if, for example, there is a consistent but unknown error in the roll pointing direction of the lidar (in effect a geolocation error). This could lead to an atmospheric wind-state dependent error. If such an error was suspected, then a pointing correction in the L2B HLOS wind observation operator could be applied (i.e. a delta in the azimuth angle) and the minimum variance of O-B determined, in a similar manner to [RD6].

Unfortunately, errors of different physical origins may be manifested in similar O-B patterns or in very complex patterns making it difficult to hypothesise the reason for the error; therefore some careful detective work is necessary for such problems.

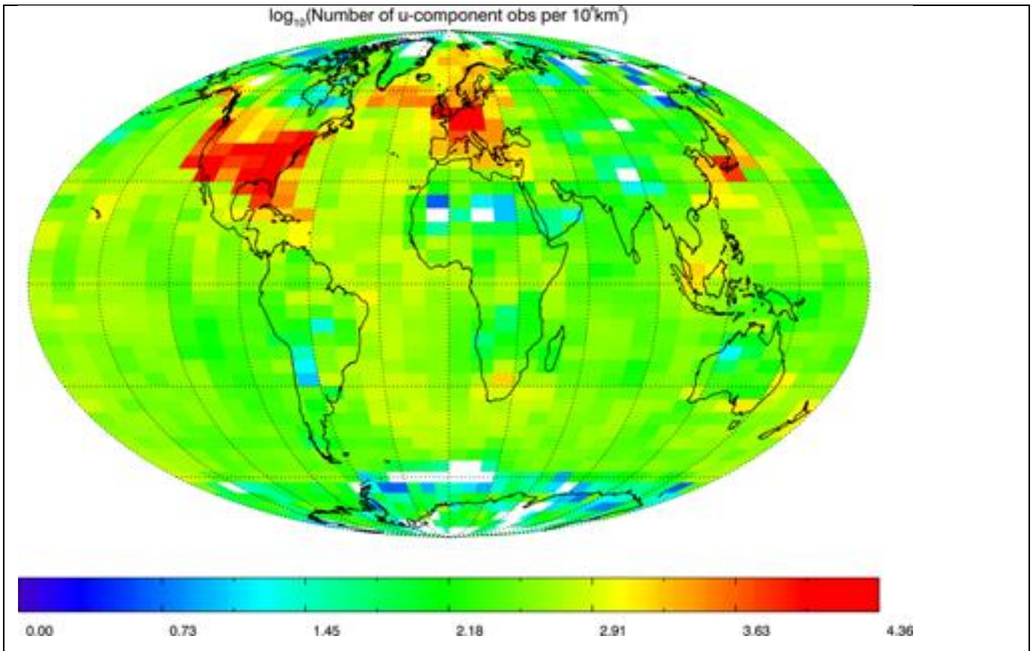
3 An assessment of the ECMWF model wind accuracy

To justify our suggested use of the ECMWF NWP model as a reference dataset for Aeolus monitoring, we will provide an assessment of its accuracy. The model assimilates information from a large variety of observations from the global observing system. In theory at least, the NWP analysis is the most accurate estimate of the atmosphere available i.e. it should be more accurate than any particular assimilated observing system in the given cycle, because information from past observations is also propagated forward via the background forecast.

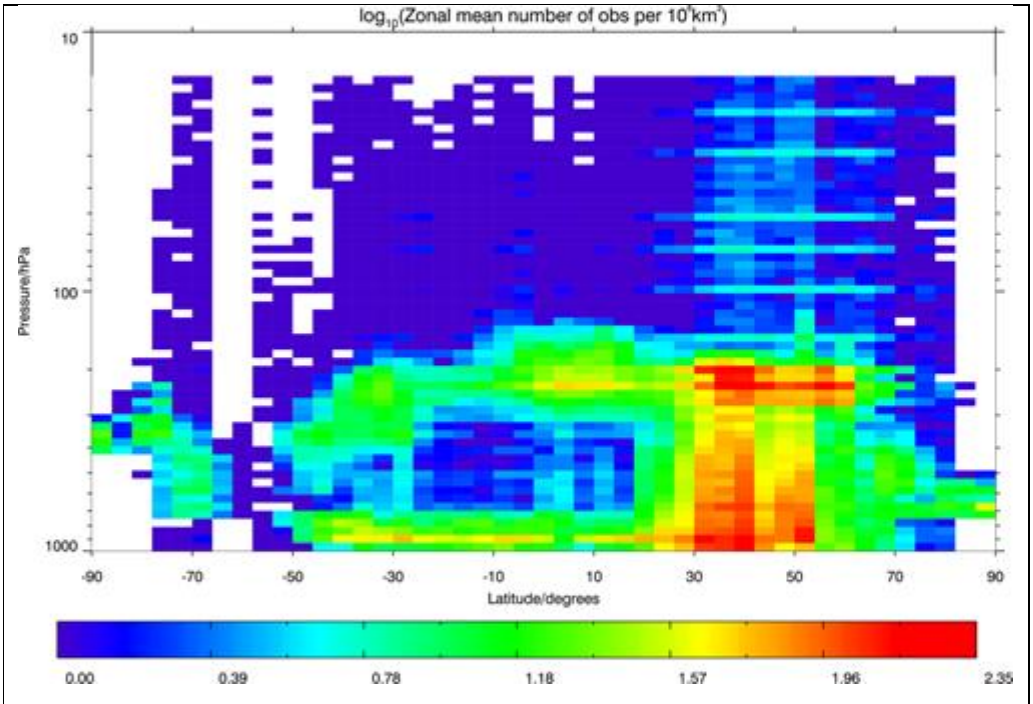
The atmosphere mass field (e.g. temperature, pressure information) is much more densely sampled by observations than the wind field at the time of writing. The background forecast mass field has been demonstrated to be sufficiently accurate to assess new passive sounding missions that are sensitive to temperature [RD7]. It is unclear if NWP model winds are accurate enough (outside of the limited well observed areas for wind) to be used as a reference for doing similar investigations with Aeolus; this Section will try to address this issue.

The spatial sampling of the assimilated wind observations (of a typical 12 hour assimilation window in 2014) at ECMWF is shown in Figure 4. In comparison, the sampling of mass observations is more consistent and larger in number, thanks to the many passive sounding satellites (not shown).

For wind observations, the aircraft, radiosonde and wind profiler data are well sampled in the horizontal domain over the USA, Europe and around Japan, but relatively sparsely elsewhere, i.e. there is a very inhomogeneous horizontal coverage of assimilated wind observations. Note the figure has a logarithmic scale, so the in homogeneities are rather large. In the vertical dimension aircraft do not fly higher than around 200 hPa; AMVs provide good coverage in the tropical lower and upper troposphere, but radiosondes are the only wind observation to sample the stratosphere. This suggests that Aeolus Rayleigh winds will be very useful in the stratosphere. Some zones in the southern hemisphere do not have any wind observations assimilated above 300 hPa. The increased sampling at particular stratospheric levels in the northern hemisphere are from radiosondes reported at standard pressure levels.



a)



b)

Figure 4. Spatial sampling of u-component wind observations assimilated per 12 hour DA window at ECMWF a) horizontally, b) vertically (zonal average vs. pressure). Number of observation per 10^6 km^2 area are shown, with a $\log_{10}$ scale (because of large range).

A key aim of the Aeolus mission is to bolster the global observing system with the goal to significantly improve NWP analysis in parts of the world which are currently lacking wind observations. Wind observations are critical for analysing the ageostrophic wind (i.e. the part of the wind field not in balance with the mass field; typically important for dynamical features at smaller horizontal scales, deeper vertical scales and closer to the equator where the Coriolis Effect diminishes). It has been demonstrated that mass observations constrain the wind field in the tropics to only a very small degree e.g. Žagar 2004 [RD10]. However the geostrophic balance of wind with the mass field strongly influences the large scale wind in the extratropics, hence through the multivariate nature of 4D-Var, the mass field (and to some extent the humidity field) determines the winds — therefore these are the areas where the NWP model winds are most accurate and hence the best reference for investigating Aeolus wind observation problems (e.g. systematic errors).

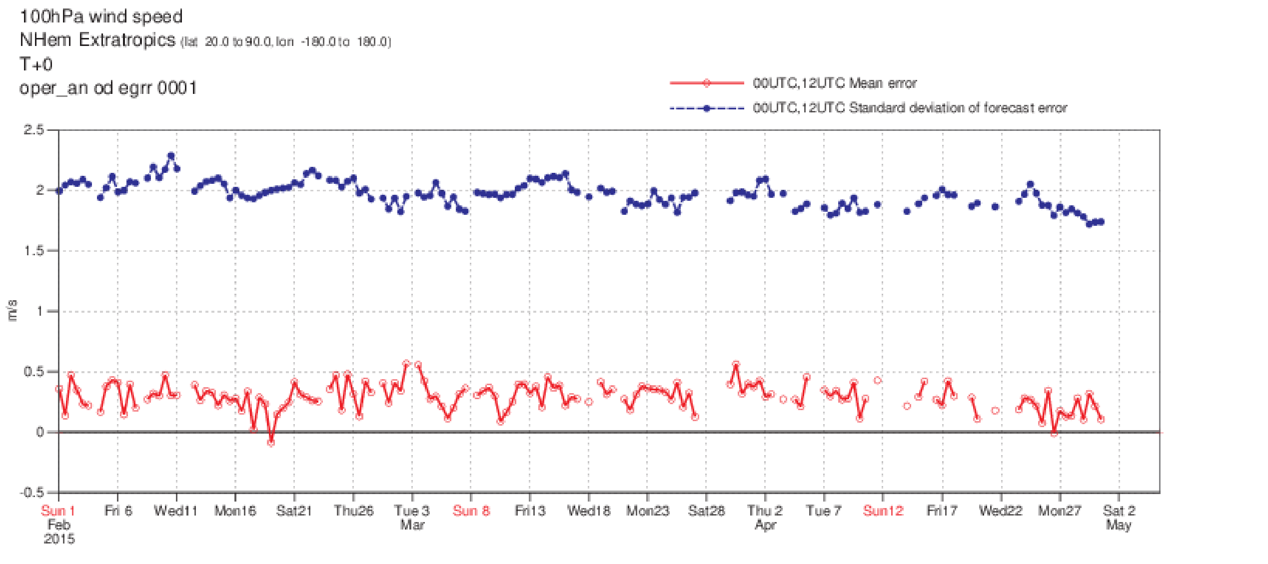
In areas where wind observations are lacking, in combination with certain meteorological conditions (e.g. tropical convection) the ECMWF short-range forecast winds may suffer from biases. For example, Podglajen et. al 2014 [RD9] found ~8 m/s u-component wind biases at 16-18 km altitude for large periods of time versus stratospheric balloon winds (not assimilated) in 2010. The study found several events of large-scale equatorial wave packets that were poorly represented or absent in the ECMWF operational analysis. Therefore care should be taken in using the tropical lower stratosphere as a wind NWP reference dataset. However this is an area where good quality Aeolus observations are expected to be very useful to help initialise the tropical waves.

Equatorial waves can be absent from the ECMWF analysis in the upper troposphere/lower stratosphere, meaning that large and persistent differences between observations and model can exist in this region.

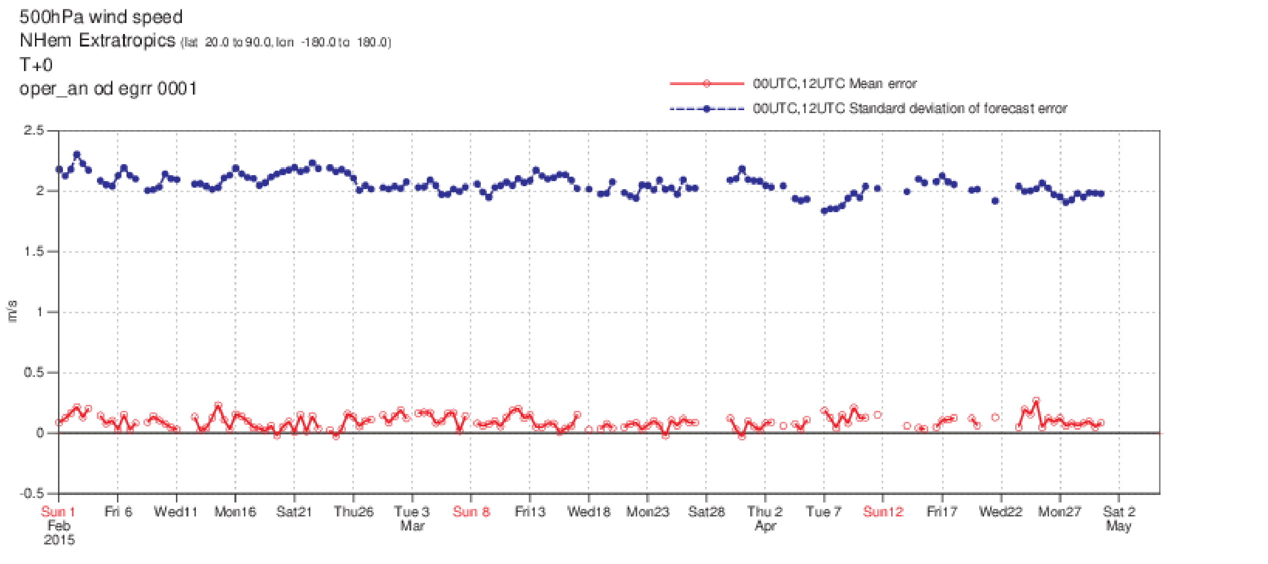
3.1 A comparison of ECMWF and Met Office model wind analyses

An indication of the accuracy of the NWP winds can be obtained by comparing the analyses of two state of the art models; ECMWF and the Met Office. Differences between the analyses can arise from errors in either system. Note that by and large the same observations are assimilated in both models, so we should expect increased similarity between analyses where such observations are densely sampled in space and time. More information (e.g. independent accurate observations) are required to determine which model is more accurate.

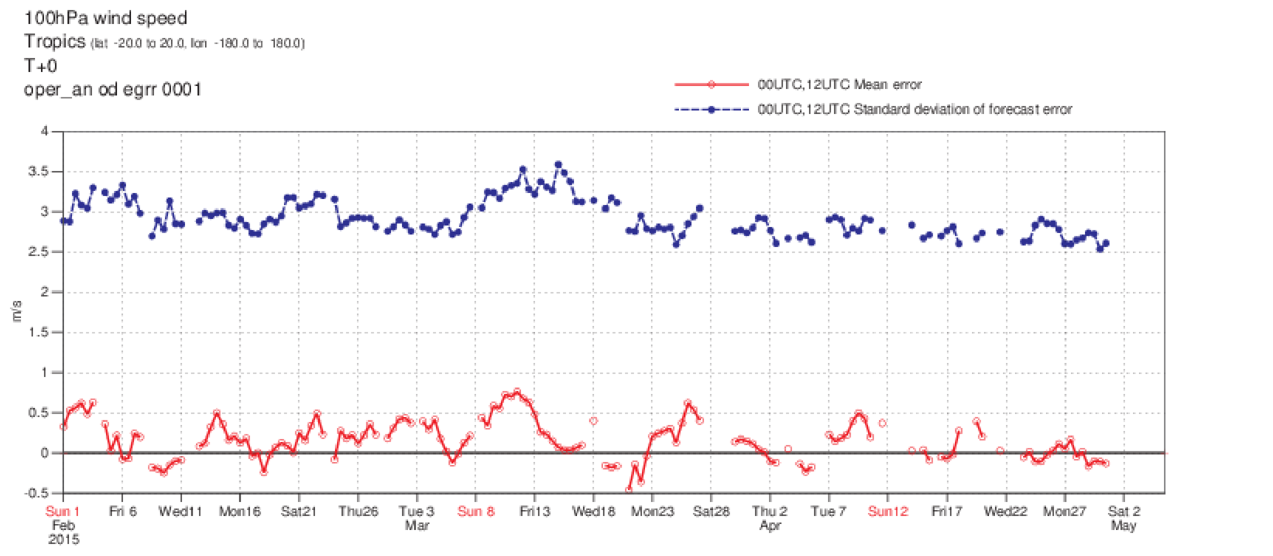
Figure 5 shows time-series from February to May 2015 of statistics of the difference between the Met Office and ECMWF wind speed analyses at three selected pressure levels.



a)



b)



c)

Figure 5. Time series of Red=spatial mean of the difference UKMO-ECMWF for each cycle, Blue=STD of the difference. a) 100 hPa wind speed in NH, b) 500 hPa wind speed in NH c) 100 hPa wind speed in the Tropics.

Due to the averaging over large areas (northern hemisphere, tropics and southern hemisphere) and therefore over a large range of meteorological conditions, the mean differences are fairly small, typically 0.1 to 0.5 m/s (i.e. on average the Met Office have slightly stronger winds than ECMWF). Random differences (standard deviation) are around 2 m/s in the NH and 3 m/s in the tropics; the magnitude of differences varies a bit with time. In terms of global statistics the ECMWF and Met Office analyses agree fairly well, as expected. Note if we assume both models are equally accurate (and their errors are uncorrelated, which is perhaps unlikely), then the error statistics of each model would be $1/\sqrt{2} \sim 0.71$ times that shown in Figure 5.

It is interesting to see the magnitude of differences for different geographical areas on a day to day basis. An example of this is given in Figure 6: the difference between the analyses (ECMWF - Met Office) for one analysis on 10/5/2015, 00 UTC, for 100 hPa (~15-17 km). The differences often exceed 2 m/s and are spatially coherent for hundreds of kilometres (in line with what is expected of error correlations length-scales). The tropics has the largest differences at this level. You can see how with spatial averaging the mean errors are small. **This regression to an almost zero mean error over large areas is promising for the use of NWP models to help determine Aeolus wind biases**. The differences are smaller in magnitude at lower altitudes (not shown), probably because of the increased availability of wind observations, which are assimilated by both assimilation systems.

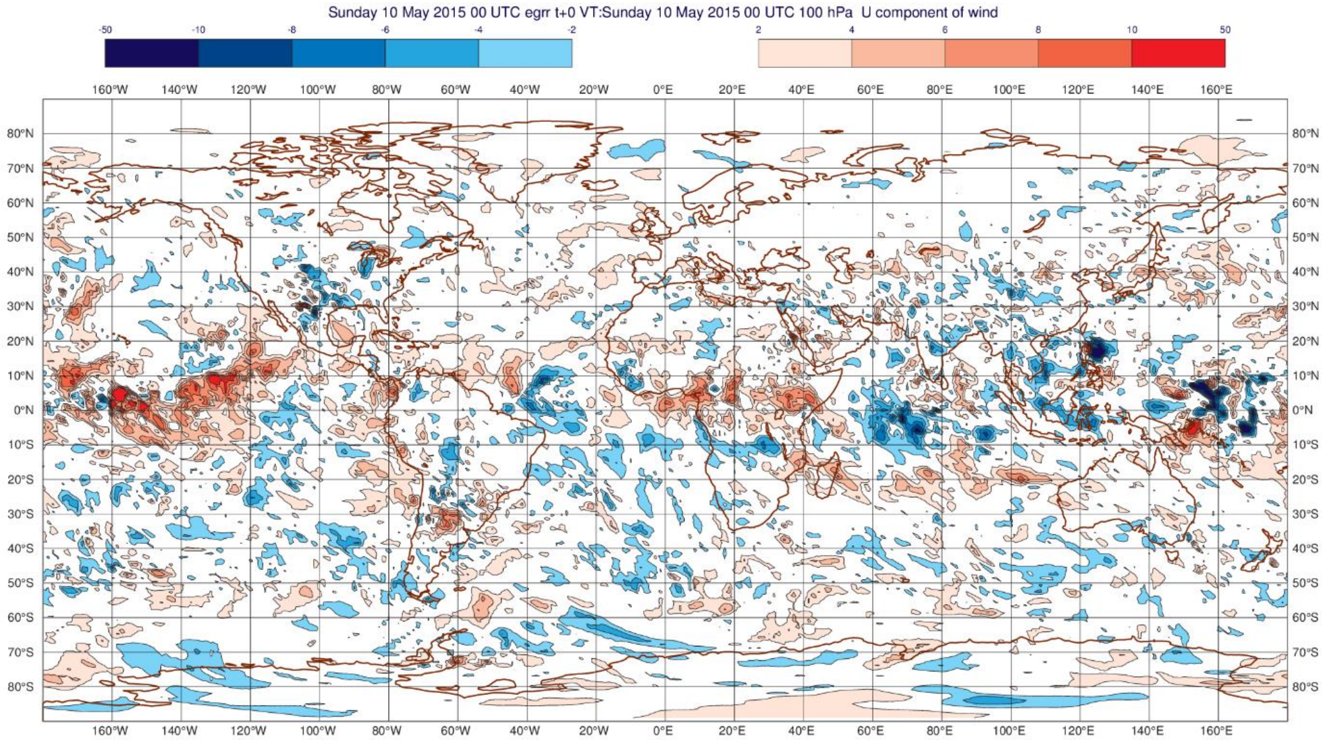


Figure 6. ECMWF minus Met Office analysis for u-component wind at 100 hPa (~15-17 km). For one analysis on 10/05/2015 00 UTC. Only differences greater than 2 m/s are shown by the colour scale.

The tropical differences are actually more systematic than elsewhere, as shown by Figure 7 at 100 hPa, which shows the ECMWF mean analysis minus Met Office mean analysis over a 7 day period (only vector wind differences greater than 2 m/s plotted). The systematic differences are much smaller at other pressure levels and away from the tropics.

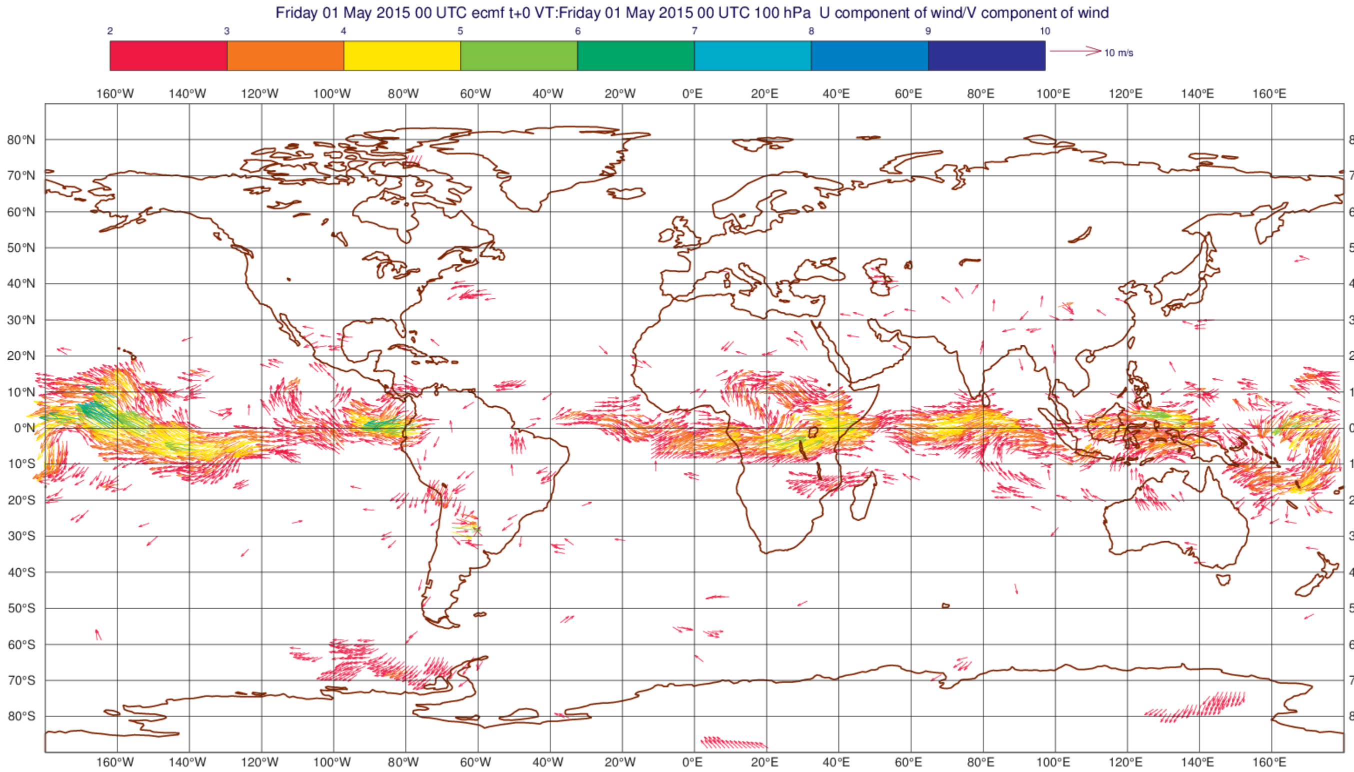


Figure 7. Mean(ECMWF analysis) - mean(Met Office analysis) from 1st to 7th May 2015 for vector wind at 100 hPa. Two analyses per day: 00 and 12 UTC. Only wind vectors > 2 m/s wind speed are plotted to highlight the problem areas.

The tropical wind bias between ECMWF and the Met Office shown in Figure 7 is mostly in the zonal wind component and is negative over most of the Pacific, and positive over Africa/Indian ocean/maritime continent. On closer inspection it was found that Met Office winds tend to be stronger in the tropics i.e. if westerlies (easterlies) are present, then Met Office is more westerly (easterly); which agrees with Figure 5 c). 100 hPa pressure is a level of the upper outflow for tropical convection (the bias feature appears to be associated with the ITCZ). It is not clear which is more truthful without comparing to trusted wind observations like radiosonde and dropsonde wind profiles (of which there is a distinct lack in the tropics at this level away from land, see Figure 4 b). It was noticed when comparing the Met Office to the operational ECMWF output and also to the e-suite output (CY41R1 at the time of investigation), showed a small change in the mean ECMWF tropical winds at 100 hPa, in which apparently is due to a modification in the convection parameterisation for the e-suite (Peter Bechtold, personal communication) Wind errors in this area are the largest in the troposphere and lower stratosphere.

Examination of the few tropical radiosonde's O-B statistics (not shown) for ECMWF indicates O-B biases of the order 1 m/s at around 100 hPa, suggesting ECMWF has systematic wind errors at this level (there is no reason to suspect the radiosondes). The radiosonde O-A (observation minus analysis) statistics are almost unbiased, implying that the analysis can pull towards good observations, when they are available.

ECMWF (and other NWP centres) model winds in the tropical upper troposphere/lower stratosphere are prone to biases, therefore care should be taken if used as a geophysical reference dataset for Aeolus.

Mean temperature differences, on a day to day basis, between ECMWF and the Met Office of 1 K or more are fairly common at many levels (not shown), which is a minor concern for the Level-

2B processor Rayleigh-Brillouin correction which relies on a priori temperature information from an NWP forecast— temperature biases of this magnitude will translate into Rayleigh HLOS wind bias of ~0.16 m/s.

The size of the random differences between ECMWF and the Met Office for zonal wind are shown by the standard deviation of (ECMWF minus Met Office) analyses in Figure 8 at 100 hPa (for a similar time period as Figure 7). The largest random differences coincide with the largest mean errors, with standard deviation reaching ~5 m/s. This adds to the unsuitability of the model data this area as a reference dataset.

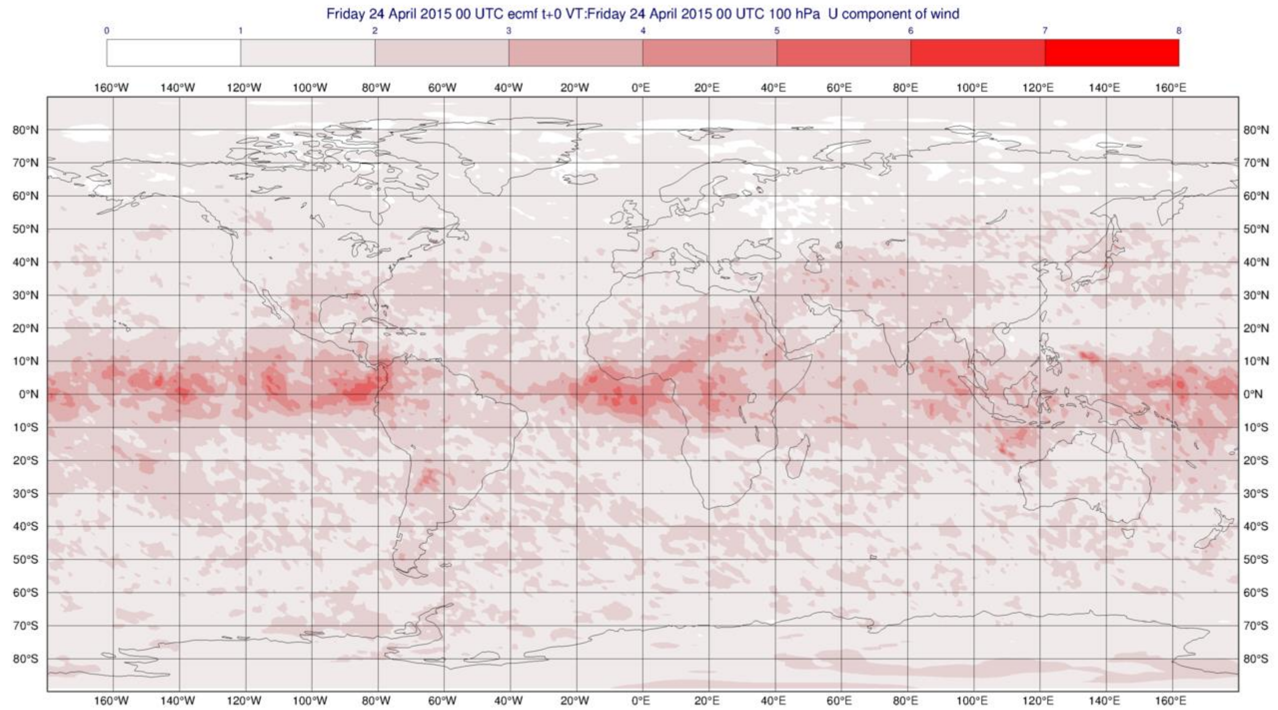


Figure 8. The standard deviation of (ECMWF - Met Office) analyses for the period 24 April to 7 May 2015. Zonal-component wind at 100 hPa; colour scale is in units: m/s.

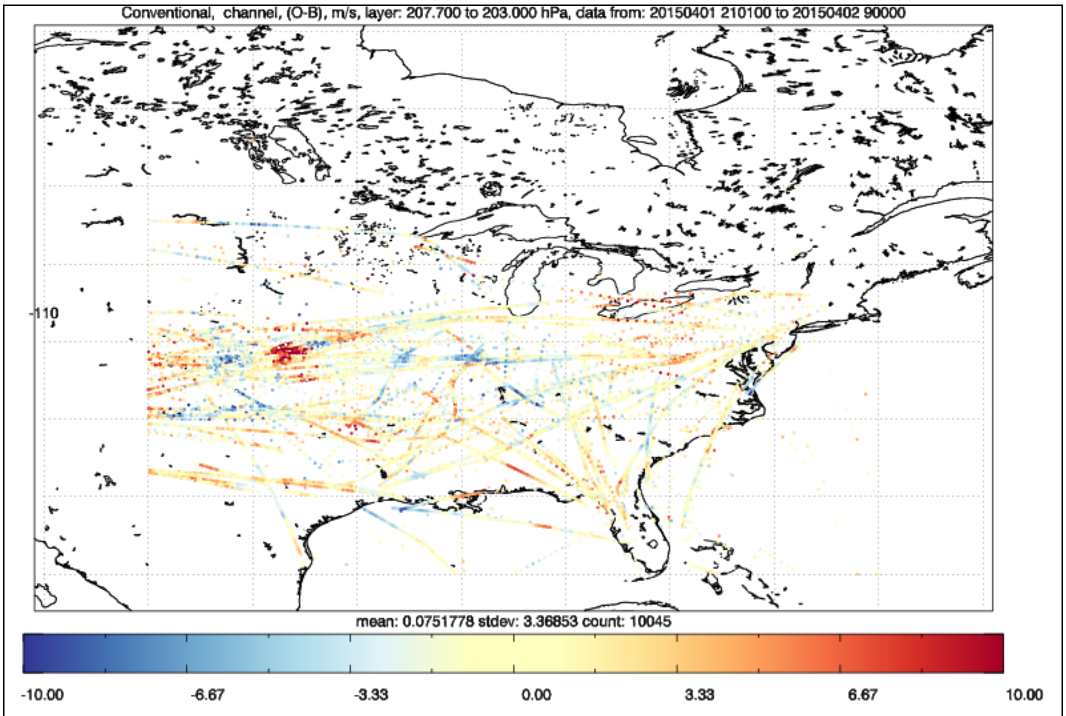
3.2 Model performance in convective outbreaks over North America

Following reports at ECMWF of many aircraft winds being assigned low weight in data assimilation over North America an investigation was performed. It was found that during severe convective outbreaks over North America, which develop into mesoscale convective systems (MCS), often a poor fit between the well sampled 200 hPa aircraft winds and the ECMWF model background/analysis occurs. It appears that it is difficult for the model to represent these features correctly. In some cases the ECMWF analysis winds can be a worse fit to the observations than the background; for example Figure 9 shows such a case (at around 35 °N, 90 °W for a particular DA window). The analysis has larger departures than the background in a dipole pattern (magnitude reaching more than 10 m/s). There is no reason to suspect the aircraft wind observations are at fault here. Similar behaviour has been found on a number of occasions with severe convection.

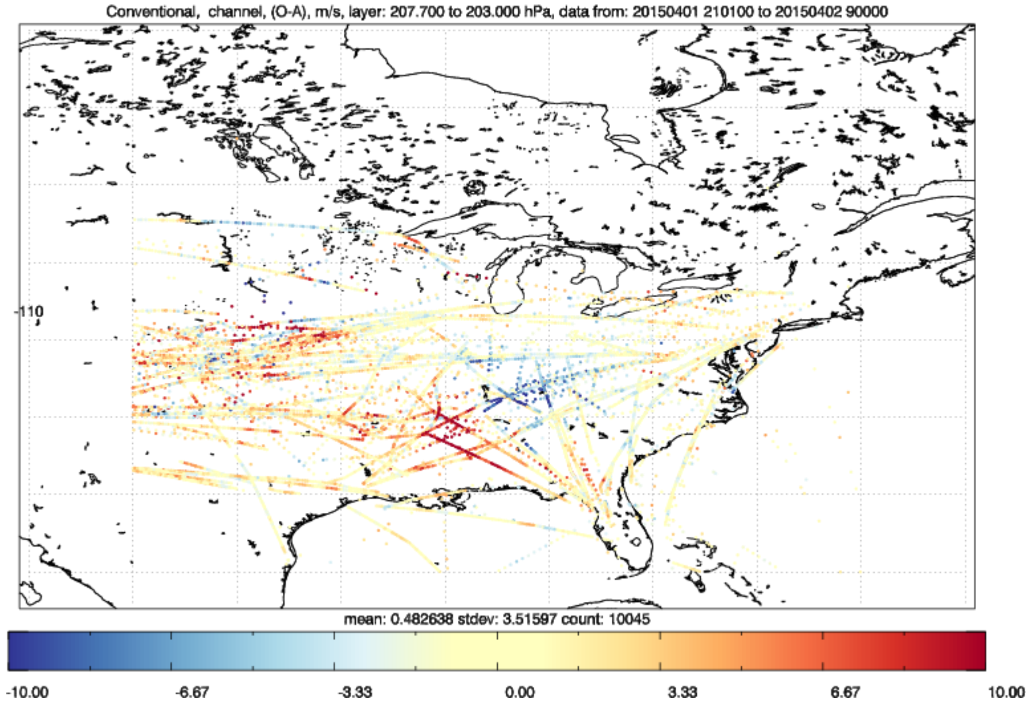
Figure 10 shows a comparison of geostationary satellite IR imagery to the ECMWF model simulated imagery, six hours into the data assimilation window for the same case as Figure 9. It appears that the ECMWF model (CY40R1) is missing convective clouds near where the analysis winds are in error. The model can fail to capture the convective developments which grow from nothing to large systems in a matter of hours. In some cases it appears that the background forecast convection is too weak and tops out too low. The outflow winds of such MSCs can interact with the polar jet stream winds and erroneous corrections to the jet stream winds may occur in the analysis. There is some evidence for this causing forecast busts over Europe 3-5 days later, see [RD15].

However for this case, the CY41R1 e-suite (which became operational in May 2015) had a much better fit of the analysis to the aircraft observation winds (not shown) in the problem area. Figure 11 shows that for the e-suite simulated imagery the clouds are in better agreement with the real imagery around the problem area compared to CY40R1 i.e. the convection is captured better. Peter Bechtold (ECMWF, personal communication) said that all upper level wind scores, especially above 200 hPa were improved in CY41R1 because of an improvement in convective detrainment (temperature and wind effect).

The ECMWF model (and other NWP models) can occasionally be significantly wrong for winds at 200 hPa associated with extreme convection, hence care should be taken when monitoring Aeolus against the ECMWF model in such scenarios, so as to assume Aeolus is the cause of the discrepancy. The high density of cruise level aircraft winds over North America and Europe will be a valuable reference dataset for comparison to Aeolus. Aeolus may not penetrate deeply into the high extinction clouds associated with convection, however we can expect Rayleigh winds above the cloud and Mie winds from the top of the clouds and associated outflow cirrus, which may coincide with the aircraft.



a)



b)

Figure 9. ECMWF operational (o-suite, CY40R1) departures for aircraft u-component wind ~205 hPa for a 12hr LWDA cycle on 20150402 00 UTC. a) O-B b) O-A values.

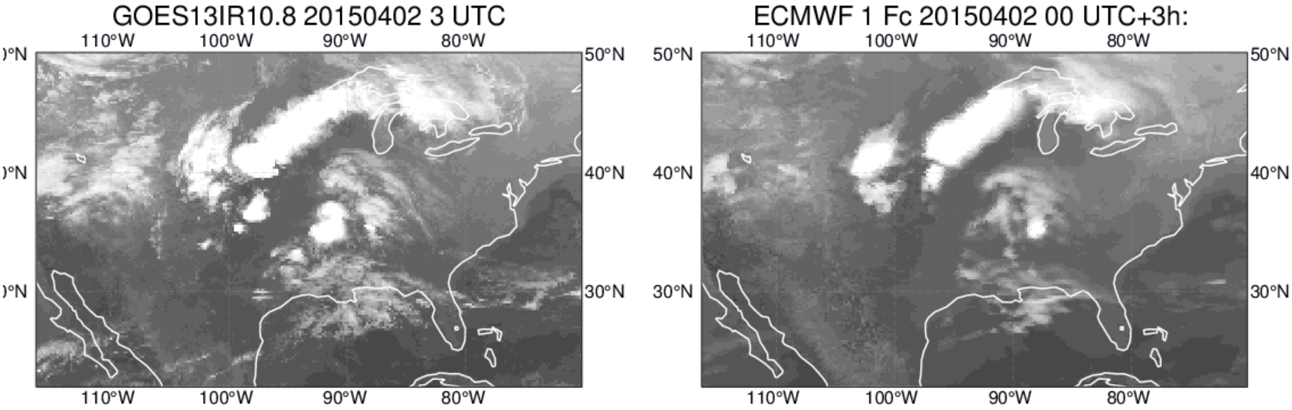


Figure 10. GOES 13 IR imagery (left panel) and equivalent simulated imagery (right panel) from ECMWF model (CY40R2) forecast at 03 UTC on 2015/04/02 (i.e. 6 hours in to the DA window of Figure 9).

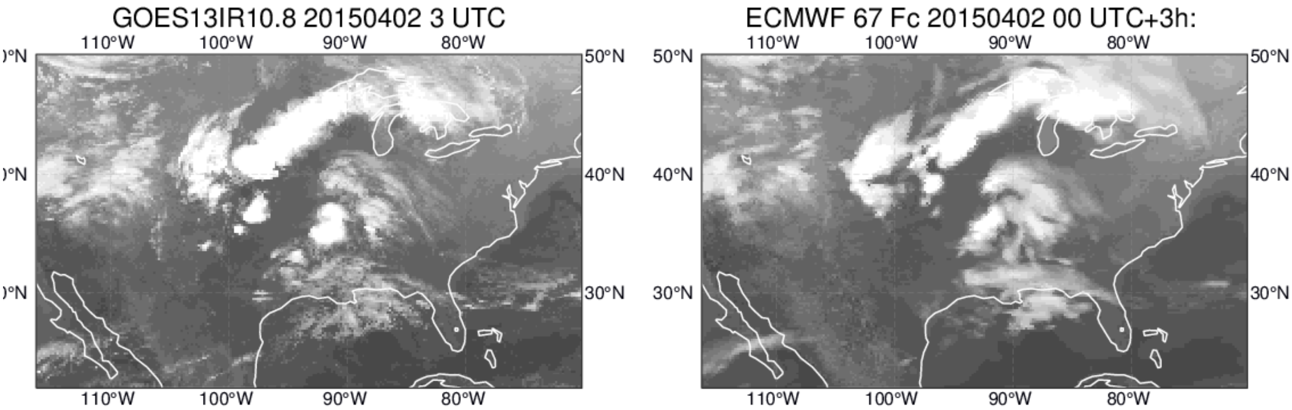


Figure 11. Same as Figure 10, but with simulated imagery from the ECMWF CY41R1 e-suite (right panel).

3.3 Background forecast wind error in comparison to highly sampled aircraft data and conventional wind observations

Figure 12 shows an example of the wind errors that can be encountered in the background forecast occasionally when comparing to highly sampled aircraft wind observations (compare blue to black points). It can be seen that the background forecast can underestimate the maximum winds in the jet stream winds, by as much as 10 m/s. The data presented here covers a 12 hour sample of data over the North-East USA from January 2011. The observations are densely spaced aircraft observations known as Global Aircraft Data Set (GADS), the data comes from flight data recordings of British Airways Boeing 747-400 aircraft that are not used in operational analyses (the data was provided courtesy of Joel Tenenbaum). The analysis shown here (in orange) include the assimilation of the GADS data (as HLOS wind, in the zonal direction). It can be seen that with such densely sampled data the 4D-Var analysis pulls very close to the observations i.e. the jet streams winds in the analysis can be corrected rather well. The filtering properties and lower resolution of the analysis increments results in the analysis producing a smooth fit to the observations over hundreds of km (note that 1 hour corresponds to roughly 930 km horizontally).

Note that similar biases in the ECMWF jet stream winds were found back in 2004 in [RD16].

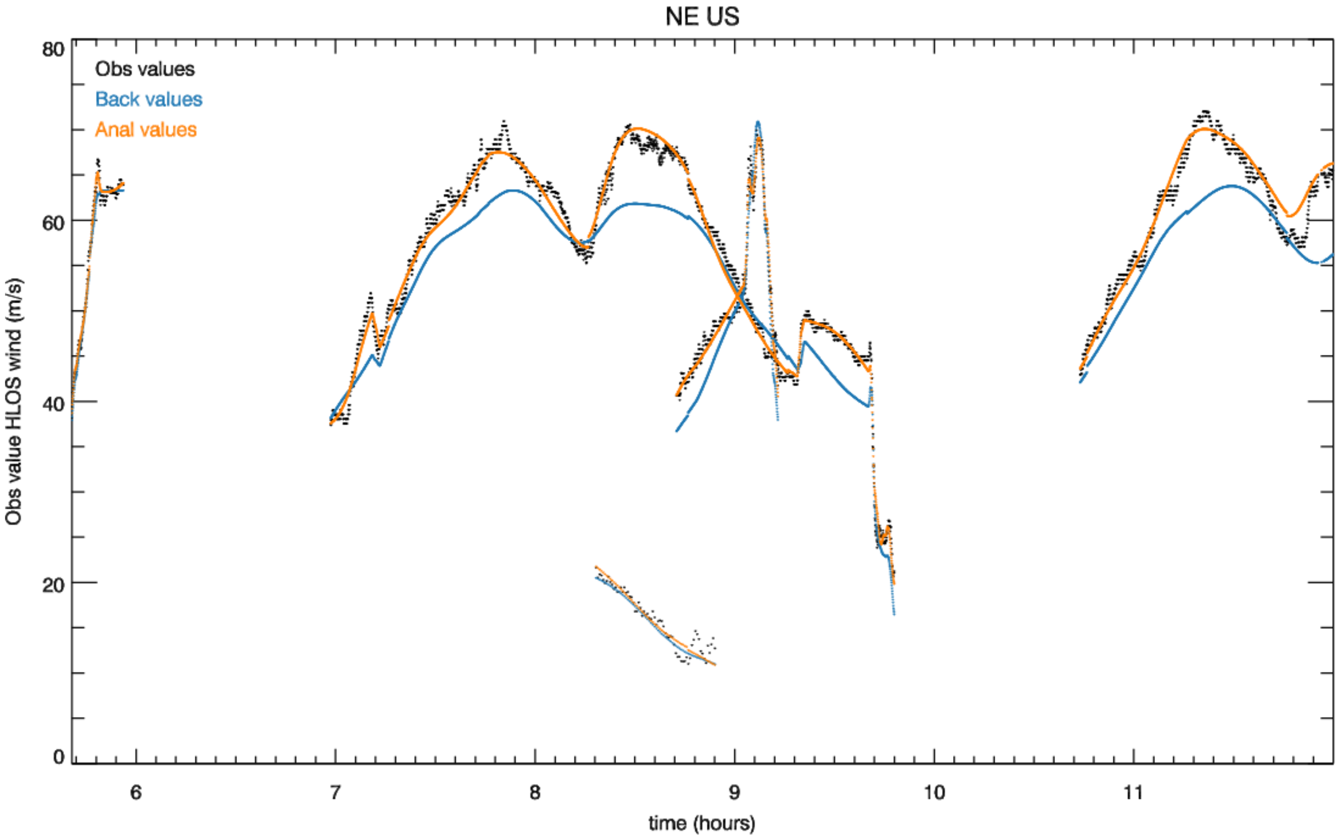


Figure 12. GADS aircraft u-component wind data (black points), compared to the ECMWF model (background forecast blue, and analysis orange, when GADS is assimilated). 12 UTC 25/01/2011.

Positive biases in ECMWF model wind speed for upper levels 0-400 hPa are evident against radiosondes see Figure 13 i.e. the radiosondes observe stronger wind speeds than the model on average by around 0.5 m/s. Note the biases are smaller in the lower troposphere. Similar behaviour is seen for aircraft winds at these levels. Bruce Ingleby (in charge of radiosonde assimilation at ECMWF) was asked about this bias and he said he would tend to be concerned if the bias exceeds 0.5 m/s. It may be possible that the model is lacking kinetic energy at the small-scales (as demonstrated in kinetic energy spectra plots) which leads to the bias. Observation minus background forecast is positive for wind speed so the model lacks some kinetic energy.

Combined ECMWF global O-B statistics for "conventional" data u-component wind (from aircraft, radiosonde and wind profilers) are shown as a function of u-component wind in Figure 14 for a pressure range in the upper troposphere/lower stratosphere. There is a suggestion of biased O-B values (~1-2 m/s) for the extreme wind values — however this may be an artefact of the errors in the B values (see Section 5.1.5). In a different time period (in late January/early February 2016) the positive O-B bias for larger B is not present; suggesting the biases are dependent on the weather regime.

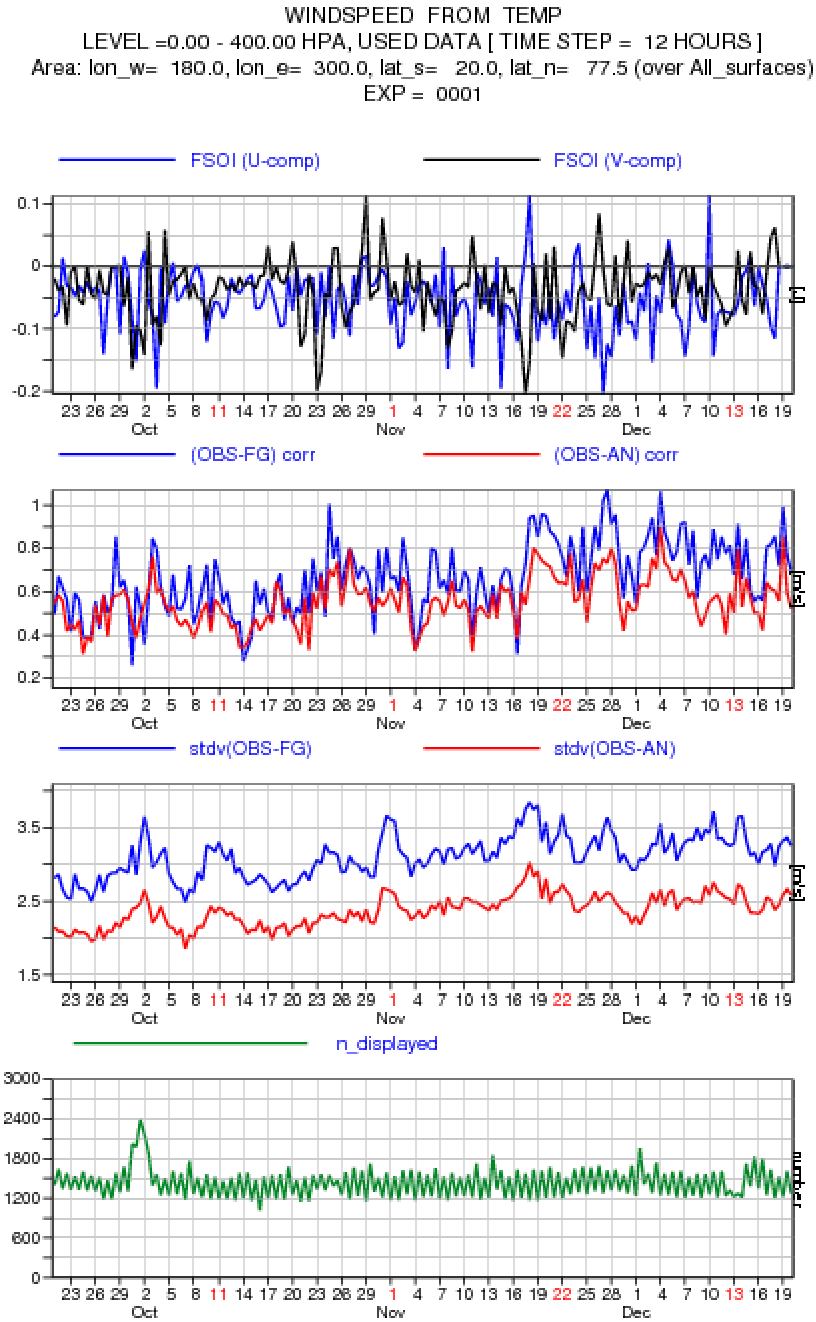


Figure 13. Time series of O-B and O-A error statistics for radiosonde wind speed in the operational ECMWF data assimilation in the northern hemisphere. Top plot is forecast sensitivity to observation impact, 2nd plot down is the mean of O-B and O-A, 3rd plot down is the standard deviation of O-B and O-A and the bottom plot is the number of observations.

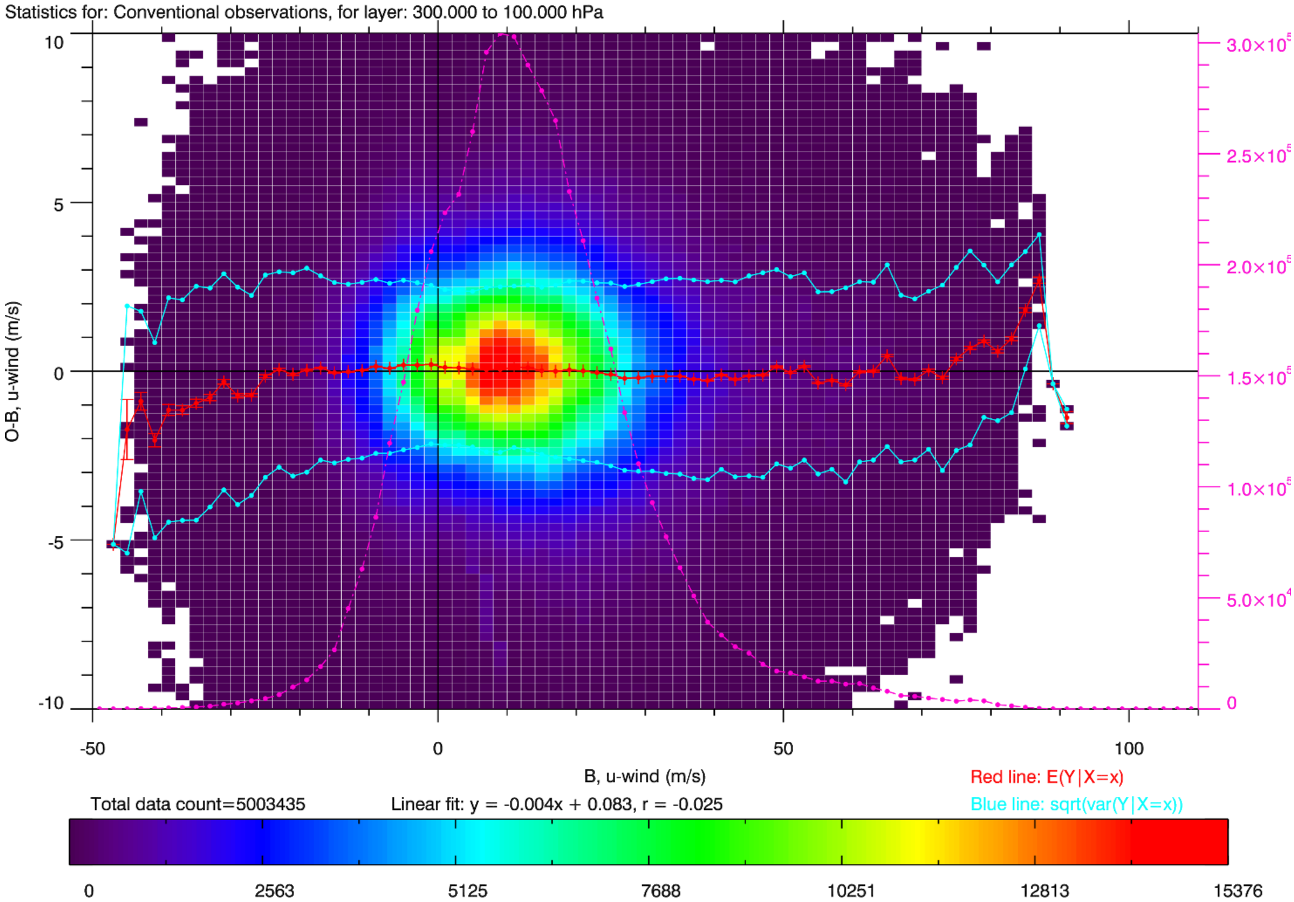


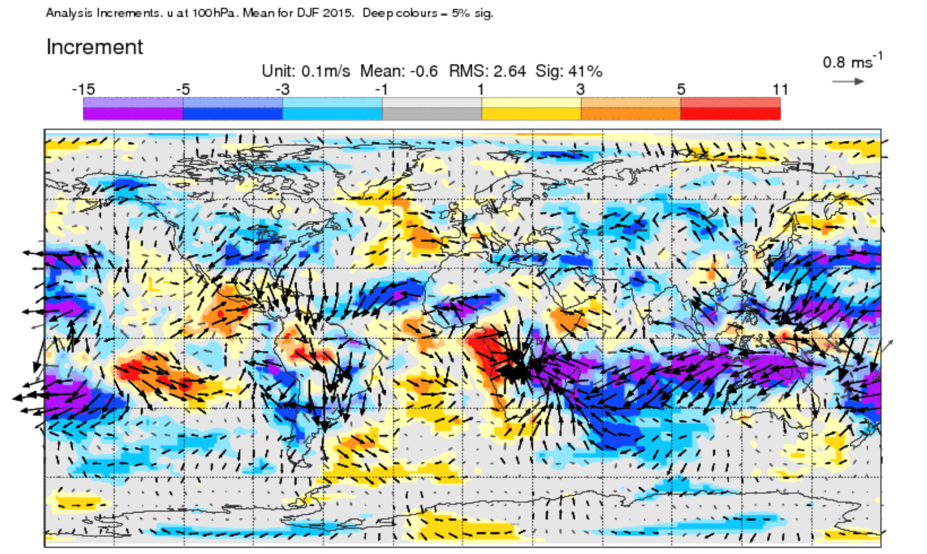
Figure 14. Dependence of "conventional" observations u-component wind O-B on the B value within the 300 to 100 hPa vertical range. Consisting of 61% aircraft, 17% radiosonde and 22% wind profiler by observation count. Data from all 12 hours cycles from 13/8/2016 to 20/8/2016. Only data that passed first-guess check are used.

3.4 Mean analysis increments — indications of model or observation bias

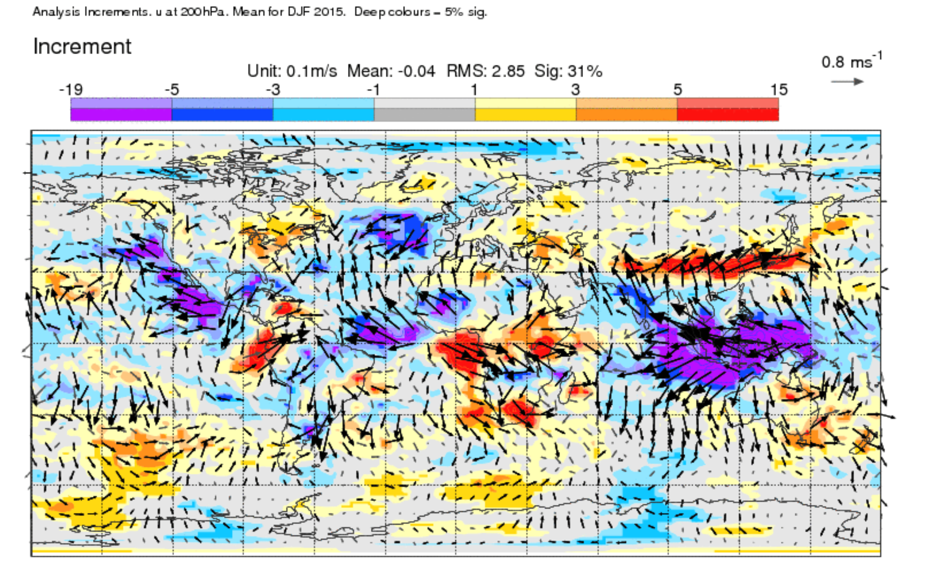
A symptom of bias in data assimilation is the presence of non-zero systematic time or space averaged analysis increments. If mean increments are a large fraction of increment standard deviation of each assimilation window then it is important to try to understand these biases. It is not easy to do so, because bias both in the model or the observations can be responsible for the systematic analysis increments.

Systematic model error for winds can e.g. exist when there is an imbalance between the model tendencies of the dynamics, radiation and convection; one of the processes can be too strong or too weak. In such circumstances accurate observations will continually try to correct the model bias (leading to non-zero mean analysis increments), see [RD3] which attempts to correlate imbalances in the model tendencies with the mean analysis increments and hence help to determine model bias.

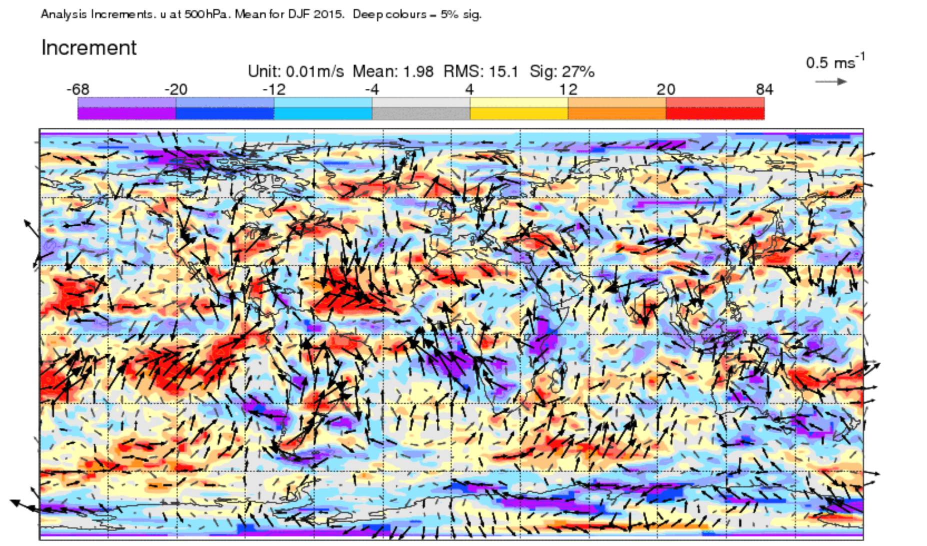
Diagnostics of the mean wind analysis increments from operations are monitored at ECMWF. These can help to identify conditions in which the analysis wind is biased. However further independent information is needed to determine if the observations or the model is the cause of the systematic increments. Some examples of mean analysis increments for wind are shown in Figure 15.


Analysis Increments. u at 100hPa. Mean for DJF 2015. Deep colours = 5% sig.
Increment
Unit: 0.1m/s Mean: -0.6 RMS: 2.64 Sig: 41%
0.8 ms-1
-15 -5 -3 -1 1 3 5 11

a)


Analysis Increments. u at 200hPa. Mean for DJF 2015. Deep colours = 5% sig.
Increment
Unit: 0.1m/s Mean: -0.04 RMS: 2.85 Sig: 31%
0.8 ms-1
-19 -5 -3 -1 1 3 5 15

b)


Analysis Increments. u at 500hPa. Mean for DJF 2015. Deep colours = 5% sig.
Increment
Unit: 0.01m/s Mean: 1.98 RMS: 15.1 Sig: 27%
0.5 ms-1
-68 -20 -12 -4 4 12 20 84

c)

Figure 15. Mean analysis increments for the wind vector (wind arrows) and the u component wind (colours) at a) 100 hPa, b) 200 hPa and c) 500 hPa for the period December 2014, January and February 2015. Note that wind arrow scale varies for each plot.

Figure 15 shows the mean analysis increments in the wind field for three vertical levels covering DJF 2015. In many areas the mean analysis increments differ significantly from zero, implying model or observation biases exist. They can be fairly large and are rather broad-scale spatially.

It is possible that some types of wind observations (or other observation types through the multivariate nature of 4D-Var) are biased and hence responsible for the mean analysis increments. For example AMVs can have biases due to height assignment errors, which could persist with the same meteorological conditions.

The mean analysis increments in Figure 15 exceed 1 m/s in some areas, particularly in the tropics, over oceans and in the upper troposphere.

There appears to be a correlation between the 100 hPa (around tropical tropopause) mean analysis increments for wind and the position of the ITCZ in January (not shown) which perhaps indicates the model has a systematic problem with the winds associated with deep moist convection (note this conclusion was also made in Section 3.1 comparing ECMWF and Met Office analyses). Note there is a distinct lack of wind observations at altitudes higher than 150 hPa but there are mass observations from radiance satellites and GPS radio occultation (see Figure 4b).

Therefore we reiterate that upper tropospheric convectively active areas in the tropics are probably unsuitable for assessing Aeolus wind quality using the ECMWF model (and other global NWP models).

There is considerable variation in the analysis increments for different seasons indicating the biases are linked to the meteorological conditions.

Figure 16 shows the zonal mean analysis increments for the zonal-component wind. It is clear from the maps of Figure 15 that the averaging in the longitudinal direction leads to smaller mean analysis increments i.e. averaging over different meteorological conditions. The mean wind increments are very large between 100 hPa and 10 hPa (typical maximum height for Aeolus), typically reaching 2-3 m/s in certain geographical areas (maps not shown). There are very few direct wind observations available at these levels, so presumably the increments are driven by mass observations or background error correlations from lower level observations.

The large magnitude of the mean wind increments in the stratosphere suggests caution should be taken using the ECMWF model to be a bias reference in the stratosphere.

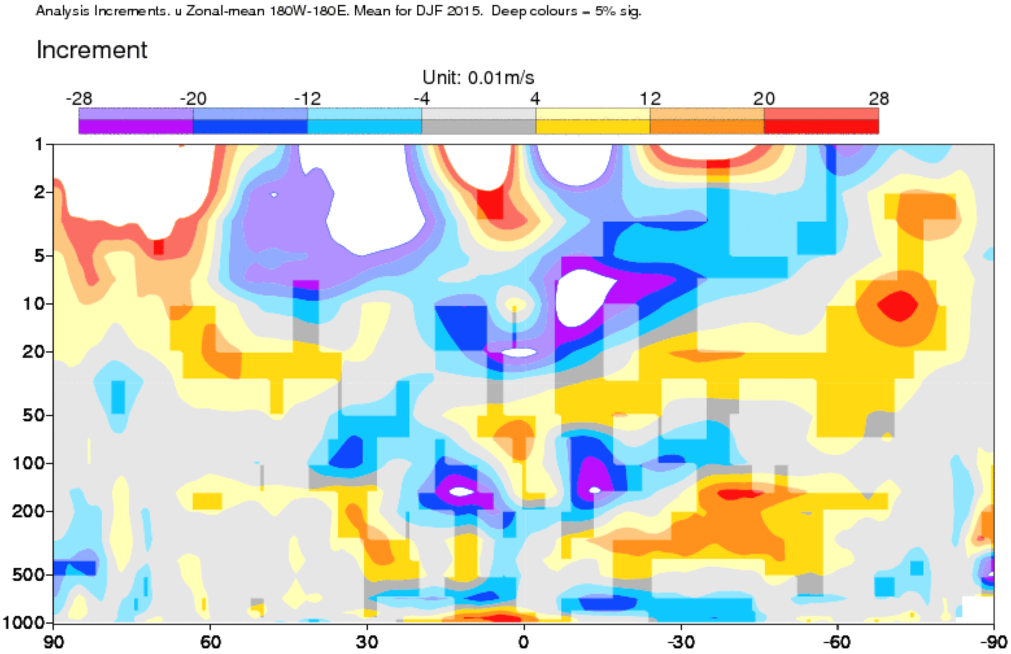


Figure 16. Zonal mean u-component wind analysis increments for DJF 2015. The horizontal axis is latitude (degrees) and the vertical axis is pressure (hPa).

3.5 Summary of NWP wind quality for use as a reference in Aeolus monitoring

In summary, ECMWF NWP model winds generally should be of sufficient accuracy for the advanced monitoring Aeolus winds for: detecting changes in Aeolus observation quality; determining observation systematic errors which are large relative to those of the NWP model i.e. > 0.5 m/s.

However, there is strong evidence that NWP winds suffer from systematic errors and larger random errors in certain conditions, in particular:

- Fairly large systematic wind errors (e.g. > 2 m/s) are in evidence near the tropical tropopause in association with the ITCZ along with larger random error (5 m/s).
- Occasional large systematic errors in upper level outflow (~200 hPa) of strong convection over the continental US.
- Wind speeds in/around polar jet streams are been found to be underestimated in the ECMWF model. Underestimation of the wind speed up to 10 m/s (10%) has been shown with recent evidence. This agrees with the findings of peer reviewed work from 2004. Also radiosonde O-B statistics for conventional wind observations (aircraft, radiosondes and wind profilers) show evidence for such a bias.

Therefore the NWP winds in these conditions should not be considered the truth by which Aeolus can be assessed.

4 Using NWP to mitigate observation systematic errors

The evidence provided here and from other studies indicates that over sufficiently large averages in space or time in the troposphere the ECMWF model wind mean error are expected to be smaller in magnitude than the biases predicted to occur for Aeolus (with some notable exception areas). Therefore it should be possible to use the ECMWF NWP model to detect/correct Aeolus biases.

Using advanced monitoring of O-B statistics, it should be possible to compute Aeolus bias as a function of a number of predictors i.e. a bias prediction model:

$$b(\boldsymbol{\beta}, \mathbf{p})$$

where **p** are the dependent variables or bias predictors and **β** are the, to be determined, bias coefficients — this is analogous to the observation operator. The bias prediction model should be guided by expectations of the physical origin of the bias. The predictors could be properties of the observation such as the geolocation of the observation (e.g. range, elevation angle), or if the predictors are found to be some function of the atmospheric state it may be useful to use the model variables as bias predictors (e.g. vertical wind shear may indicate Mie bias for thick range-bins).

In practice, bias models are often derived empirically from monitoring against the NWP model e.g. microwave radiance departures relative to the ECMWF model were found to be air-mass dependent due to radiative transfer model errors (see [RD11]) — in this case it was found to be important to bias correct the forward model equivalents to the real observations (so that the zero bias assumption in data assimilation is more closely adhered to). The predictors for the bias were in this case the model forecast air-mass fields.

It is our intention to develop the Aeolus advanced monitoring tools which will help determine a bias prediction model for Aeolus L2B Rayleigh and Mie winds — if it is found to be necessary.

4.1 VarBC — automated observation bias correction

Many observations are biased relative to the model, and the characteristics of bias varies widely between types of instruments. Ideally the data assimilation should be driven by observations which are unbiased relative to the model.

Variational bias correction (VarBC, see [RD2]) involves augmenting the data assimilation state vector to include bias prediction parameters (different for each observation type or satellite channel) which are estimated in the variational analysis along with the meteorological state variables. The predicted bias is subtracted from the departure before the assimilation process (i.e. the observation departures are modified to reduce the mean difference). The bias correction is adaptive, since the parameters can change from cycle to cycle, and during each 4D-Var minimisation process.

Note that VarBC may not remove the true bias from the observations (i.e. relative to true atmosphere), it may instead simply pull the observations to the model bias. However if the analysis has a sufficient sample of unbiased (anchor) observations, this will help to constrain the bias correction to be a bias correction towards the true atmospheric state.

VarBC is particularly useful if the observation bias varies in a complex manner in time or space. VarBC replaced the tedious job of estimating observation bias off-line for each satellite instrument or in-situ observation network by an automatic self-adaptive system. Depending on the assigned error covariance for the bias predictors, VarBC can respond very quickly (large error assigned to predictors) or very slowly (small error assigned to predictors) to observation bias changes.

Given that wind observations are lacking in many areas of the world and the model is known to suffer from some systematic errors, particularly in the tropics and stratosphere, then it is unclear if Aeolus winds can be successfully corrected (if needed) using VarBC. Therefore it would be a research project to attempt VarBC on Aeolus L2B winds (if found to be necessary after launch). Careful masking and data selection may be needed to avoid problem areas e.g. tropical model biases, which could be aliased into incorrectly changing the observations.

VarBC has been used operationally at ECMWF since 2006 for many observations types (mainly for satellite radiance measurements). The bias prediction model may depend on the model meteorological state. Some Aeolus biases are expected to be related to instrument properties; the suggested Aeolus bias prediction model is presented later (see section 5.1). The Rayleigh and Mie winds would require a separate set of bias predictors, due to being effectively different observation types.

An extreme example of how the VarBC correction (applied to a satellite radiance observation channel) adapts to the changing observation bias is shown in Figure 17 (an example from the ECMWF reanalysis group); see the almost step changes in early November and early December.

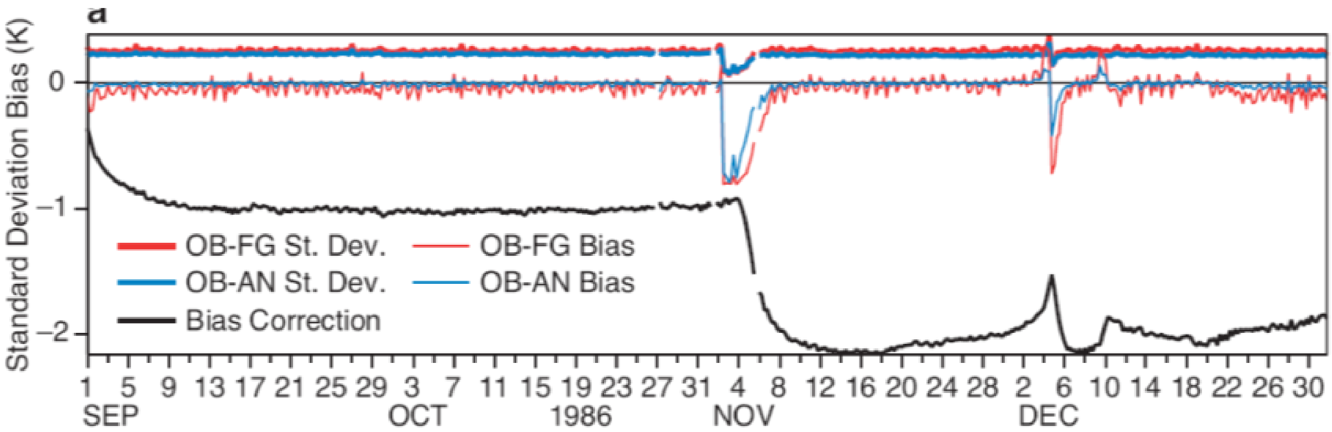


Figure 17. Example of how VarBC bias correction (black line) changes with the observation bias changes. NOAA-9 MSU channel 3 bias corrections (cosmic storm).

In this case VarBC smoothly handles the abrupt change in observation bias: initially the QC applied in the screening task rejects most data from this channel, then the variational analysis adjusts the bias estimates and the bias-corrected data are gradually allowed back in. There is no shock to the system.

Note that currently no wind observations are bias corrected using VarBC at ECMWF (although reanalysis work at University of Vienna on radiosonde wind direction correction is underway; the same authors discuss radiosonde temperature bias correction here [RD13]). Note that scatterometer wind observations are bias corrected with a fixed correction in pre-processing steps.

An implementation of VarBC for Aeolus at ECMWF will be suggested as a work package after launch if found to be necessary; the suggested bias predictors of Section 5 will help in such work.

5 Assessment of Aeolus systematic error sources

In industry's (ADS) error budget documentation, see [AD3], Aeolus observation biases which exist after all the instrument derived calibration/corrections have been applied in the processing steps are discussed.

In particular the [AD3] document includes:

- **Unknown biases:** a slowly varying (changing over many observations, on a time scale between 1 and 50 minutes) offset of the observed winds with respect to the true winds, determined at zero wind speed after correction using the results of any in-flight calibration.
- **Slope Error:** A systematic error which is proportional to the measured wind speed.

Based on experience with E2S simulations and L1B to L2B processing, it is expected there will be other forms of bias that also need consideration.

5.1 Predictors for Aeolus systematic errors

The following section lists (with our justifications) the variables we believe could contribute to Aeolus wind observation bias and so should be considered as variables to monitor against in the advanced monitoring. One could mistakenly think there is a causal relationship between the bias and the variable, however a variable may have a dependence upon the true causal variable e.g. presence of convective clouds correlated with non-zero vertical wind velocities (which alias into HLOS winds).

5.1.1 Bias predictors: observation based

The following are variables that are part of the Aeolus observation (although not necessarily available in L1B and L2B products) that may help to predict Aeolus wind biases.

- HLOS wind value:
    - If errors occur in the response versus frequency calibration, then the atmospheric wind value (i.e. atmospheric Doppler shift) determines where in the calibration curve is being sampling and hence which error is induced (this is illustrated in Figure 18). The HLOS wind value was found to be a useful variable for predicting bias in the testing of L2B winds derived from the E2S.

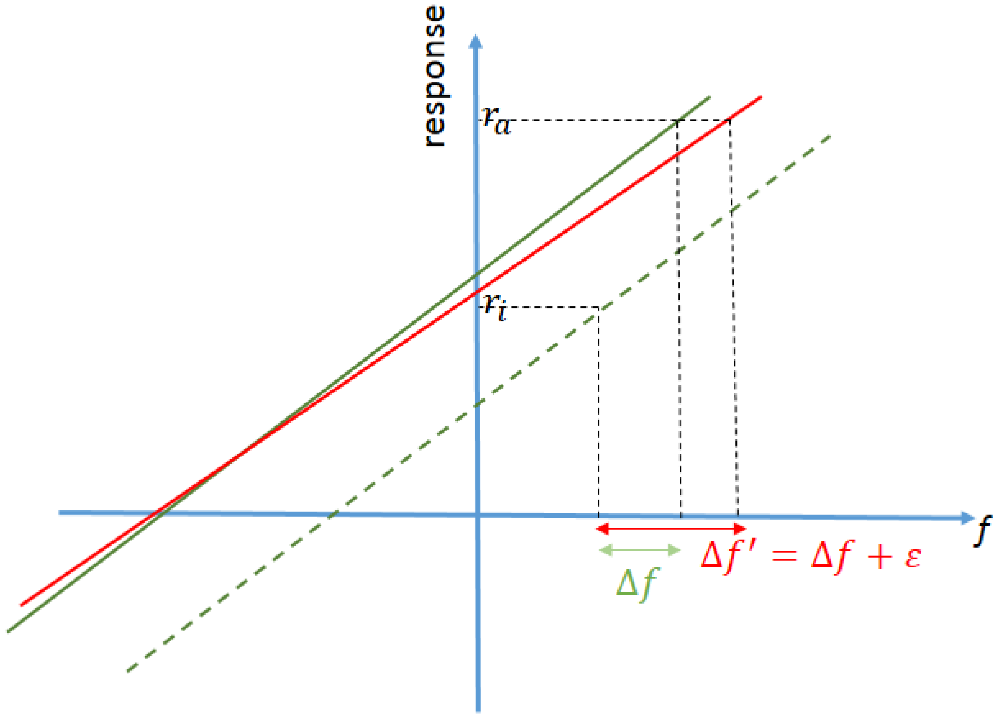


Figure 18. Diagram showing how an error in the calibration procedure leads to an error in the Doppler shift frequency. Here the red line is the imperfect atmospheric return calibration which differs from the ideal atmospheric calibration (green line). The dashed green line is the ideal internal calibration. The error in Doppler shift (and hence in the retrieved LOS wind) varies with the value of the atmospheric response measurement (and hence depends on the true LOS wind in the atmosphere).

- Time passed since the last calibration (e.g. for these calibrations: ISR, IRC, HBE)
    - If the instrument responses drift with time, then this could be modelled as a function of time since last calibration. If this is the case then a reduction in bias whenever a new calibration file is applied may be observed, followed by the slow change (degradation) in bias with time.
- Spectrometer/instrument temperature readings[1]
    - Temperature affects the spectrometer, and hence the measurement response.
    - Temperature of Optical Bench Assembly (emit and receive optics) can also affect the response.
- Laser frequency stability and energy (instrument internal readings available in HK data)
- Direct solar radiation at the satellite.
    - Affects the spectrometer temperature[2], telescope properties, which then affects

[1] Info from ESA: There are several temperature sensors on-board Aeolus, and also a detailed thermal model used by ESTEC and industry. Spectrometer temperature readings are only available in housekeeping data (HK, i.e. not in L1B data). One tool shown is more high-level illustrating platform illumination at a given time (SAMI). However, this is all qualitative. Two software diagnostics tools (EDDS and MUST) for the satellite monitoring is used at ESOC and ESTEC. These are very detailed expert tools with no user support. Both allow expert users to display the various HK data. The current planning is to give a hand-full of users in the L1 and L2 core teams' access to these tools for monitoring purposes.
[2] Info from ESA: This coupling has been made very small by design. RSP of ALADIN is well thermally shielded by a thermal hood to decouple it from temp environment around it. A2D much more suffering from this by design, but this has been improved for A2D in recent design upgrade.

responses and systematic errors.

- Orbit argument of latitude angle (i.e. position within the orbit) of the observations
    - A combination of sources may lead to an overall bias varying harmonically with orbit argument of latitude:
        - Harmonically varying solar radiation with the orbit argument of latitude; then perhaps easier to monitor against this variable than solar radiation.
        - Varying thermal radiation from the Earth surface below
        - Laser pointing knowledge errors
        - Moon blinding. This happens a few times per month. The moon is blinding the startrackers, which can then not be used for AOCS for some minutes (see ADS document).
        - Radiation conditions along the orbit:
            - From cosmic radiation (solar wind) leading to detection noise. Depending on the Earth magnetic field strength and direction, the spacecraft will be sensitive to cosmic radiation. Areas of particular concern are the South Atlantic Anomaly (local weak spot of Earth magnetic field) and around the magnetic south and north poles where the field lines bend down towards the Earth surface.
            - Possible sensitivity to increased background UV radiation from the ionosphere from plasma interaction with charged particles from solar wind (TBC)
- Observation satellite range (distance to satellite):
    - The incidence angle of backscattered light upon the spectrometers changes with satellite range due to satellite's rotation in near circular orbit. Range has a linear relationship to incidence angle according to ADS derivations.
    - If the applied RDB correction is imperfect, then will have residual range dependent bias. Will also partially manifest as a dependence on altitude (but not linear, since Earth in not spherical and the orbit is roughly circular).
- Retrieved scattering ratio (SR); averaged over the observation scale:
    - For Rayleigh: If L1B derived SR has systematic errors then this is an erroneous input to the Mie cross-talk correction, i.e. introduces bias in Rayleigh winds.
    - For Mie: SR indicates the Mie signal level (relative to molecular background) which could correlate with systematic errors which depend on signal levels or on type of backscatterer, e.g. strong returns on thin clouds may indicate geolocation representativeness errors.
    - Classification: Biased SR values may lead to biases in winds due to incorrect classification of measurements into clear/cloudy.
- Observation signal levels:
    - Low signal levels allow uncorrected effects to become more prominent e.g. imperfect DCMZ correction. However, low signal levels also mean larger random error, therefore the bias is less of an issue in data assimilation. Note that since the signal

levels are also a function of the atmosphere i.e. amount of attenuation, then should be careful not to misinterpret such biases as being causally related to the atmospheric conditions i.e. an instrument error rather than geophysical error.

  - Related variables: L2B estimated standard error (derived from signal levels)

- Bin thickness of the observation:
  - Biases related to vertical bin overlap effects; wind shear issues; vertical placement issues)
- ZWC values from the two different schemes implemented (last valid ground echo or HBE value):
  - Monitoring of L2B wind quality with and without applying the ZWC will help determine if this is a useful correction. Also can analyse the quality of the two ZWC schemes "last valid ground echo" and "HBE correction value" to assess which is best. This analysis quantifies the effectiveness of the ZWC scheme.

5.1.2 Bias predictors: meteorological conditions from the ECMWF model

Here we suggest possible useful bias predictor from the ECMWF model fields. This assumes they are accurate enough to be useful bias predictors. Generally this is concluded to be the case for wind data from Section 3; some non-wind meteorological properties from the ECMWF model are also considered that could help to predict Aeolus wind biases.

- Wind fields in (around) the observation sampling area:
  - Wind shear (vertical and horizontal):
    - The assumption (in current ECMWF data assimilation code) that Aeolus winds are point-like (in the observation operator) rather than spatially averaged winds may lead to observation operator induced biases (not a "real" observation bias i.e. more the fault of the user of the data) in strong wind shear conditions.
    - However, note that the ECMWF model significantly underestimates wind shear; see [RD12]. So care should be taken when using ECMWF derived wind shear in predicting such observation operator related error.
    - Estimates of atmospheric wind turbulence as parameterised from the ECMWF model can indicate likelihood of unresolved turbulence or gravity waves (*to be investigated further*).
  - Surface wind:
    - Non-zero near surface winds can have a causal effect on L1B ZWC values (the ground return is mixed with return just above the surface). Which can then propagate to HLOS wind bias when the ZWC corrections are applied (either directly or via the HBE). For the Mie this effect occurs when there is aerosol loading in the range-bin overlapping the ground. Therefore perhaps increased signal strength (to that expected for the ground albedo) of the total return could be used to flag atmospheric wind contamination.
    - The strength of the ECMWF model predicted surface wind may correlate with such biases.

  - Vertical wind velocity:
    - This has a causal effect on HLOS wind bias (since the L2B HLOS wind product assumes w=0 m/s). N.B. LOS wind is still a correct value however.
    - Important for RRC mode, where the assumption is made that w=0 m/s for the response calibration. Note that in IRC mode the laser is pointing near nadir, so vertical winds have a stronger effect than in off-nadir WVM mode. Deviations from w=0 m/s will lead to errors in the RR calibration, and hence systematic wind errors.
    - Vertical wind is a diagnostic variable in ECMWF model (TBD if this could be made available for AUX_MET file). A quick investigation into the magnitude and distribution of vertical velocity predicted by the ECMWF model is given in the Appendix (see section 9.4).
- Cloud fields above/within observation sampling area:
  - May indicate conditions in which Aeolus winds are systematically in error due to for example:
    - Certain cloud types are correlated with vertical velocity being non-zero. This will be more of an issue for Mie winds from the top or within clouds.
    - The cloud top will generally not be positioned at the bin centre, introducing a HLOS wind bias in wind-shear conditions [RD12].
    - Rayleigh winds in the presence of polar stratospheric clouds without Mie range-bins available for cross-talk correction. Note that these conditions are likely to be detectable with the Optical Properties Code using only the Rayleigh channel; this is in the process of being implemented in the L2Bp. Regarding the ability of the ECMWF model to represent PSCs, the ECMWF cloud expert (Richard Forbes) reports:

      In the operational HRES at the moment, we do get clouds occurring in the stratosphere up to about 20 hPa (~26 km) in the Southern Hemisphere winter (Jun/Jul/Aug) over Antarctica. They are associated with tiny amounts of ice water content so have very little radiative impact. There are two observed types of polar stratospheric clouds; Type I made of e.g. nitric and sulphuric acid droplets, which the IFS model cannot capture because it doesn't have the chemistry; and Type II, nacreous cloud made of ice crystals, which are observed over Antarctica in the polar winter, which the model is trying to capture. Both can occur together in reality. It would be worth evaluating stratospheric clouds in the model against CALIPSO before trusting it for Aeolus monitoring purposes.
  - Cloud conditions above the observation range-bin predict signal attenuation; this could create vertically correlated observation errors due to laser frequency jitter (only a concern if small fraction of measurements penetrate below cloud, according to recent studies).
  - Opaque clouds lead to increased random errors on ground-return velocities (ZWC), which could lead to biases when applying the ZWC.
- Temperature of observation sampling area:
  - If a problem exists in the AUX_RBC file e.g. wrong RB spectrum model used, or the

RBC L2Bp algorithm, then the bias may be correlated with atmospheric temperature. Or if the a priori AUX_MET temperature data is biased.

- Pressure of observation sampling area:
  - If a problem exists in the AUX_RBC file or the RBC L2Bp algorithm, then the bias may be correlated with atmospheric pressure. Or if a priori AUX_MET pressure data is biased.
- Hydrometeors in the observation sampling area:
  - Perhaps backscatter from hydrometeors could in certain conditions be significant, therefore fall-speeds of hydrometeors will be aliased into the Mie channel HLOS wind of atmosphere.
- Model orography
  - Greater chance of gravity waves associated with orography which may lead to noisier winds (more wind variability in the Aeolus averaging "cell"). Since the gravity waves are generally downwind of the orography, this will not be a simple tool for predicting such biases.
- Other variables possibly available from NWP output:
  - The following may be useful for predicting bias:
    - Ocean wave properties, snow/ice conditions, ground-type, and albedo. All can influence ZWC values and so may indicate sources of bias.
    - Aerosol optical properties forecasts at ECMWF. The Composition-Integrated Forecast System (C-IFS) forecasts is used in the Copernicus Atmosphere Monitoring Service (CAMS) and predicts concentrations of reactive gases (ozone, CO, SO2, NOx, etc.), greenhouse gases and aerosols (sea salt, desert dust, sulphates, organic matter and black carbon) initialized from an analysis based on available satellite observations.
    - Background top-of-atmosphere UV radiation levels as predicted by model radiation schemes — a background noise that particularly affects Rayleigh wind observations.
    - Convective instability (e.g. CAPE). However, ECMWF model winds may be the source of bias in such conditions.

There will also be observational sources (e.g. satellite observations of TOA UV radiation) for the potential meteorological bias predictors suggested above and such observations may be useful in particular case studies for trying to understand Aeolus biases. However, the advantage of the ECMWF model predictions of such variables is that they are generally more easily available for the routine monitoring that we describe in this TN.

5.1.3 Aeolus bias detection using NWP model output

Table 1 lists some potential sources of unknown bias for the Aeolus mission and our expectations as to whether the biases could be detected with ECMWF NWP model output.

Table 1. Sources of unknown bias for Aeolus and detection possibilities with NWP model data

#	Name	Physical source	Calibration strategy	Stability	Bias prediction model form	NWP correction?
1	Range Dependent Bias (RDB)	SP sensitivity to angular incidence	Exists for mission. But may have residual bias.	Possibly stable for mission lifetime. Will vary with orbit altitude.	Constant plus linear function of range	Yes, given its persistence, should be detectable against NWP model winds.
2	Thermo-elastic effects	SP sensitivity to ambient instrument conditions	Partially exists. Regular IRC should account for drifts of time-scales > week. Harmonic variations in solar heating may be partly corrected by HBE	Stability on < IRC time scale unclear	Constant plus linear function of HLOS truth value (slope error)[3] and a harmonic function of orbit argument of latitude	Depends on magnitude of biases and if truly harmonic. May benefit from VarBC since will change on ~weekly time scale
3	AOCS errors	Imperfect pointing knowledge (sat, earth velocity aliased into HLOS wind), imperfect geolocation of wind.	Partially exists. ZWC → HBE, residual bias will probably exist	Unclear	Small errors in e.g. yaw steering may give bias that varies harmonically with orbital phase. May also be a function of surface wind conditions if ZWC has used "contaminated" scenes.[4] *Moon-blinding could give extreme pointing errors (best to reject data)*	If truly a harmonic function of the orbit phase then probable yes (if large in magnitude). VarBC should help if parameters drifting.
4	IRC error, ISR error	Errors during calibration → systematic errors in winds	N/A	Fixed per calibration file	A fixed slope and offset bias per calibration (can be a non-linear bias). Covered by the bias function of row 2	May be detectable as a slow drift in bias coefficients followed by a jump when applying new IRC. Incorporation through VarBC would be useful.
5	Retrieval errors	Unknown systematic retrieval errors e.g. uncorrected effects, imperfection calibration processing assumptions, imperfect a priori T, p in RBC	N/A	Fixed for each processing chain version.	Unknown	If persistent and large enough then should be detectable, unless strongly meteorological state dependent, in which case will appear more like a random error.
6	Forward model errors	Incorrect assumptions in NWP FM e.g. vertical wind is zero, point-like wind FM (when Aeolus is really an	N/A	Reproducible for each FM version.	Unknown	If persistent then should be detectable, unless strongly meteorological state dependent (e.g. wind shear), in which case more like a random error. Solution is to

[3] Note that the predictor is the L2B HLOS wind truth value (which we don't have!), so we have to compromise with the

		average)				improve FM.

use of the ECMWF forward modelled HLOS wind value. The HLOS observation value is the variable we are trying to bias correct, hence it would not be a good choice of predictor.

[4] Here we can use the ECMWF model surface wind conditions to predict the bias.

5.1.4 Suggested bias prediction model for Aeolus

Based on the expected dependencies for the various sources of Aeolus bias, our suggested bias prediction model for Aeolus L2B HLOS winds (y) is:

$$\mathrm{b}(\boldsymbol{\beta}, \mathbf{p}) = \sum_{i=0}^{N_p} \beta_i p_i = \beta_0 + \beta_1 h(x_b) + \beta_2 r_y + \sum_{j=1}^{N_h} \left(\beta_{3j} \sin(j u_y) + \beta_{4j} \cos(j u_y)\right)$$

It is constructed of bias coefficients (β_i) and bias predictors (p_i). This model is linear in the predictor terms, which is a strategy often used in VarBC, however this may be unsuitable for Aeolus. If used in ECMWF VarBC then the coefficients are assumed to be applicable during a 12 hour data assimilation window period.

The bias predictors are:

- $p_0=1$, A constant term.
  - Accounts for a constant bias, the same offset to all HLOS winds
- $p_1=h(x_b)$
  - The forward modelled L2B HLOS wind from the background forecast state, i.e. to account for potential slope-error (error dependent on HLOS wind value).
  - There are caveats when using this imperfect variable as a predictor (see section 5.1.5).
  - Note that it is better to use the background derived value as the predictor rather than the observation value since they can be considered as fixed within the context of the minimisation (in VarBC). If we use the observed value (with bias correction applied) then the observed value can vary during the minimisation.
  - N.B. a non-linear function of forward modelled L2B HLOS may be necessary.
- $p_2=r_y$
  - Satellite to observation range (units of metres), to account for residual range dependent bias. This is derived by ADS to be a linear dependence.
- $p_{3j}=\sin(ju_y)$
  - sine of an integer j times the "argument of latitude" value (u_y) for the observation y. There are N_h values from j=1, to N_h. To account for bias that varies harmonically along the orbit.
- $p_{4j}=\cos(ju_y)$
  - cosine of an integer j times the "argument of latitude" value (u_y) for the observation y. There are N_h values from j=1, to N_h. To account for bias that varies harmonically along the orbit.

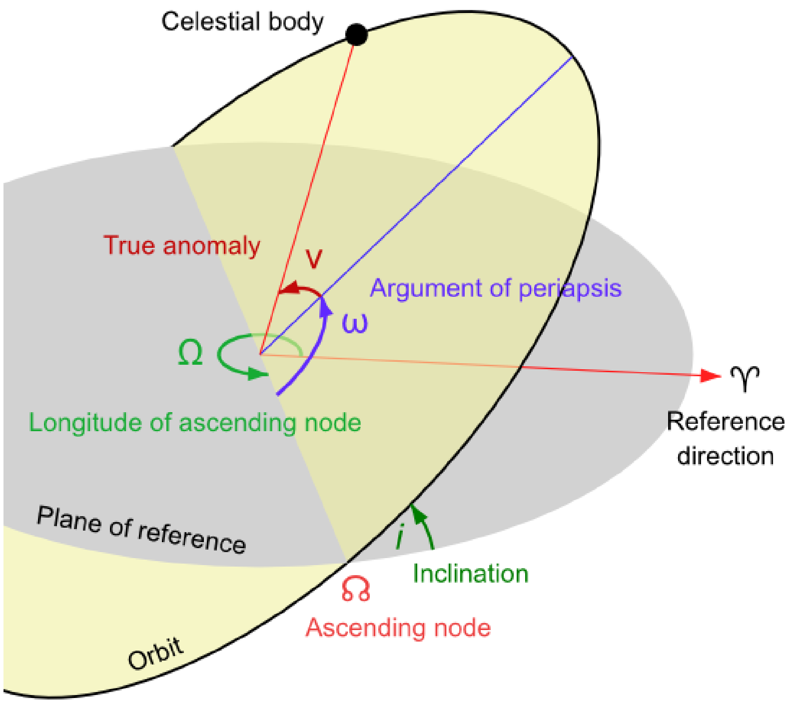


Figure 19. Diagram illustrating the orbital variables (courtesy of Wikipedia).

In celestial mechanics, the argument of latitude (u) is an angular parameter that defines the position of a body moving along a Kepler orbit. It is the angle between the ascending node and the body. It is the sum of the more commonly used true anomaly and argument of periapsis ($u = \upsilon + \omega$), see Figure 19.

The bias predictors p_{3j} and p_{4j} are in effect a Fourier series expansion of bias along the orbit. Therefore, expansions to higher values of j allow the bias prediction to vary in a more complicated harmonic function along the orbit. This formula has been used for SSMIS (Special Sensor Microwave Imager/Sounder) data at the UK Met Office, see the reference [RD4], and also the Aeolus Harmonic Bias Correction method. The required number of N_h is to be determined.

Samples of O-B will be used in some form of regression to estimate the bias model bias coefficients (e.g. off-line monitoring, or VarBC). O-B values over a period of time for which the bias coefficients are considered constant should be used. In practice the coefficients are expected to vary with time, hence the possible need for an adaptive bias correction method (see section 4.1) such as VarBC. Note that a separate set of coefficients are required for the Mie-cloudy and Rayleigh-clear observations because they will have different bias properties. The post launch advanced monitoring investigations may lead to modifications to the bias prediction model.

5.1.5 HLOS wind dependent (slope-error) bias correction issues

A concern for the bias correction of the HLOS wind dependent bias (aka slope-error) is discussed in [RD5]. That is, we do not have the “true HLOS wind”, which would be the ideal predictor, and so instead we use the ECMWF model derived HLOS wind. For other predictors like range or argument of latitude, the errors in such values are small enough to consider them as the “true” independent values.

If there are measurement errors in the independent variable of a regression scheme (for which it is assumed that the independent variables are perfect) then this can produce a bias in the estimated coefficient. For simple linear regression the effect is an underestimate of the coefficient, known as the attenuation bias (see http://en.wikipedia.org/wiki/Errors-in-variables_models). With this effect, the resultant regression coefficient is smaller than it should be as follows (where β is the true coefficient, and η is the error in independent variable x, and σ is the standard deviation):

$$\hat{\beta} = \frac{\beta}{1 + \frac{\sigma_\eta^2}{\sigma_x^2}}$$

If one where to linearly regress y against $H(x_b)$ to try to detect slope error then with 2.0 m/s standard deviation for η (approximate standard error in $H(x_b)$ from ECMWF winds) and 17 m/s standard deviation for natural variability in $H(x_b)$ (estimated from HLOS simulations from the ECMWF model) then one gets 0.986β, i.e. an apparent 1.3% slope error (gradient less steep). For our bias correction model the dependent variable is the O-B value (y - $H(x_b)$) and the independent variable is $H(x_b)$.

To test the theoretical result, some simulations of the "apparent" slope error due to random errors in $H(x_b)$ when using simple linear regression were performed using IDL. The following assumptions were made:

- y has random error of 2.5 m/s standard deviation (assume Gaussian errors, zero bias)
- $H(x_b)$ has random error is 2.0 m/s standard deviation (assume Gaussian errors, zero bias)
- The dynamic range of the true HLOS was assumed to have a mean of zero and a standard deviation of 17 m/s (this gives a dynamic range similar to that seen for ECMWF-E2S simulations of Aeolus HLOS).
- Assume there are 36000 O-B departures to regress against (conservative estimate of the number available in a 12 hour data assimilation window for the Rayleigh-clear winds).

Figure 20 confirms that even without any slope-error the effect of noise in the independent variable ($H(x_b)$) causes an "apparent" slope-error of -0.013 (or 1.3 %). This apparent slope error is greater than the ADS suggested slope error budget of ~0.5%. Note that this agrees with the theoretical estimate.

We therefore have to very careful in the interpretation of a simple linear regression against a noisy predictor, like $H(x_b)$. Things may be even worse in reality since $H(x_b)$ will not only have random, but also systematic errors, **which may make detecting and hence correcting a true slope error of order 0.5% very difficult**. Note that if the linear regression coefficient for (y-$H(x_b)$) vs $H(x_b)$ is >0, then this implies that a real slope error exists, because the artefact can only lead to negative slope coefficients.

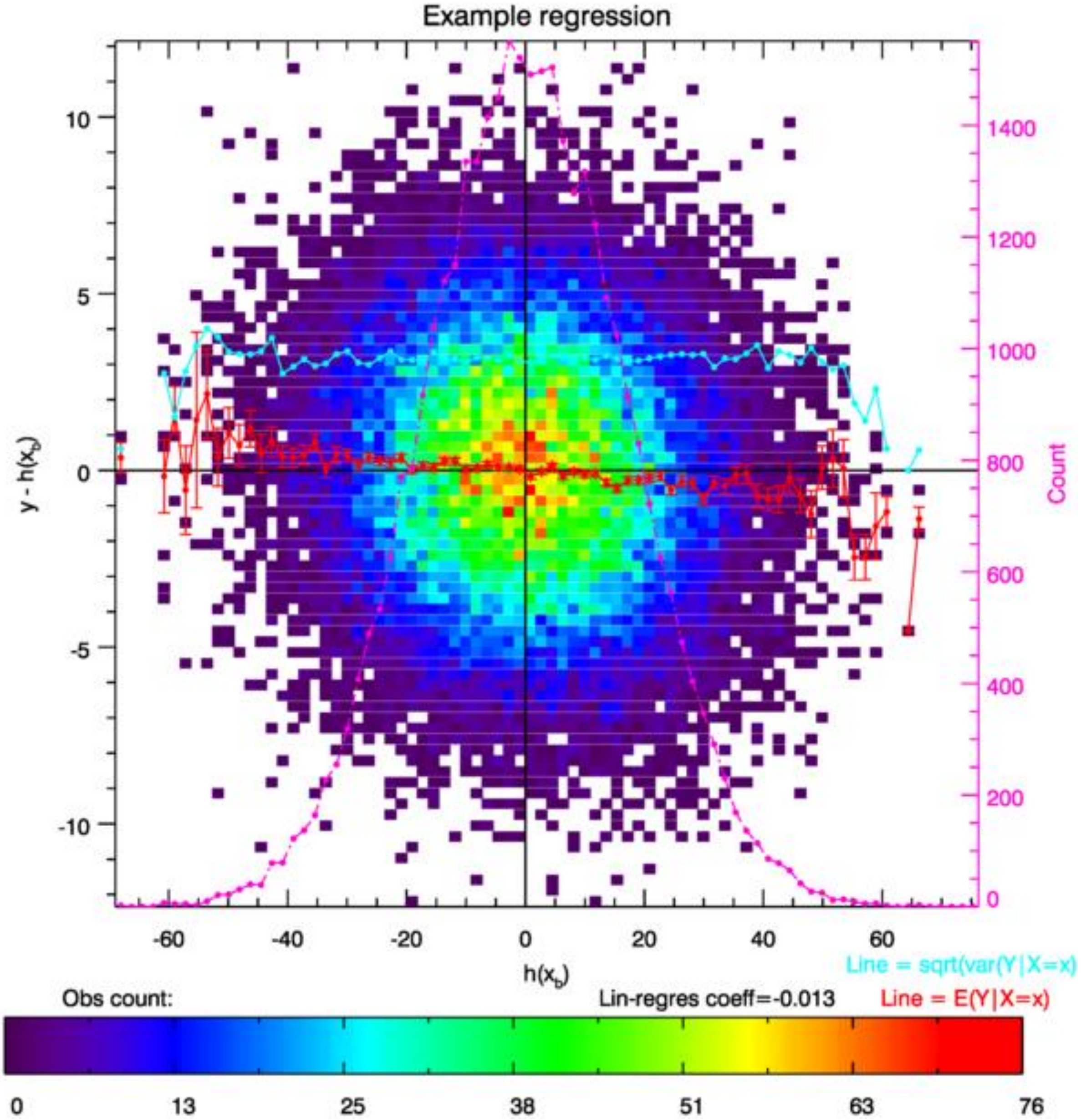


Figure 20. Example of the fit of $E(y\text{-}H(x_b)|H(x_b))$ and linear regression coefficient in the case of a zero slope error bias.

5.2 Aeolus advanced monitoring: a selection of plot types

The following table lists the Aeolus advanced monitoring verification or statistical plot types (using the ECMWF model short range forecasts, B) which we think will be useful for detecting and perhaps estimating some of the Aeolus errors discussed in earlier sections. Many of these have already been implemented in the IDL advanced monitoring software (see Section 6.2).

Table 2. Aeolus advanced monitoring plot types

#	Partitioning of (O-B) statistics by:	Purpose	Type of bias detection possible	Comments
1.	altitude	Gives an overall impression of the quality of the data throughout the vertical profile (surface to ~30 km)	General	Possible to obtain reasonably stable global statistics with only one orbit (~462 profiles) if biases are not varying
2.	O (or B) HLOS wind	Gives an indication of any biases which vary with the magnitude of HLOS wind (slope error) which could be related to calibration response curve errors	General	Found to be useful in E2S CoP verification.
3.	B vertical wind shear	Determine if HLOS wind error is correlated with the vertical wind shear. This may help diagnose vertical co-ordinate errors - either in the observation or the NWP model equivalent	General	Could also consider horizontal wind shear (may indicate representativeness issues)
4.	vertical range-bin size	It is possible that errors correlate with Aeolus vertical bin size e.g. related to vertical bin overlap, signal levels	Instrument	Larger bins may also have larger bias due to vertical placement issues. Also larger bins occur typically at higher altitudes.
5.	L2B estimated error	Indicates how well the L2B estimated standard error agrees with the true observation error + the background forecast error. std. dev(O-B) should be greater than	Instrument, processing	

		mean(estimated error) due to the inclusion of background errors.		
6.	B temperature	Indicates how well the RBC correction scheme is working for temperature. Perhaps not useful for Mie winds.	Rayleigh processing, calibration	
7.	B pressure	Indicates how well the RBC correction scheme is working for Pressure (Brillouin effect). Perhaps not useful for Mie winds.	Rayleigh processing, calibration	
8.	applied L1B-derived scattering ratio	Indicates if the Rayleigh cross-talk correction is doing a good job i.e. as the SR increases, does observation error increase? Or perhaps the SR is biased.	Instrument, processing	
9.	orbit arg. of latitude	Determine if a residual harmonically varying bias is present.	Calibration, pointing knowledge, HBE performance	
10.	local solar time	May indicate if subtle solar radiation variations on the satellite are affecting the bias	Checking uncorrected HBE	
11.	time (for a variety of altitudes)	Will show time drifts in biases or std. dev. e.g. sudden degradations in the data. Will also show changes in the ECMWF model winds	General	Time binning will be needed to get robust statistics.
12.	observation range to satellite	Indicates if a residual RDB exists.	Checking uncorrected RDB	
13.	mean versus B surface wind	See if the systematic error varies with forecast surface HLOS wind, through ZWC interaction	Calibration, geophysical	
14.	Geographical maps of mean, st. dev. at	Shows if any specific areas/meteorological conditions are causing	General	Will need to spatially bin the data to get robust

	various altitudes	problems		statistics
15.	spatially binned mean, st. dev.	Helps to show bias differences between polar, extra-tropics and tropical regions	General	Will need many days of orbits to show robust statistics
16.	latitude and time	Could help determine if e.g. there is a problem in the SH anomaly area. Or ECMWF model has a problem.	General	Helps to elucidate time development of problems in certain regions
17.	vertical correlation	May indicate if Aeolus has strong vertical observation error correlation (if have expectations on the background error vertical correlation in HLOS wind space). Relationship to vertical bin overlap.	General	
18.	spectral density	Show variances in (O-B) as a function of time-scale (TBD)	Calibration	May be useful in combination with plots versus argument of latitude. The A2D noise study found this type of diagnostic useful
19.	lidar cross-sectional views of data	Useful for gaining overall impression of the data versus the model equivalent	General	Can also be done for L1B measurement level data. Used extensively in E2S simulation testing.

6 Implementation of Aeolus advanced monitoring at ECMWF

6.1 Existing ECMWF monitoring tools

6.1.1 OBSTAT

OBSTAT is the standard operational monitoring software for observations at ECMWF, developed in collaboration with Météo-France. The following description of OBSTAT was provided by Mohamed Dahoui (ECMWF) who is responsible for the software package:

The OBSTAT program computes and plots observation related statistics for data recorded in the ODB (Observations Data Base) from the ECMWF data assimilation suites. Being systematically enabled in all IFS (Integrated Forecasting System) experiments, OBSTAT is currently considered as a key component of the ECMWF data diagnostics system. Since its first implementation at ECMWF, OBSTAT was mainly used to produce simple area and time averaged statistics. Recently, OBSTAT has been significantly upgraded to allow more flexibility in the production and plotting of statistics from many perspectives: e.g. temporal, geographical, vertical column, land and sea, data usage flags and incidence angles.

OBSTAT's purpose:

- *Production of statistics for various observations diagnostics (departures, bias correction, etc.)*
- *Production of statistics according to various data selection criteria*
- *Production of statistics from various dimensions (time, vertical, latitudes, FOV, etc.)*
- *Sufficiently generic to handle various data types*
- *Flexibility regarding input data formats*
- *Possibility to overlay results from different model versions*
- *Possibility to customize products for special investigations*

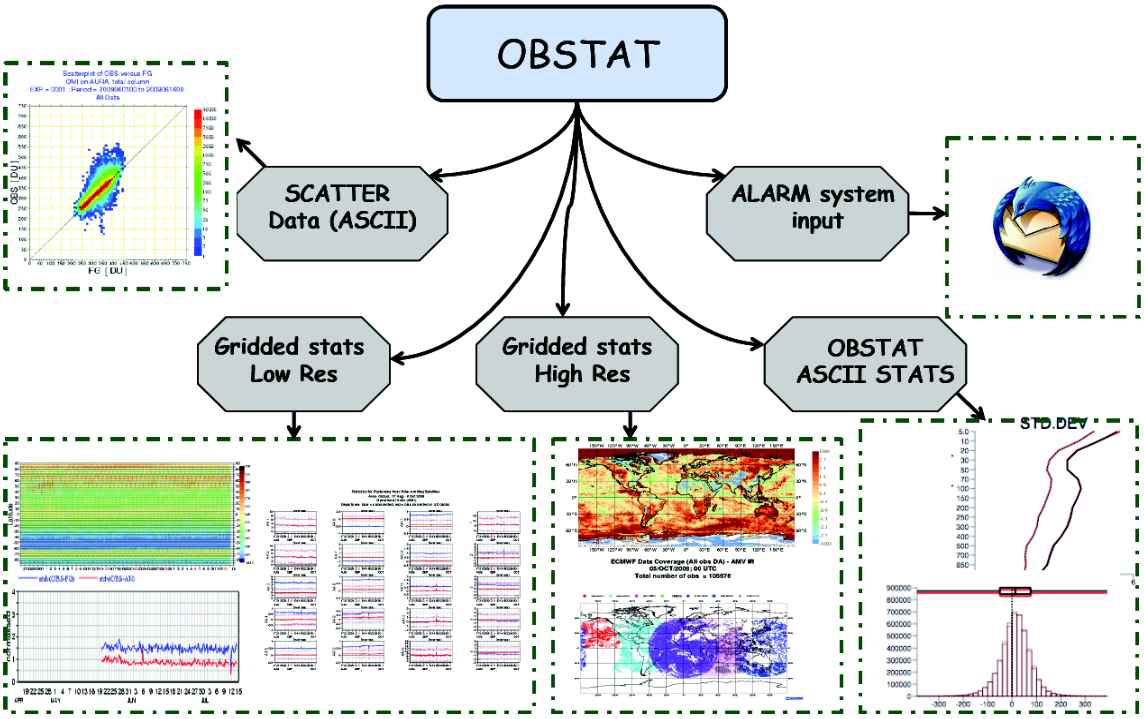


Figure 21. Some examples of what OBSTAT can produce. Courtesy of Mohamed Dahoui (ECMWF).

Types of plots available from OBSTAT:

- *Geographical means*
- *Area averaged time series*
- *Hovmoeller diagrams ([latitude vs time], [levels vs time], [levels vs latitudes] and [time vs longitudes])*
- *Scatter plots*
- *Area averaged overview time series*
- *Area and time averaged scan depended statistics*
- *Histograms*
- *Area and time averaged statistics profiles*
- *Area averaged solar-time time series*
- *Orbital statistics (Ascending/Descending nodes)*
- *Targeted area statistic*

Aeolus Level-2B ODB files can already be processed by OBSTAT (from simulated data studies). For example, see Figure 22, which is a typical example of vertical profiles plots for an experiment where Aeolus L2B winds derived from the background forecast (via E2S) are assimilated back into the same background forecast.

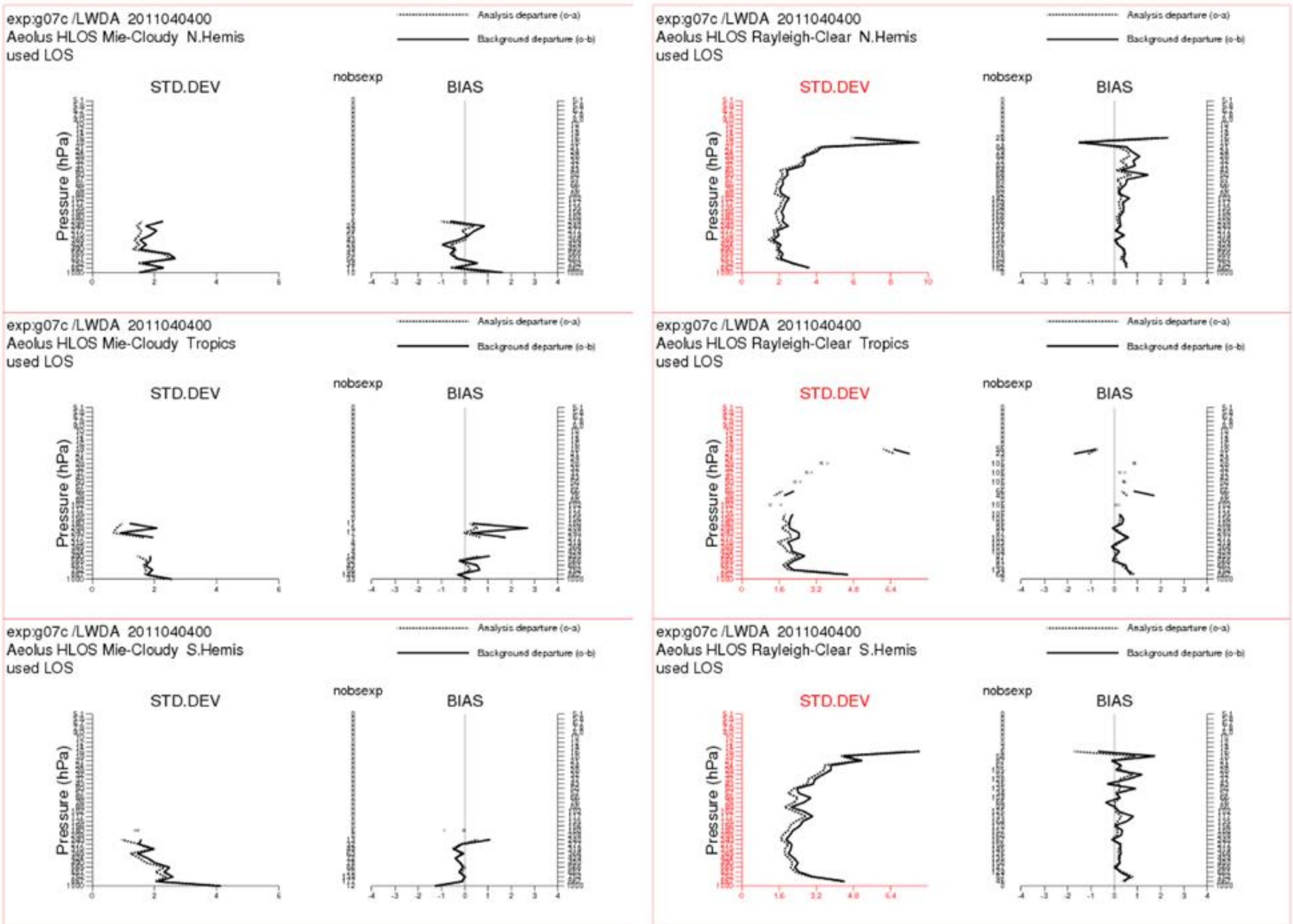


Figure 22. Example OBSTAT plots for assimilated Aeolus L2B winds. Mie-cloudy on the left, Rayleigh-clear on the right. Top row is the northern hemisphere, middle is the tropics and bottom is the southern hemisphere.

6.2 Advanced Aeolus monitoring

OBSTAT can produce many types of plots of observation statistics. However because Aeolus will be a new satellite mission, the best ways to present the statistics may differ from other satellite data — therefore more bespoke monitoring of Aeolus is needed to explore methods for verifying the data. Also OBSTAT gets the data from archived ODB files which only have a limited selection of L2B information for Aeolus monitoring purposes. For example, the ODBs do not archive L1B measurements level information and much of the detail in the L2B EE files e.g. vertical bin size, horizontal averaging lengths, laser energy, frequency of internal and atmospheric returns and calibration is not present (i.e. they contain just what is needed for the data assimilation i.e. wind observation, geolocation and error estimate; although this can be expanded if needed in OBSTAT). Archiving all this extra information would produce very large Aeolus ODBs.

In the longer term, once it is clear what operational monitoring for Aeolus is necessary, then OBSTAT will be routinely used for such plots. For example, if it turns out that monitoring against laser energy is critical then this information will be added to the ODB archive for use by OBSTAT.

6.2.1 Types of monitoring

The advanced monitoring will build upon the monitoring tools already developed at ECMWF as part of the author's L2B team work on the verification of the chain-of-processors output: E2S simulation derived L1B/L2B products e.g. see [RD14]. Also the tools developed for investigations into data assimilation case studies for conventional wind, GADS and 2-µm DWL data will be used.

Aeolus advanced monitoring tools for assessing L1B and L2B data:

- In the monitoring developed for investigating simulation studies, the usual reference is the E2S "truth" meteorological inputs. A recent feature added is that the reference can be switched to the ECMWF model background field as extracted into the auxiliary meteorological data product (AUX_MET_12 files), which by necessity will be available matching with every L2B product. Note that the AUX_MET background is not extracted at the exact geolocations of each L2B wind (as it would be in data assimilation), but as vertical profiles along the predicted orbit (or L1B wind mode, if available) ground-track. This means winds at 30 km altitude the ECMWF data be misplaced from the ground-track profiles by tan(37.5 degrees)*30=23 km, which is a source of error. There will also be along-track mismatch of up to 20 km possible (the magnitude of the error should be assessed at some point).
- The verification tools read the observation data from the L2B and L1B EE dataset (after conversion to ASCII) therefore giving the ability to monitor O-B departures against the plethora of instrument data available from the EE files.
- A disadvantage compared to ODB based monitoring is the lack of access to the ECMWF analysis fields i.e. no O-A monitoring will be available by this means.
- Plots comparing the statistics of L1B to L2B wind results can be produced. This has proven to be very useful for debugging purposes in E2S and CoP simulation cases e.g. making sure the L2B Mie winds are equivalent to or better than the L1B results. N.B. L1B Rayleigh winds have large biases due to the lack of RBC and Mie-cross talk correction.
- These advanced monitoring tool could be used by other NWP centres or ESA if they have access to AUX_MET_12 files (and to IDL software). ESA will provide the ECMWF produced AUX_MET files to the NWP community.

Aeolus advanced monitoring tools for assessing data assimilation results:

- ODB monitoring tools have been developed (independently of OBSTAT) that will be very useful in detailed investigations of the L2B observations and their assimilation. With these tools we can investigate the L2B wind O-B and O-A statistics, data assimilation rejection flags etc. in detail for case by case (or longer term averages). These tools are sufficiently flexible to also plot radiosonde, aircraft, wind profilers, AMVs and scatterometer data along-side Aeolus L2B wind results for comparison. **Effectively this can be thought as a L2C monitoring tool**. This will be particularly useful for case studies e.g. assessing in detail in what happened during a specific DA cycle where unusual behaviour is reported. These monitoring tool have proven very useful in detecting problems in the GADS aircraft data and with AMDAR (aircraft) data investigations over North America and has led to much better QC decisions before the data enter the assimilation. This tool is also written in IDL.

6.3 Examples of Aeolus advanced monitoring plots

6.3.1 Verification of L1B and L2B data

In this section we present some examples of the advanced monitoring plots (listed in section 5.2) generated with the Aeolus advanced monitoring tools for assessing L1B and L2B data. In particular this is focussed on monitoring L1B and L2B results with the reference dataset provided by the

AUX_MET_12 file (i.e. the ECMWF model). These pre-launch examples were from the chain-of-processors (CoP) run with E2S v3.05, L1Bp v6.04 and L2Bp v2.20. The E2S inputs were derived from a realistic AUX_MET_12 example file which contained ECMWF model profiles at T511 L137 resolution; one profile was extracted every 50 km. The E2S orbit was matched to the AUX_MET_12 predicted orbit, therefore the AUX_MET_12 EE file can be used as the geophysical reference for the advanced monitoring plots shown as follows. The figure captions refer to the **type of plot** as described in Table 2 of Section 5.2. The magnitudes of the mean and random errors shown are not important here; just the style of plots.

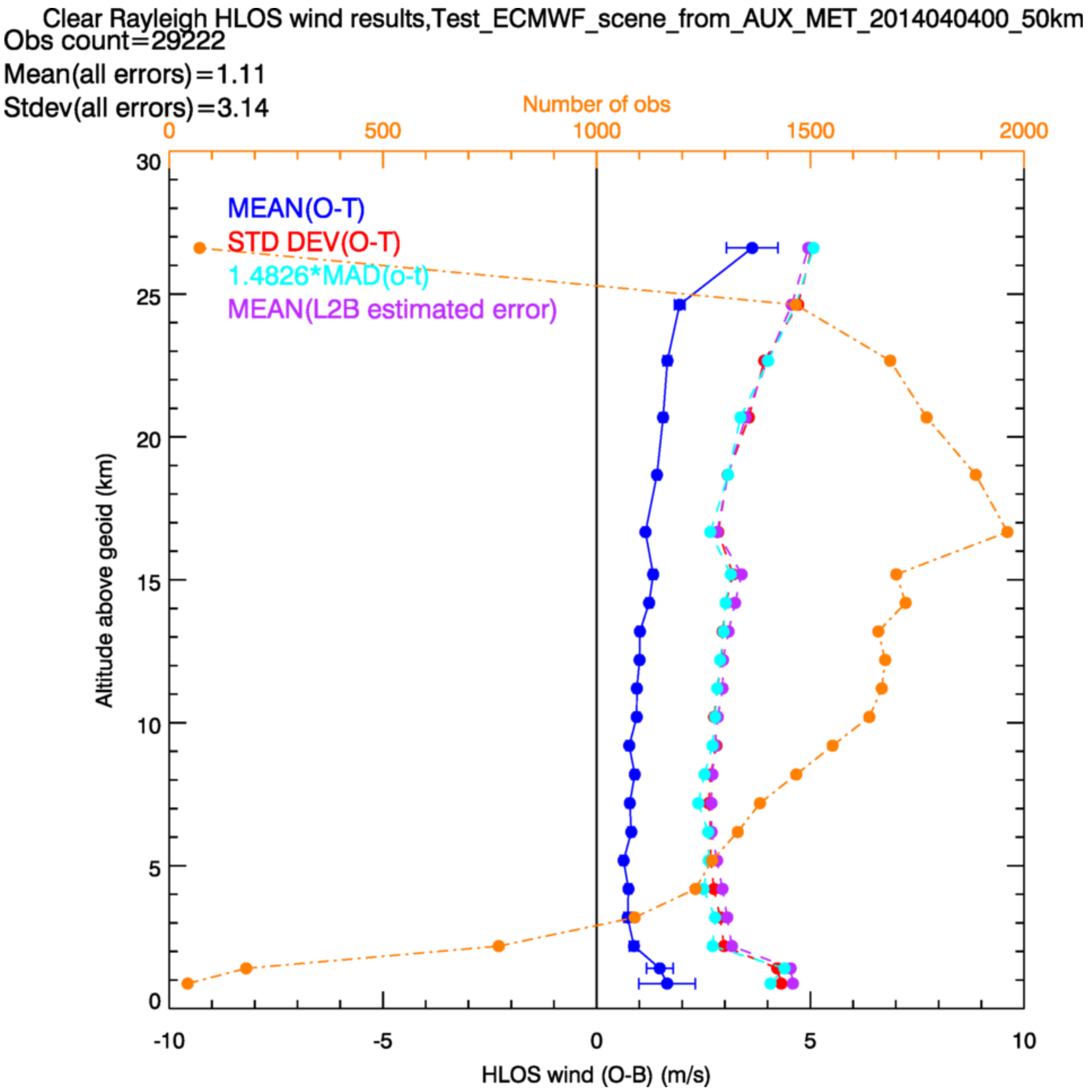


Figure 23. Example of plot type 1. L2B Rayleigh-clear HLOS wind O-B versus altitude. QC was applied: > 5 m/s estimated L2B wind error are rejected. Note the positive bias is thought to be an issue an imperfect calibration file used in the CoP.

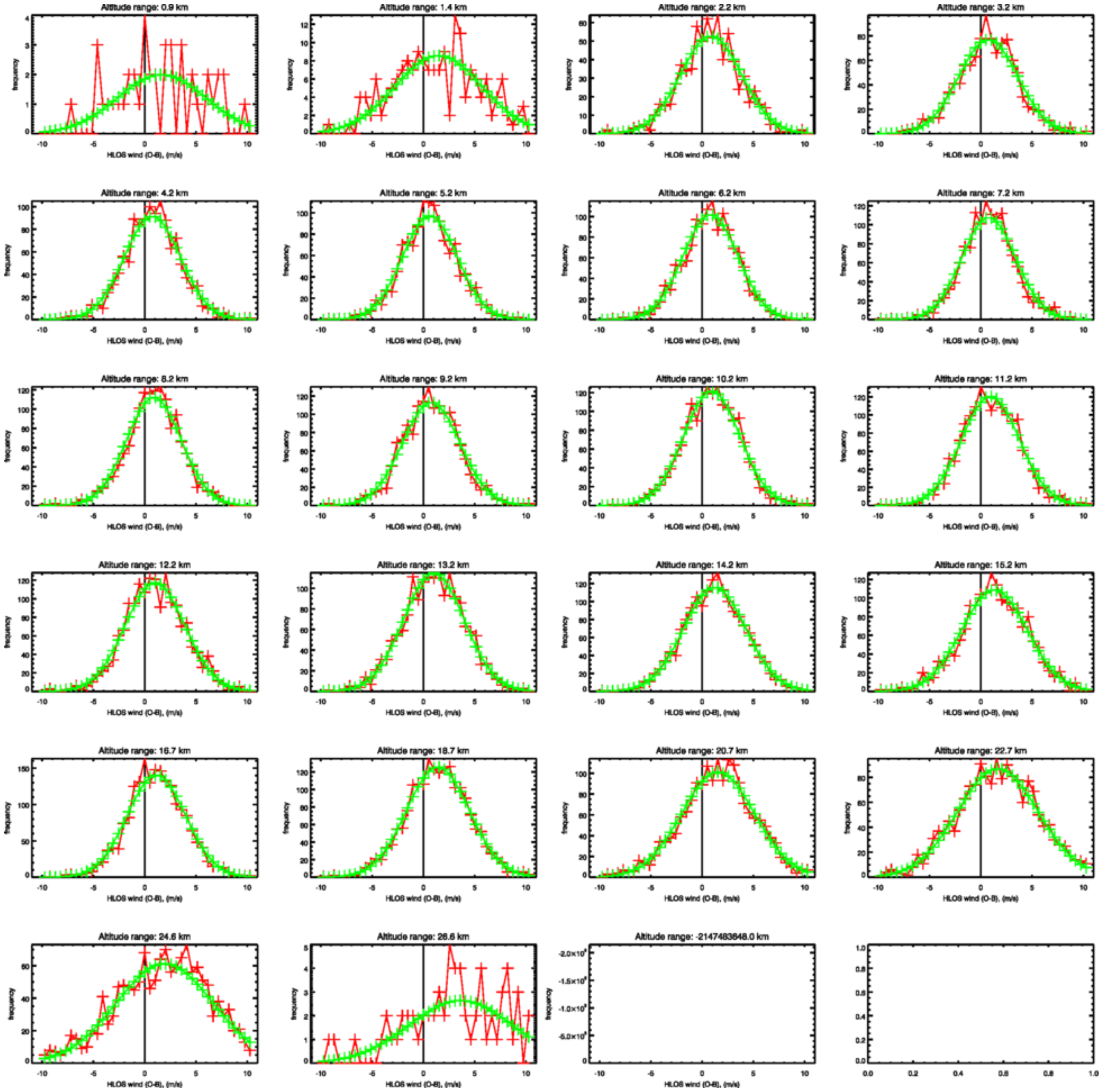


Figure 24. Example of plot type 1, but information displayed in different way. Histograms of L2B Rayleigh-clear (O-B) for various altitude bins. Red= O-B distribution, Green=Gaussian fit with same mean and standard deviation.

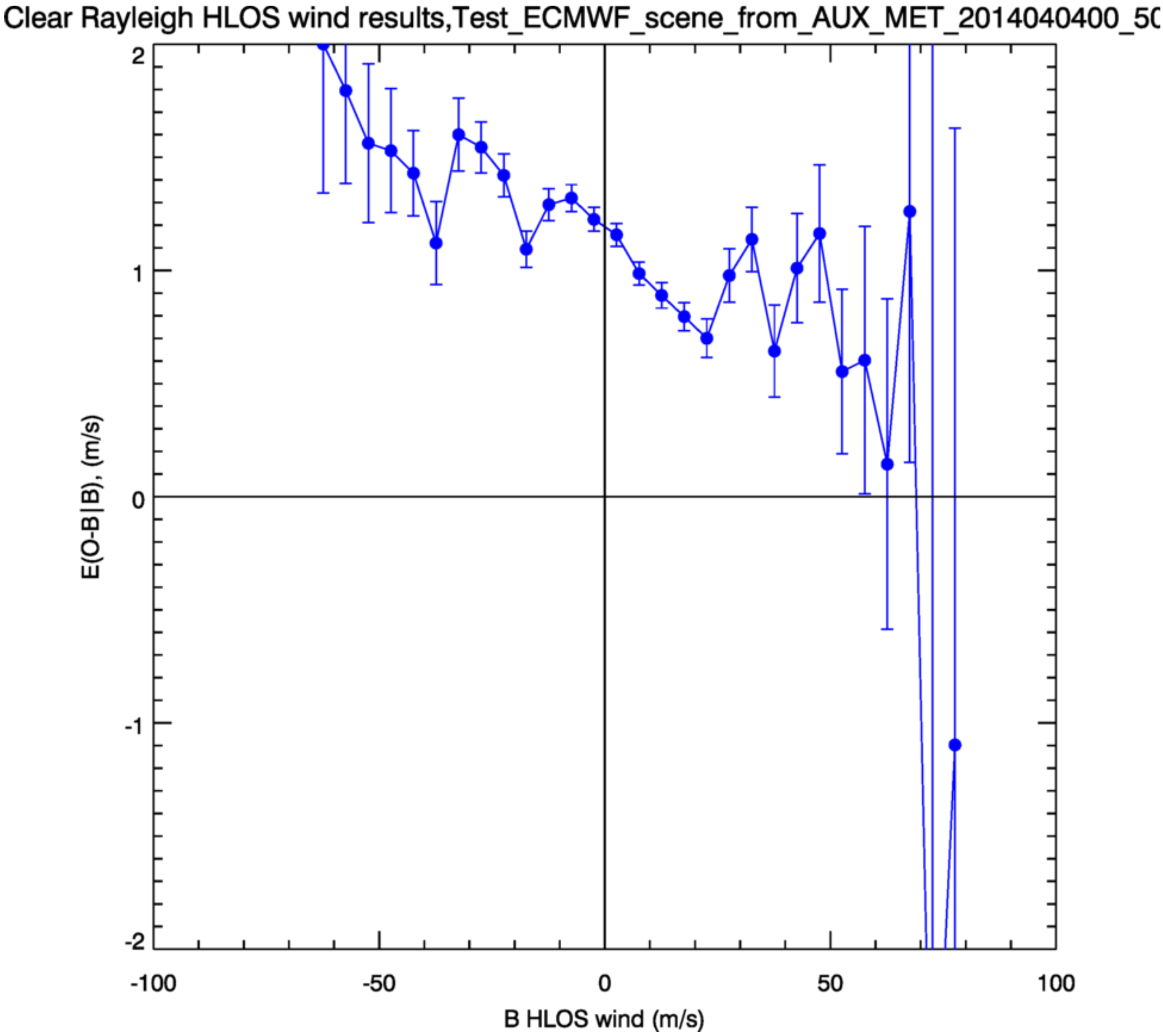


Figure 25. Example of plot type 2. For Rayleigh-clear HLOS wind observations, showing the dependence of mean O-B on B HLOS, which may diagnose slope errors.

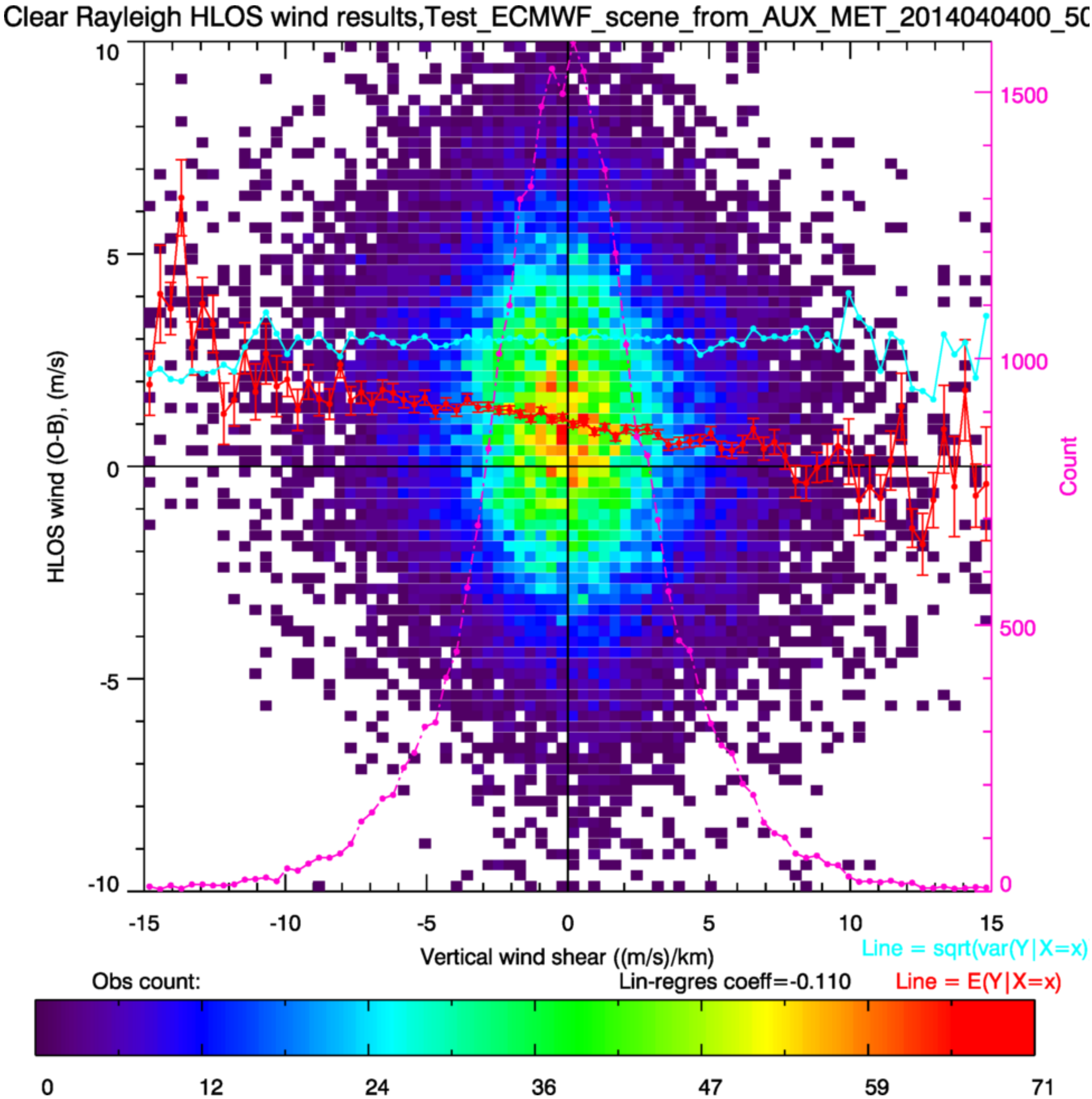


Figure 26. Example plot type 3. How the statistics of L2B Rayleigh-clear HLOS wind O-B depends on the "estimated" vertical wind shear (derived from background forecast). The coloured boxes are the density of the distribution conditioned on the x axis. This density plot subroutine is used for many of the plots, in trying to see if the O-B distribution depends upon a particular variable. There does appear to be a correlation of the mean error with the vertical wind shear.

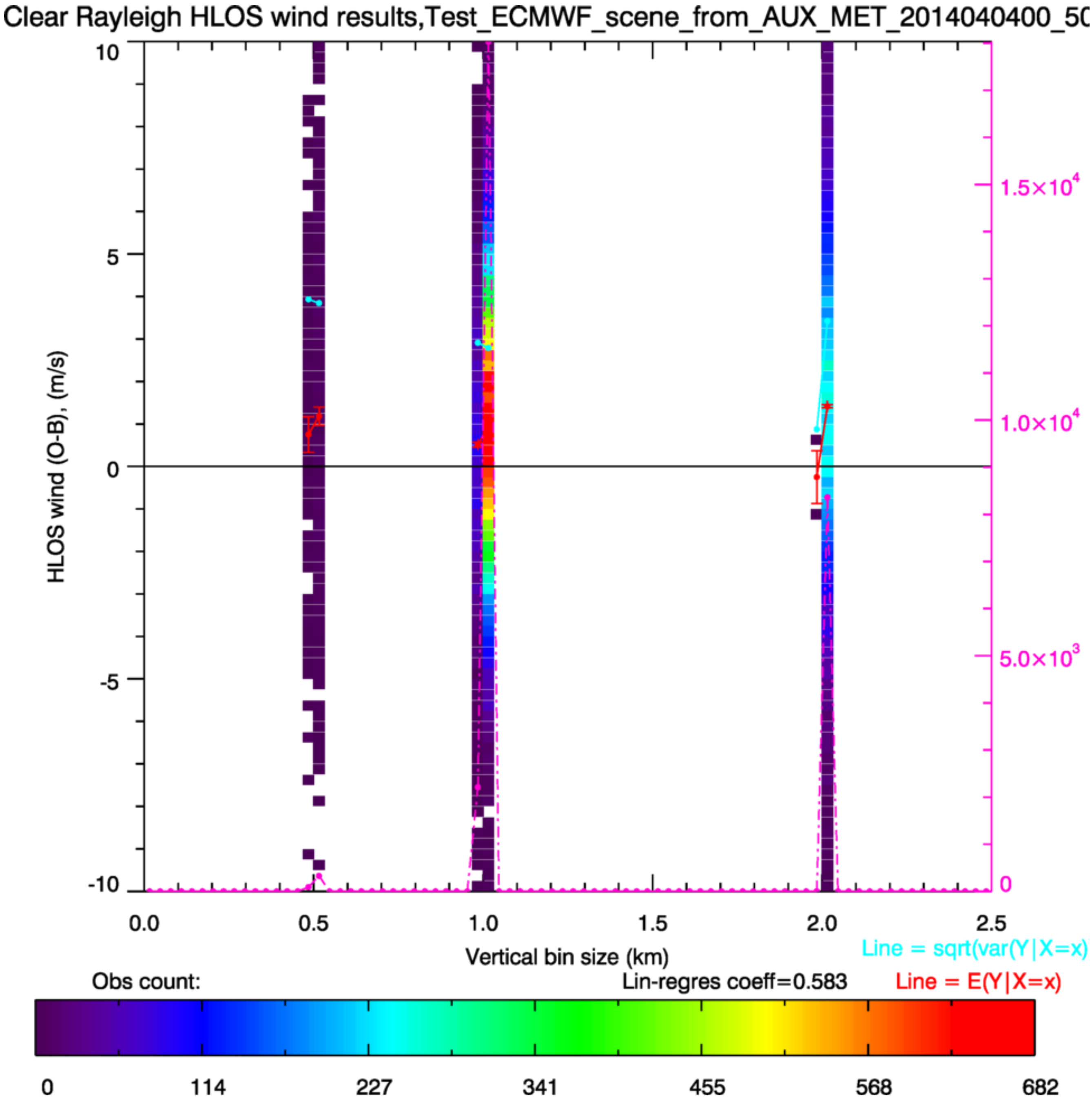


Figure 27. Example of plot type 4. Shows how the O-B distribution varies with vertical bin-size. ***This plot could be improved since not very clear.***

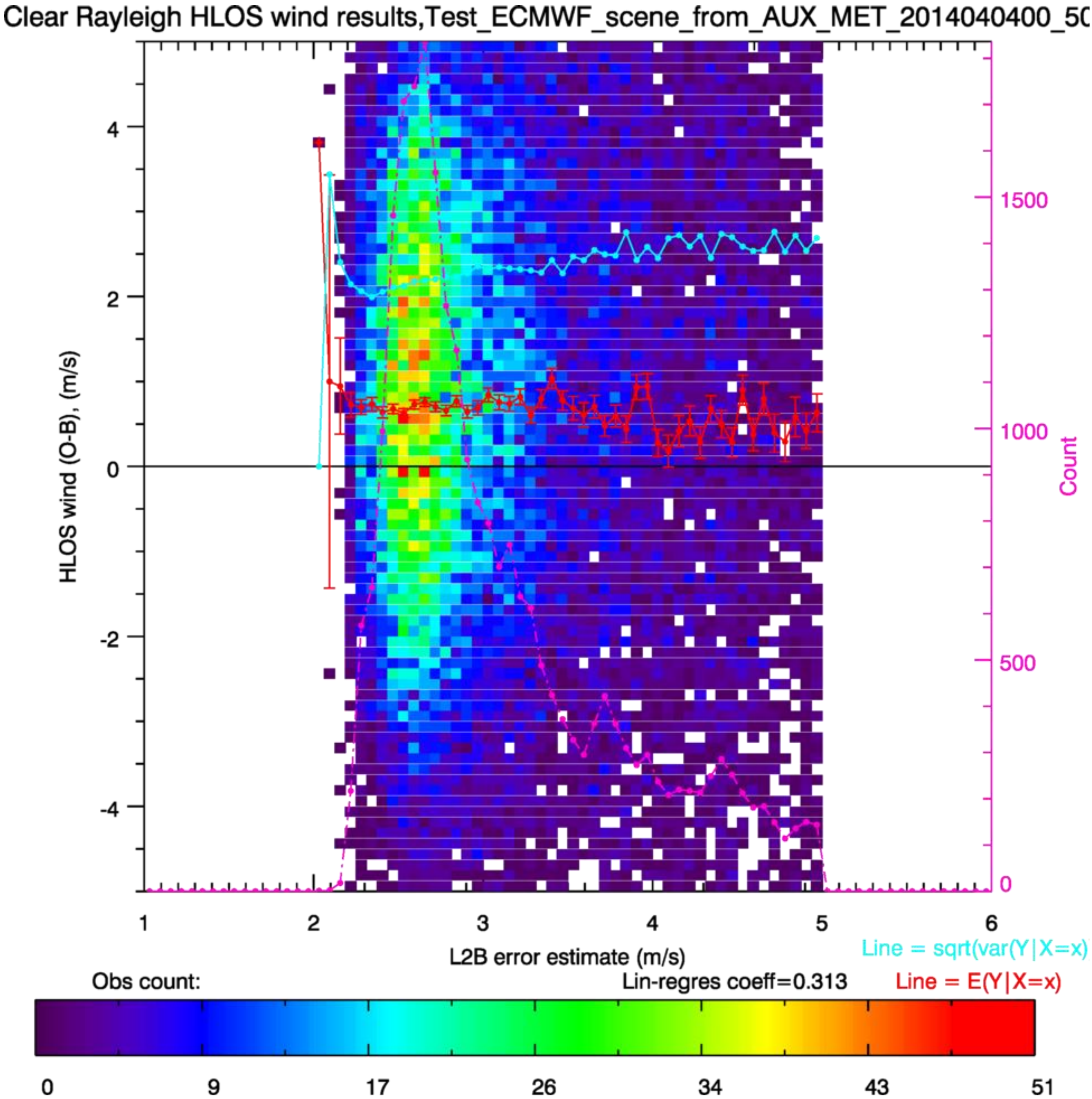


Figure 28. Example of plot type 5. How the distribution of L2B Rayleigh-clear O-B depend on the L2B estimated HLOS wind standard error. The settings of the monitoring tool restricted the maximum L2B Rayleigh estimated error to 5 m/s. The minimum estimated error was around 2 m/s.

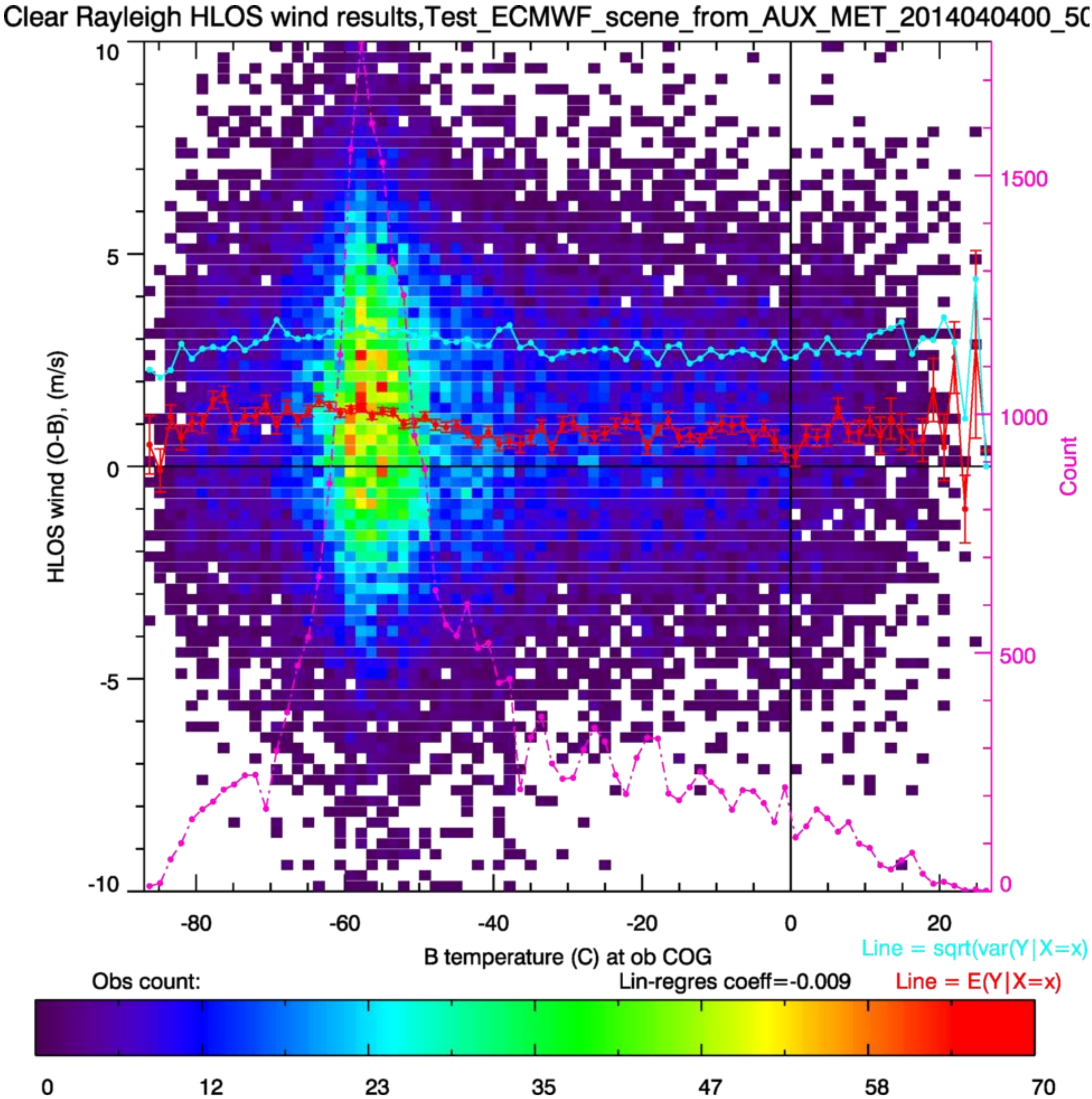


Figure 29. Example plot type 6. Plot for determining if HLOS wind O-B depends on atmospheric temperature - apparently not in this case.

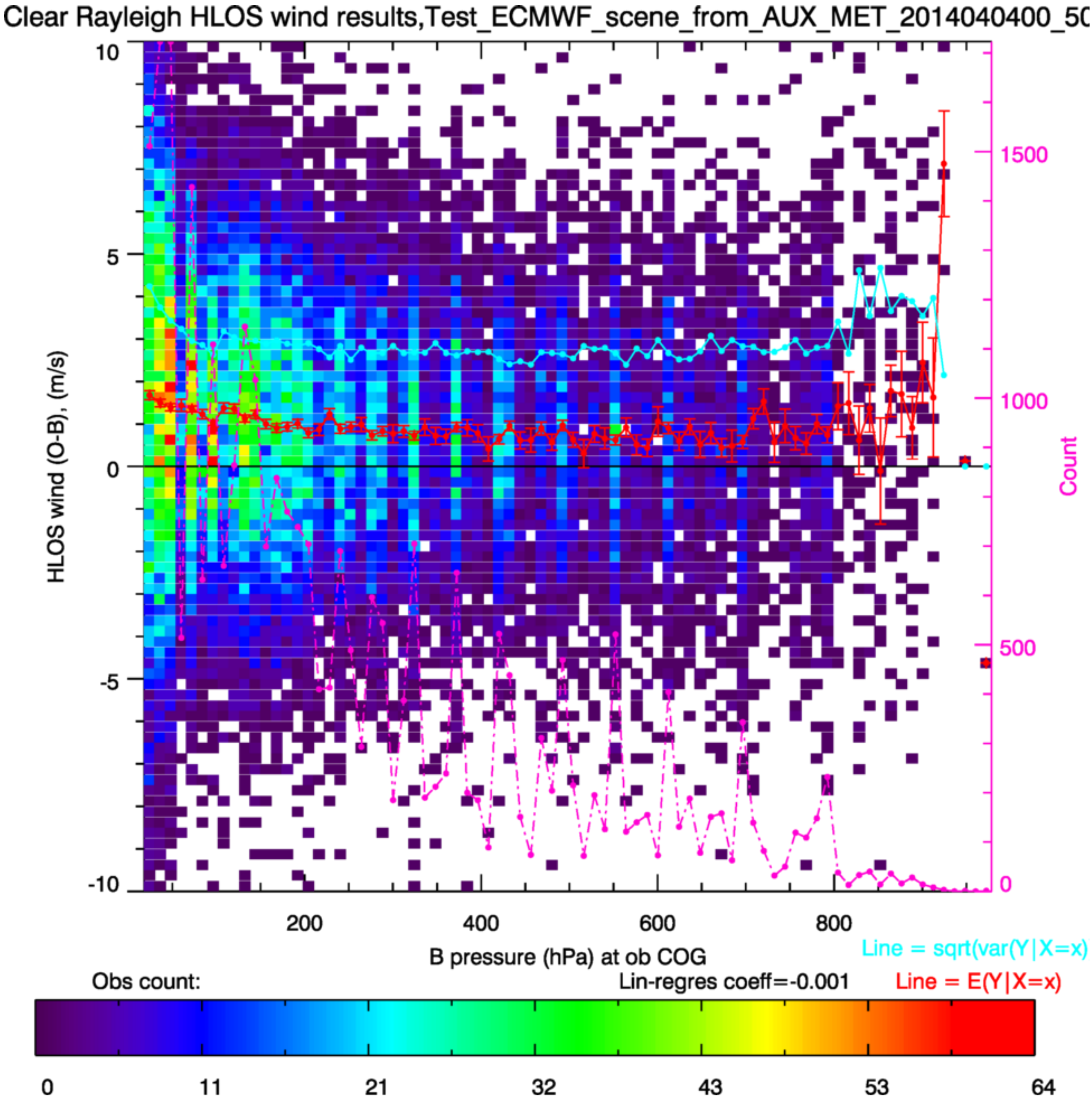


Figure 30. Example plot type 7. Plot for determining if HLOS wind O-B depends on atmospheric pressure - the bias increased for small pressure values - but this does not mean that the error depends upon pressure causally, just that the bias increases for higher range bins (probably lack of DCMZ correction in this CoP).

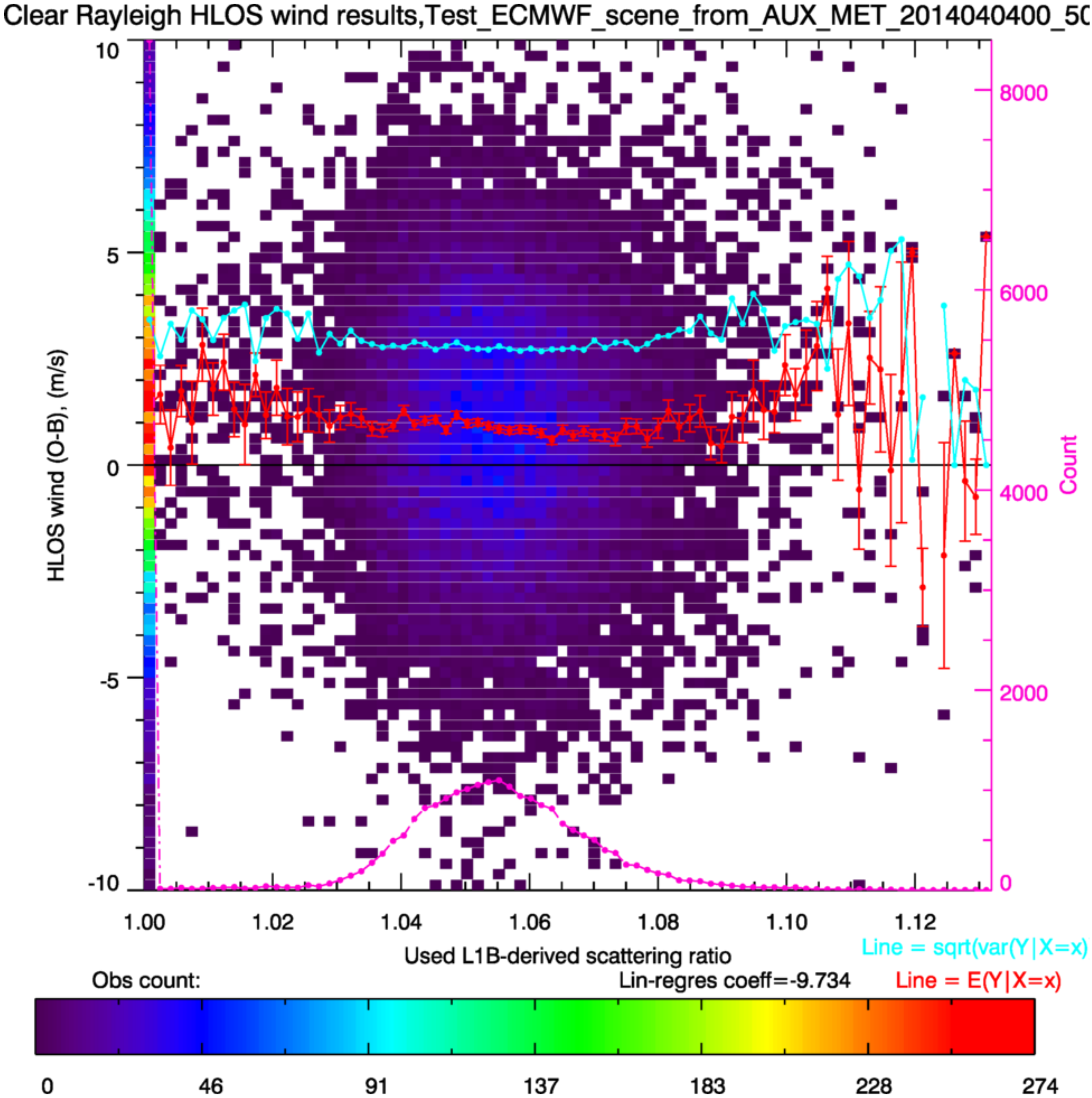


Figure 31. Example plot type 8. Does the HLOS wind O-B depend on the applied SR estimate (Rayleigh winds only)? Note the large number of points with SR=1, is due to the L2Bp defaulting to 1 when no Mie range-bins are available.

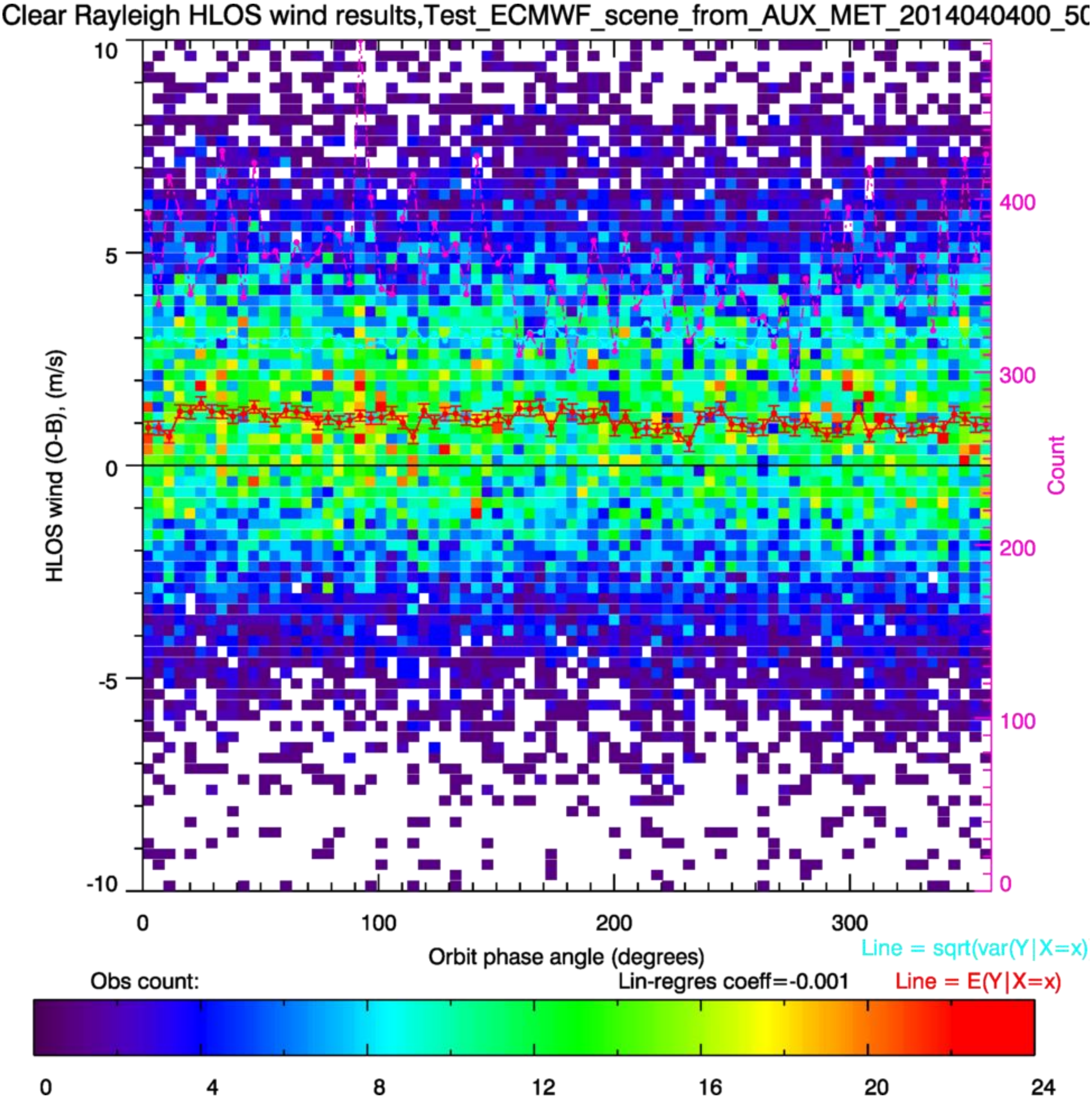


Figure 32. Example plot type 9. Does the O-B depend on orbit argument of latitude? Not in this case, because there was no such error simulated in E2S. For the real mission we may see a harmonic function appear in such statistics.

The following plots are examples of some of the lidar cross-sectional plots (i.e. plot type 19, see Table 2) that are produced with the Aeolus advanced monitoring.

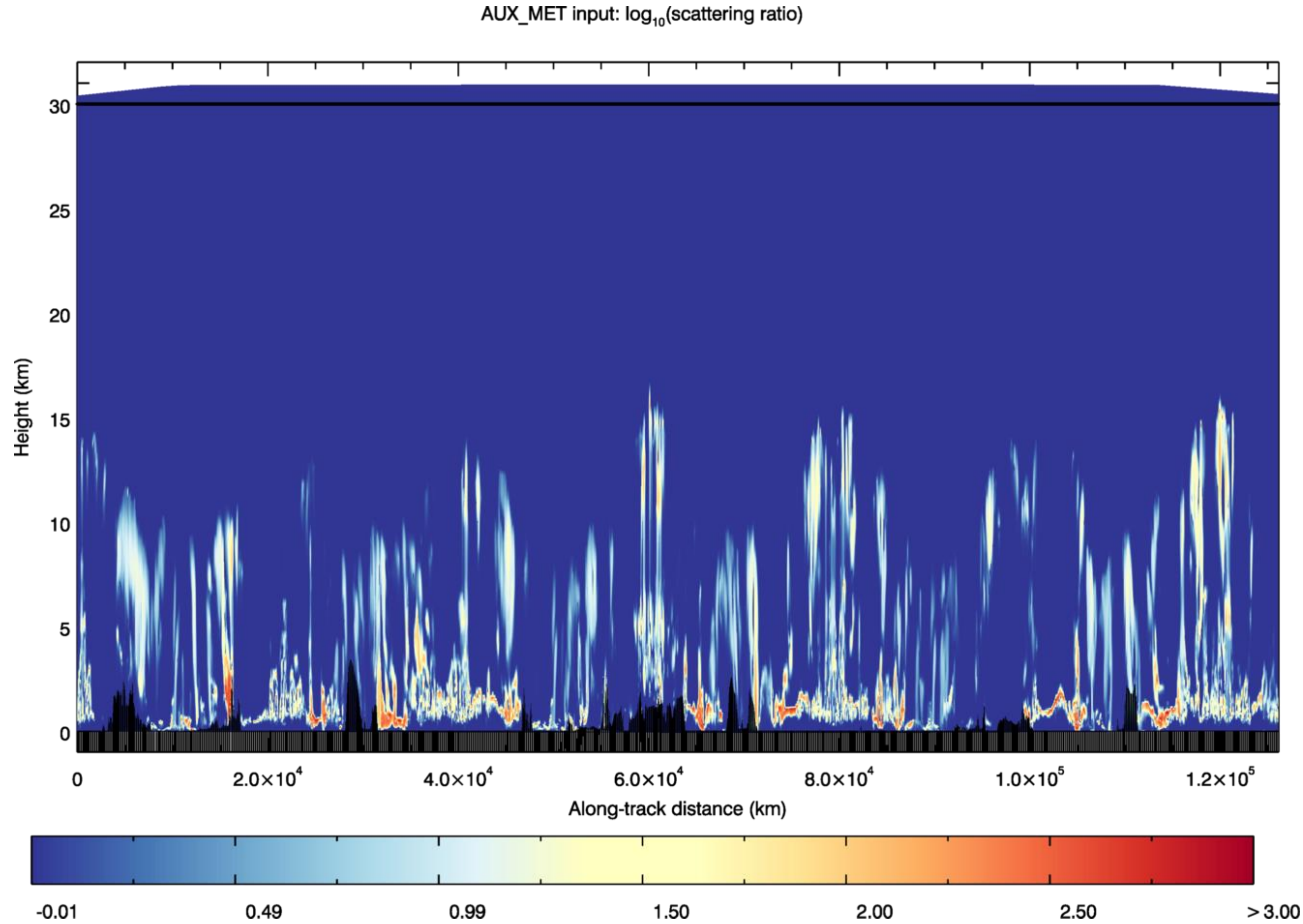


Figure 33. Along-track versus altitude view of the reference input (i.e. AUX_MET input, background forecast) *derived* estimate of the scattering ratio (cloud particles only, aerosol unavailable in high resolution ECMWF forecasts). Note SR is not available in the AUX_MET, but it is calculated from the T, p and cloud information using a parameterisation.

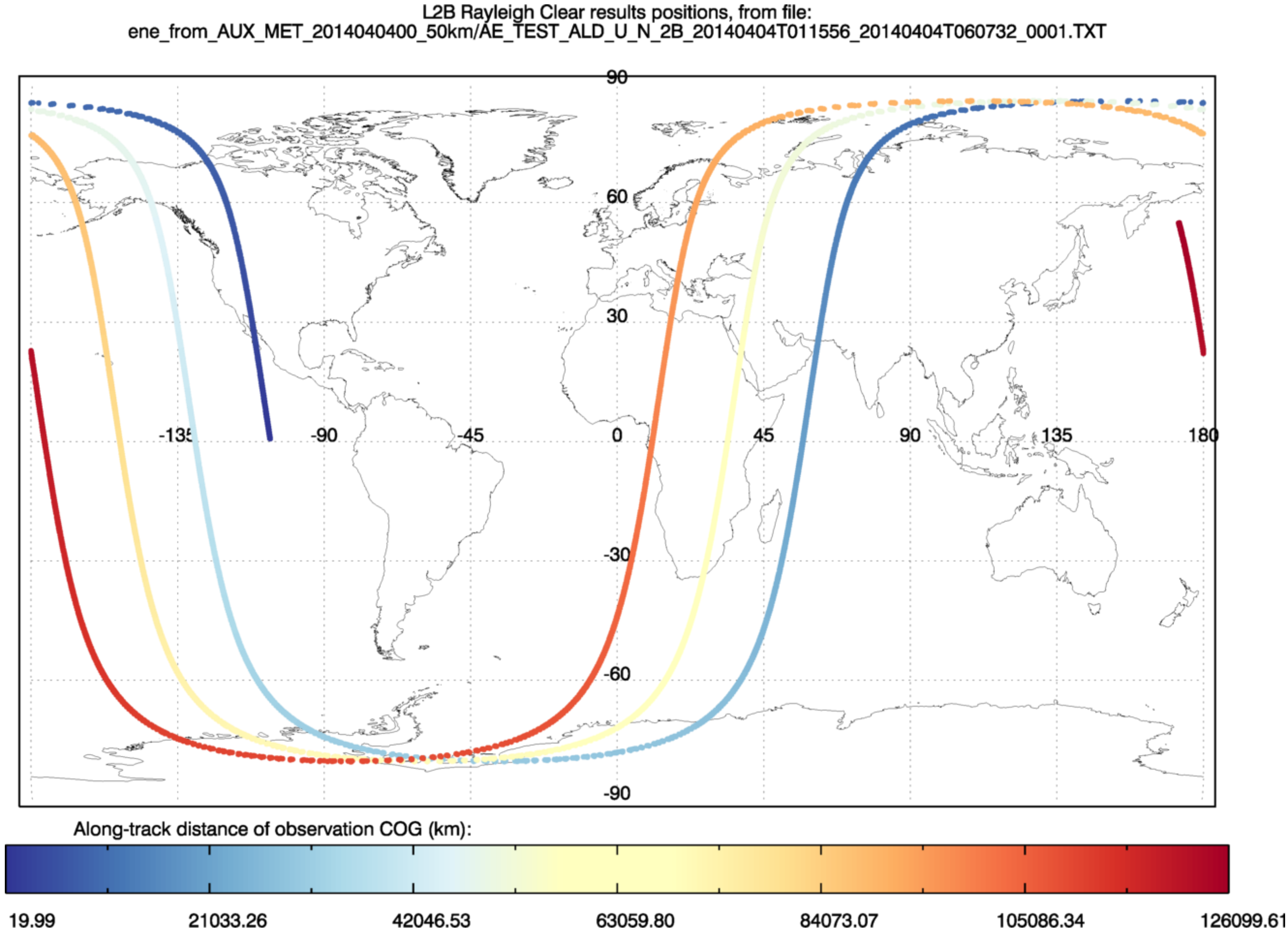


Figure 34. Map of the observation locations with along-track distance which is useful as a reference for the lidar cross-sectional plots.

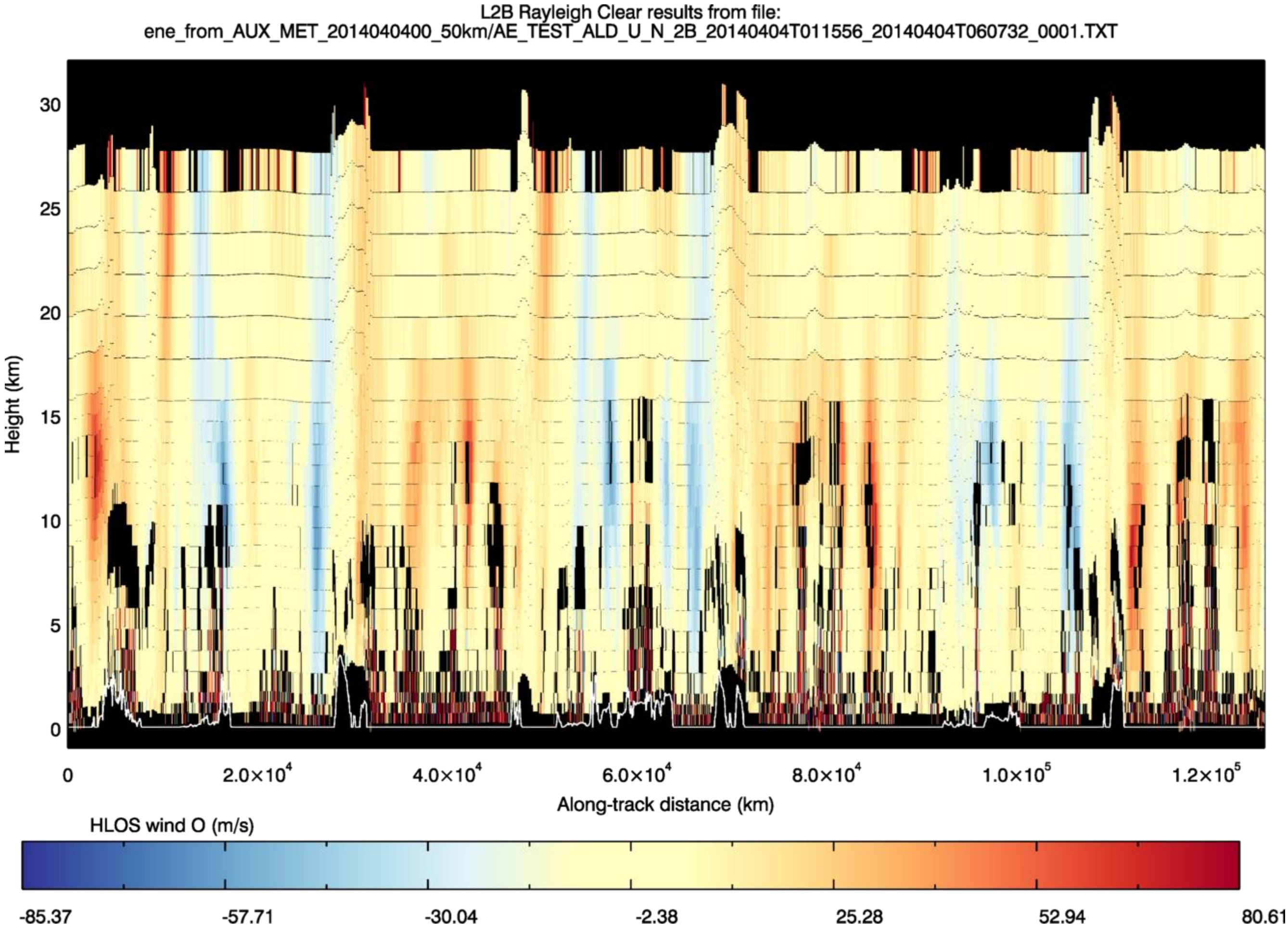


Figure 35. L2B Rayleigh-clear HLOS wind results along a ~3 orbit section. Colour scale is the HLOS wind observation value (m/s). The black background indicates an absence of wind results. The black areas around 10 km altitude are where there were no clear measurements according to the L2Bp classification algorithm.

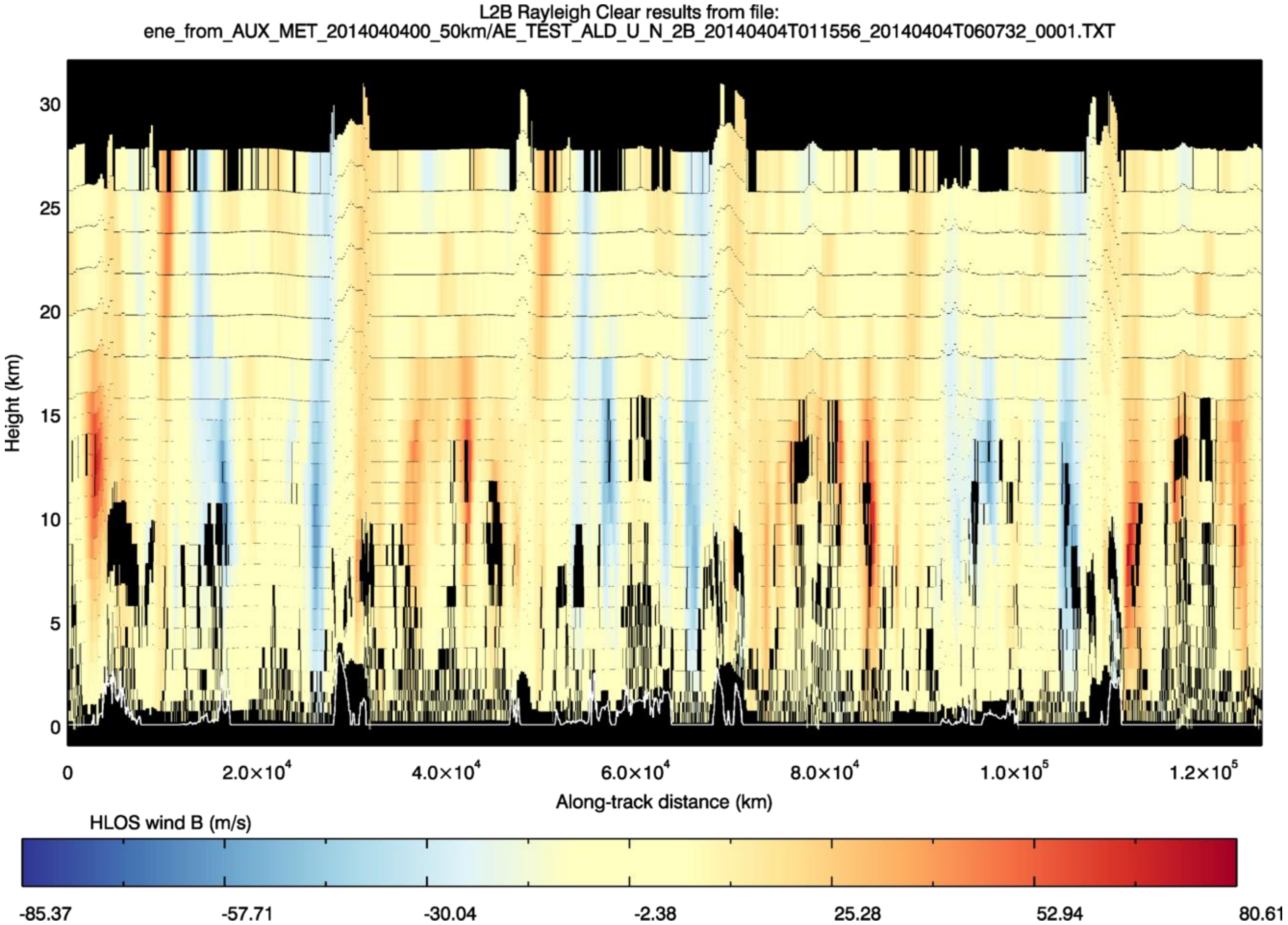


Figure 36. ECMWF AUX_MET (background forecast) derived HLOS wind results at L2B Rayleigh-clear result locations. That is, the B in O-B. This should be compared to the O in Figure 35.

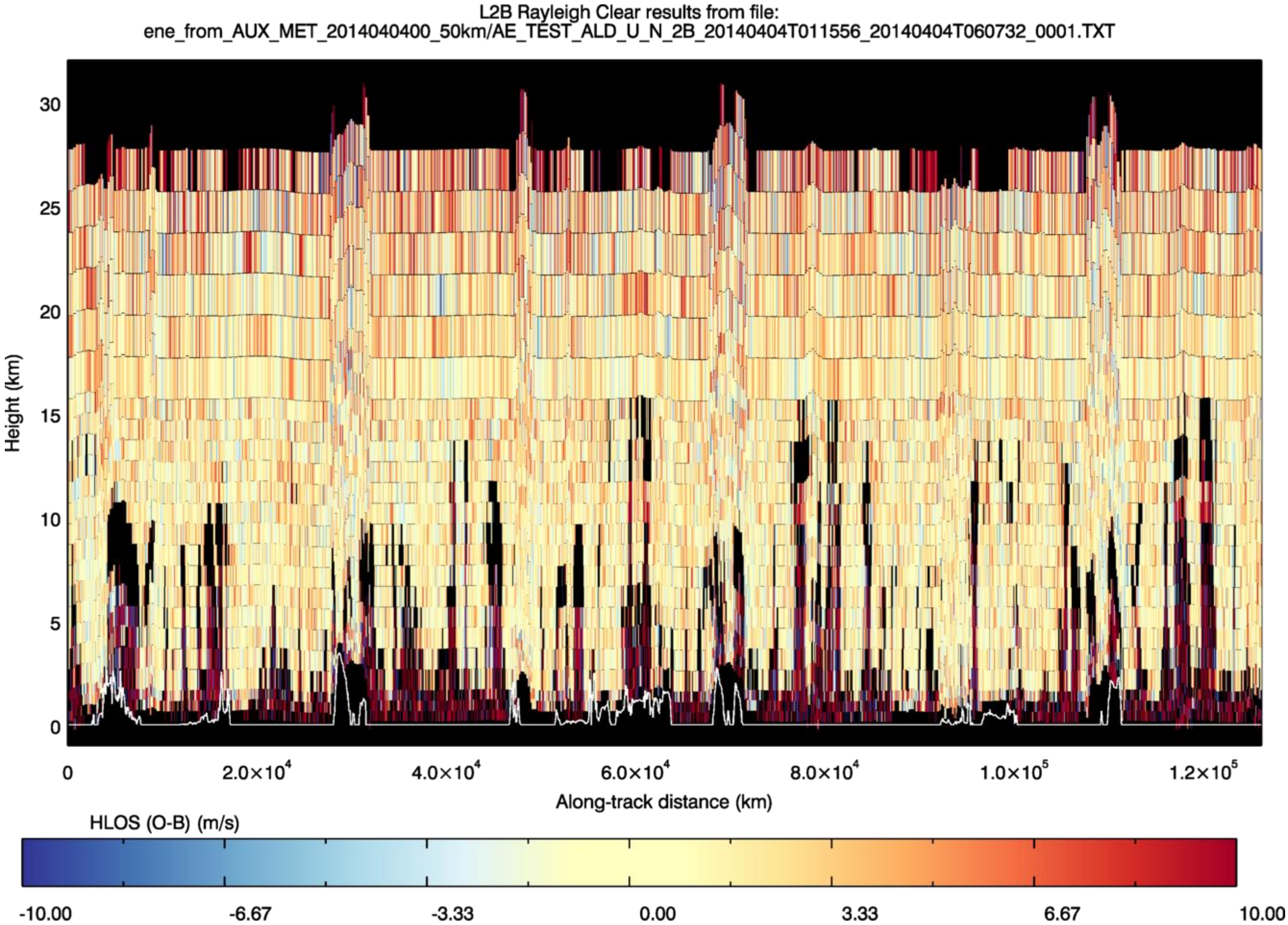


Figure 37. L2B Rayleigh-clear HLOS wind O-B results (i.e. difference of previous two plots). This is what we make statistics of in the earlier plots.

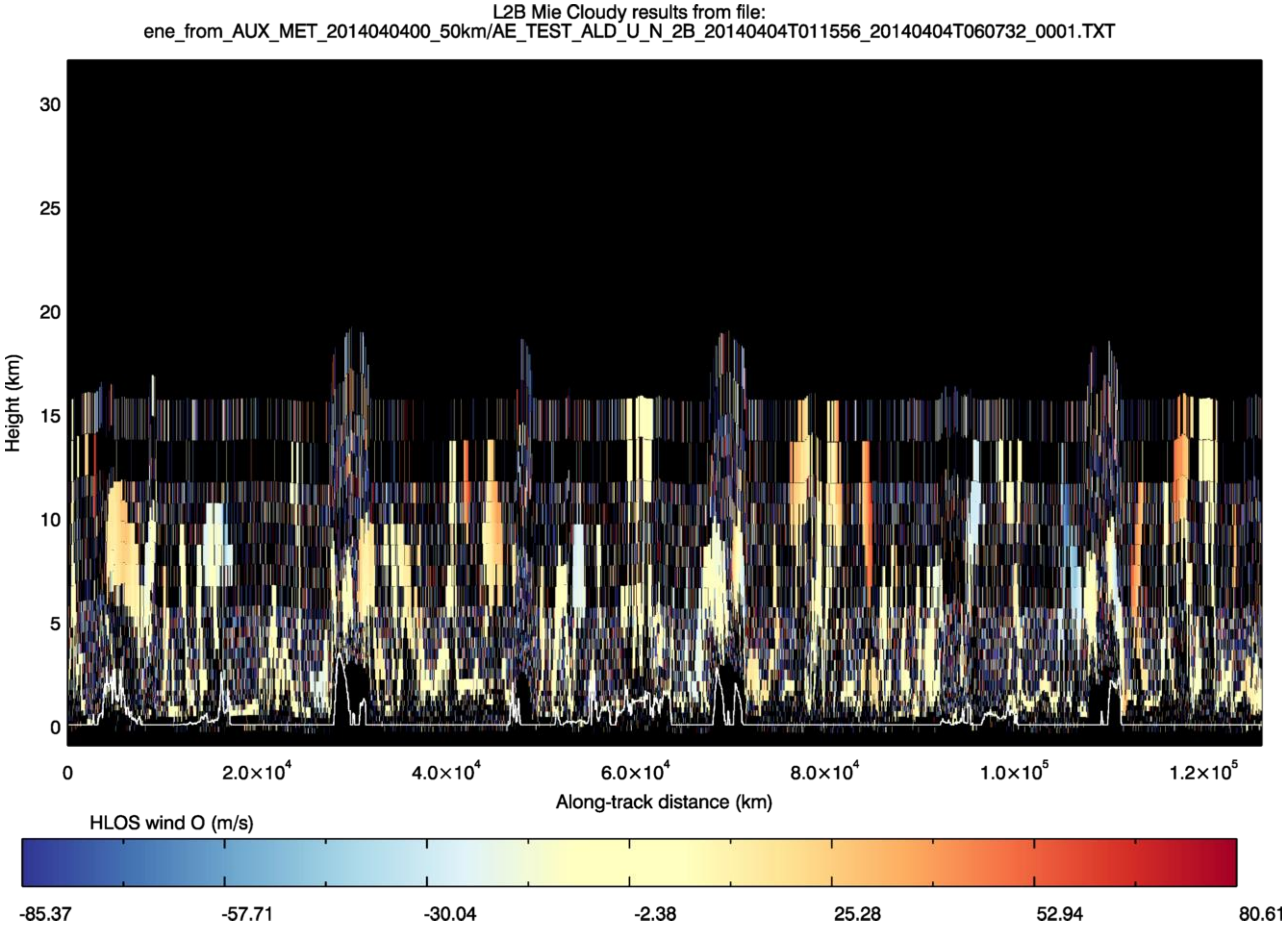
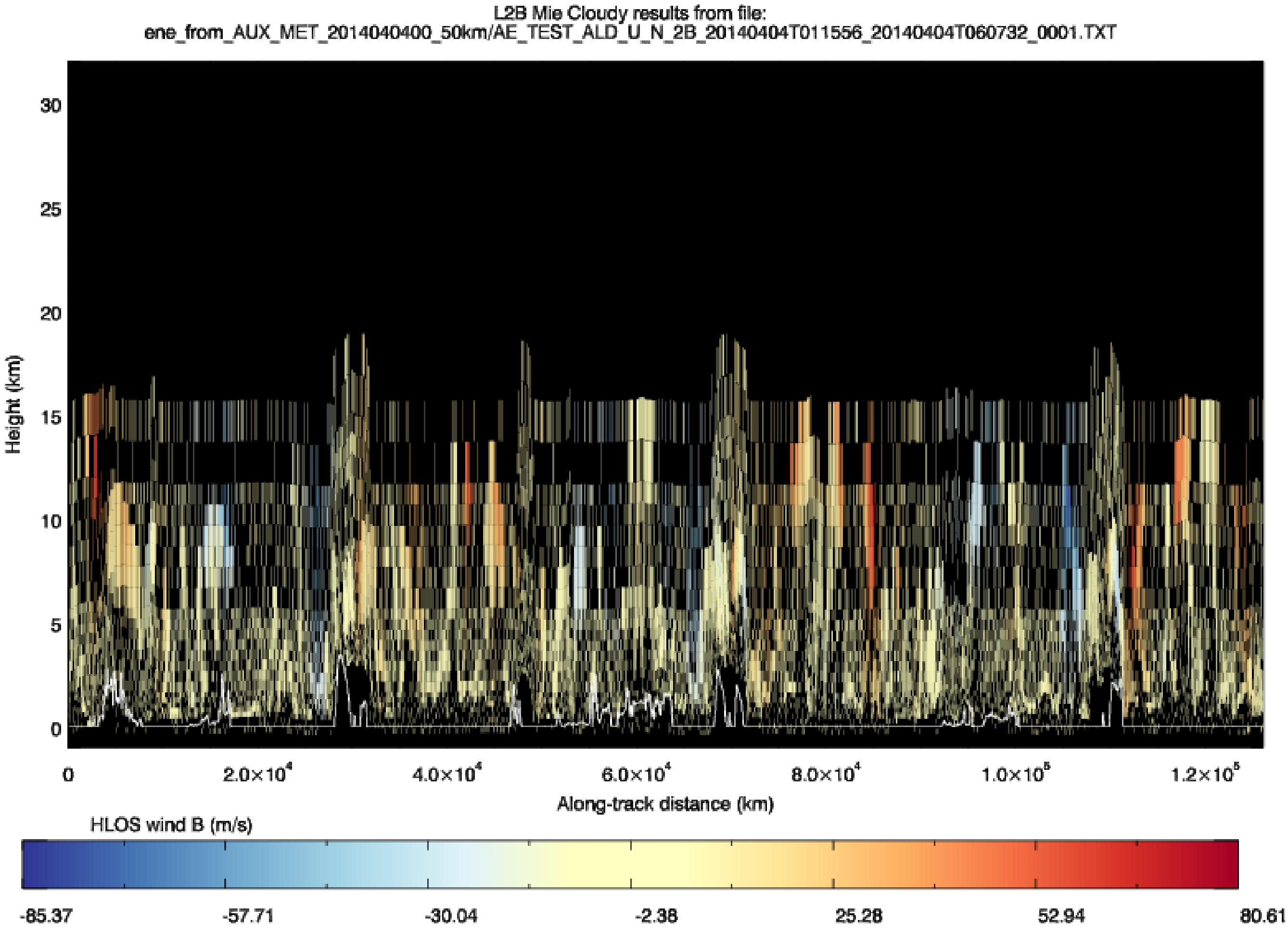


Figure 38. L2B Mie-cloudy HLOS wind results. Note no QC applied here, hence the large number of noisy results, where cloud was absent - the noise in the SR propagates to the classification algorithm, therefore many measurements bins which are actually clear are detected with SR> cloudy-threshold.



L2B Mie Cloudy results from file:
ene_from_AUX_MET_2014040400_50km/AE_TEST_ALD_U_N_2B_20140404T011556_20140404T060732_0001.TXT
Height (km)
30
25
20
15
10
5
0
0
2.0×10^4
4.0×10^4
6.0×10^4
8.0×10^4
1.0×10^5
1.2×10^5
Along-track distance (km)
HLOS wind B (m/s)
-85.37
-57.71
-30.04
-2.38
25.28
52.94
80.61

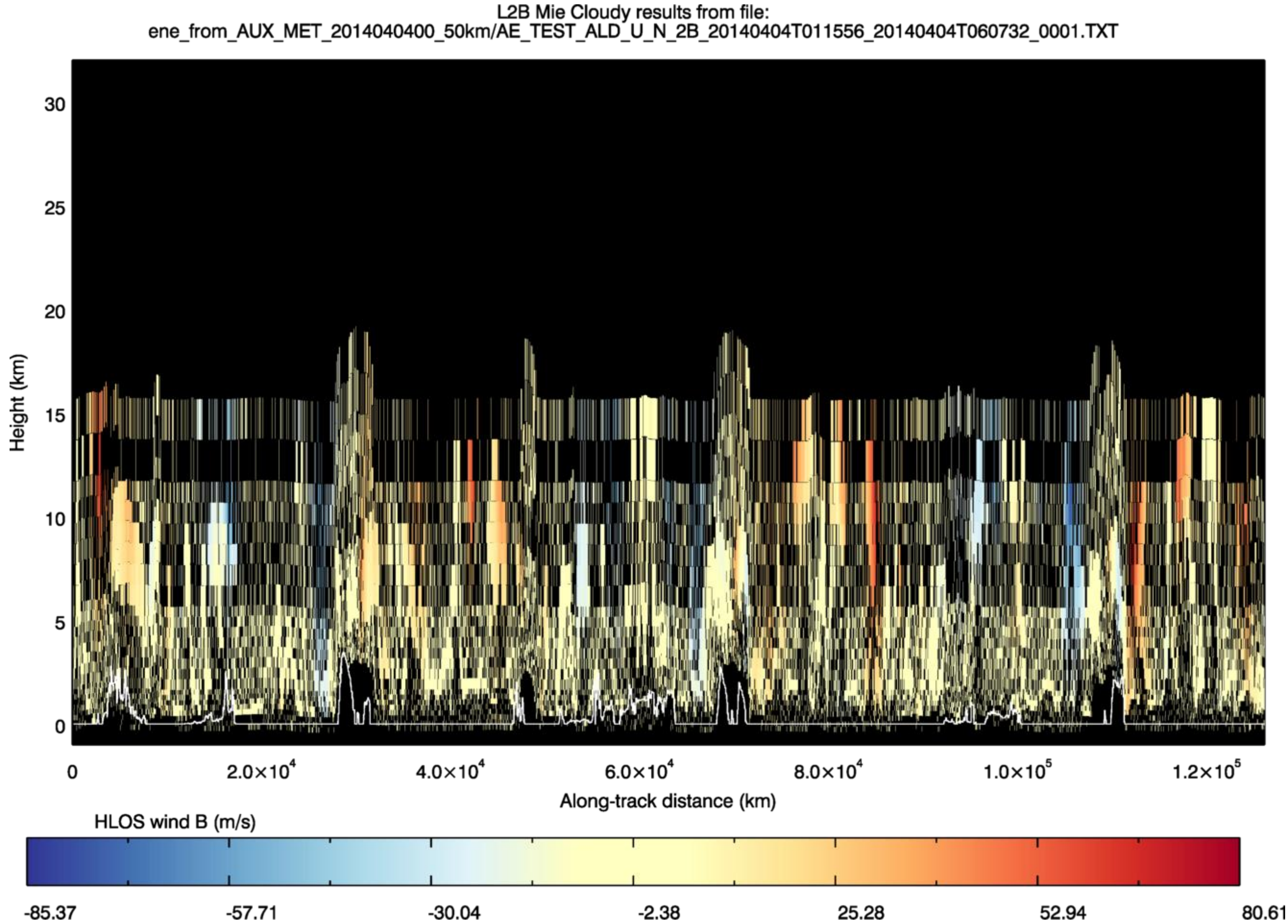


Figure 39. ECMWF AUX_MET (background forecast) derived HLOS wind results at L2B Mie-cloudy result locations.

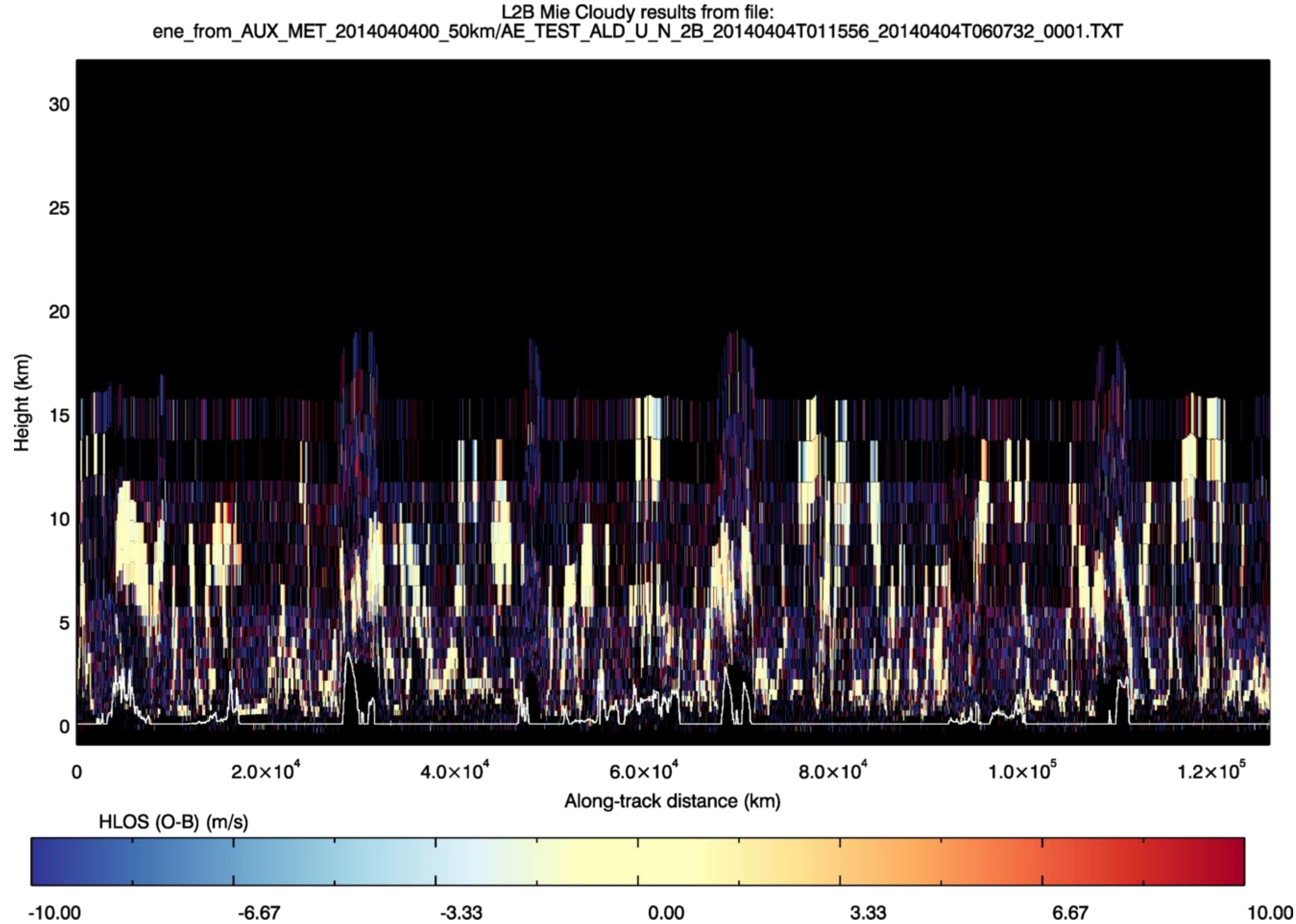


Figure 40. L2B Mie-cloudy HLOS wind O-B results. Note no QC applied here (but it can easily be done).

6.3.2 Aeolus advanced monitoring: verification of data assimilation

The following example plots have been tested (in 2015) on aircraft and radiosonde observations of wind, but are flexible to work on many data types (hence can easily be applied to Aeolus L2B winds). Here are some examples of the type of plots that can be produced:

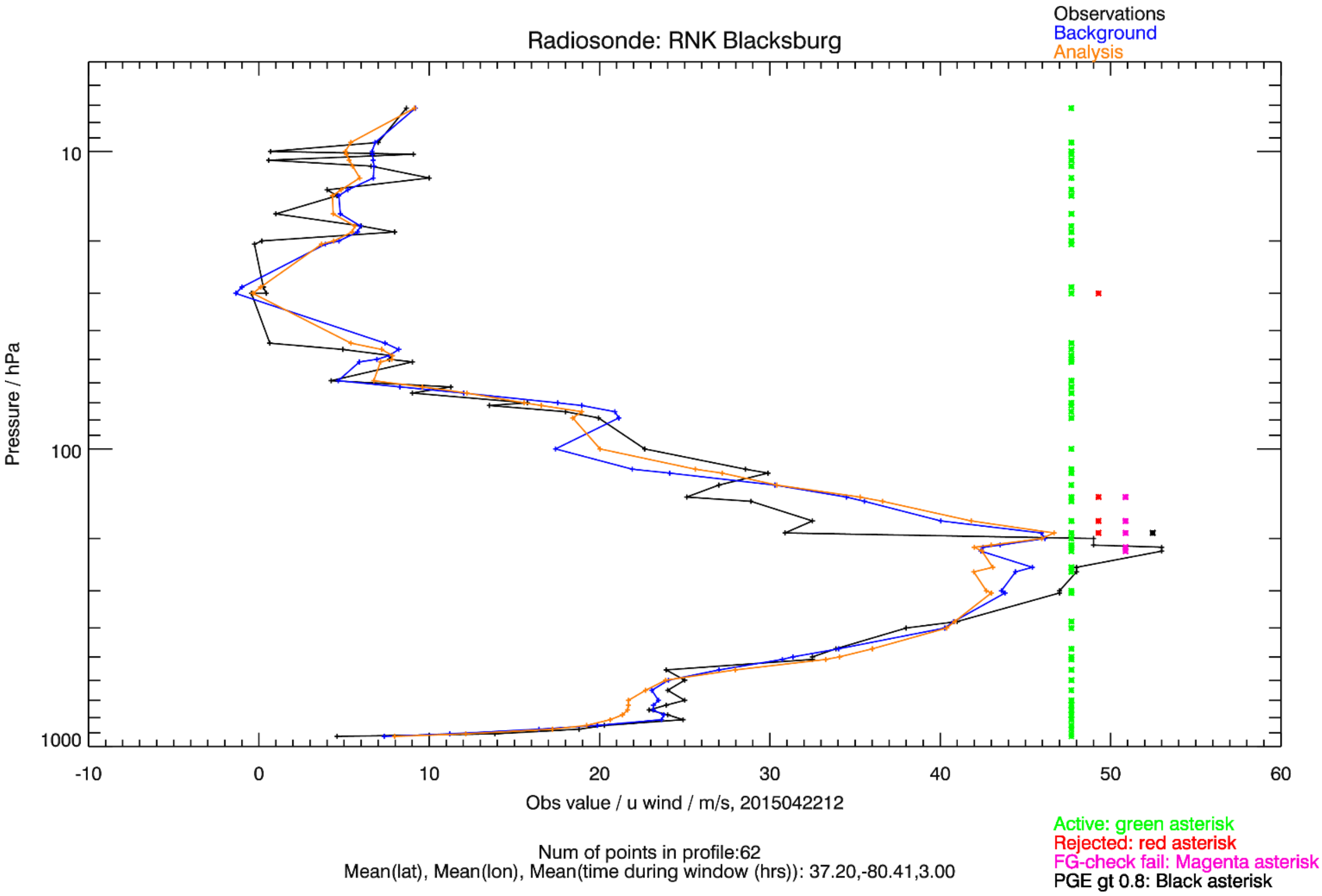


Figure 41. A vertical profile of u-component wind from a radiosonde (Observations), and the corresponding Background and Analysis equivalents. Also some DA QC information is plotted.

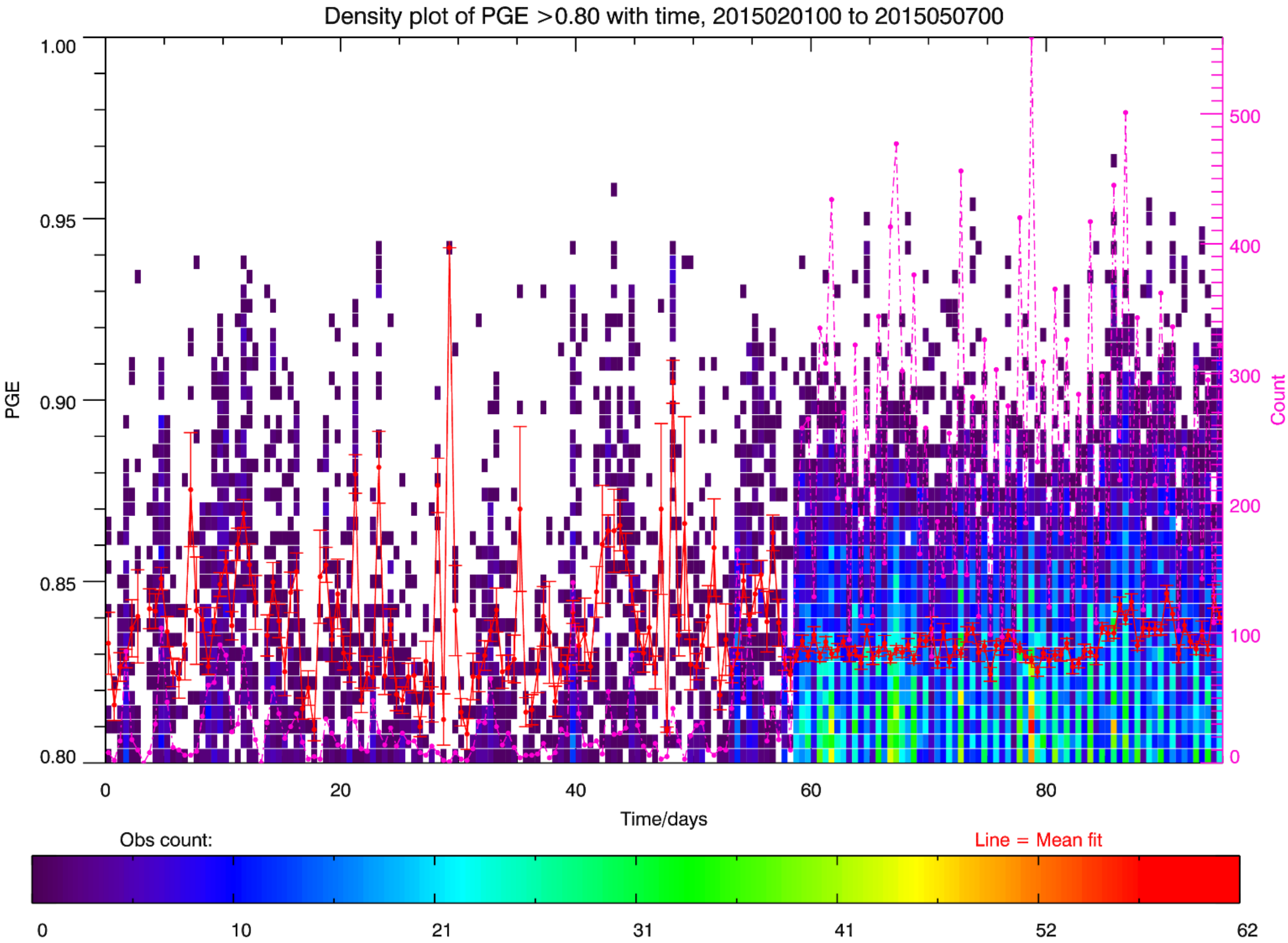


Figure 42. Plot of statistics of probability of gross error values (PGE) versus time. PGE is a variable that is output from the data assimilation indicating how likely an observation is to be a gross error in the variational quality control. Only PGE that are greater than 0.8 are plotted here, since the aim was to detect a change in the number of gross errors. This is for aircraft wind observations over North America. Note something changed in the data near day 59 of the period. Such a plot may be useful for detecting changes in Aeolus observation quality.

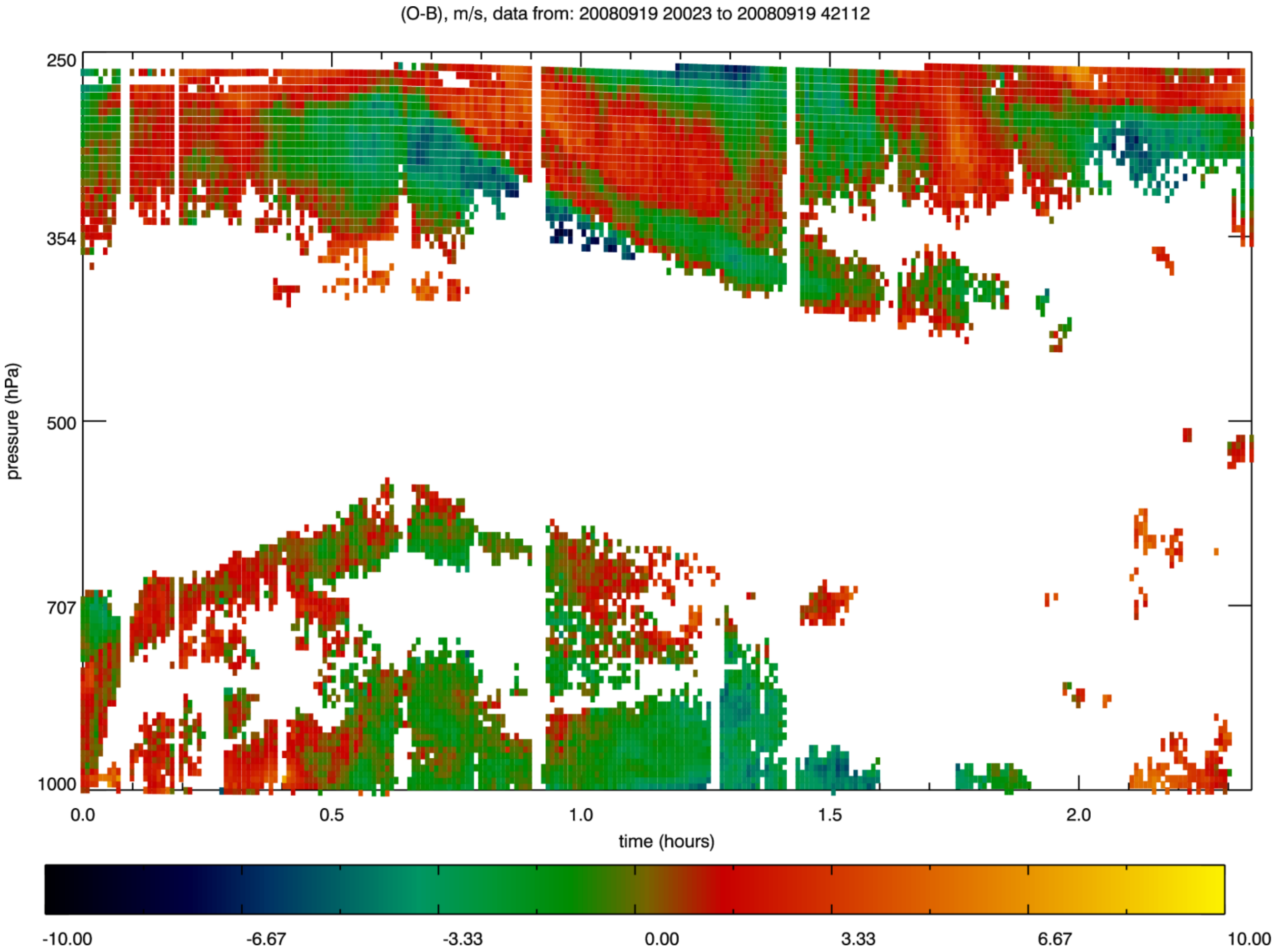


Figure 43. Example lidar cross-section of O-B values for real DWL u-component wind and the ECMWF model from a DLR 2-micron DWL campaign. Some investigations were performed with the assimilation of the DWL u-component winds as HLOS winds using the Aeolus observation operator.

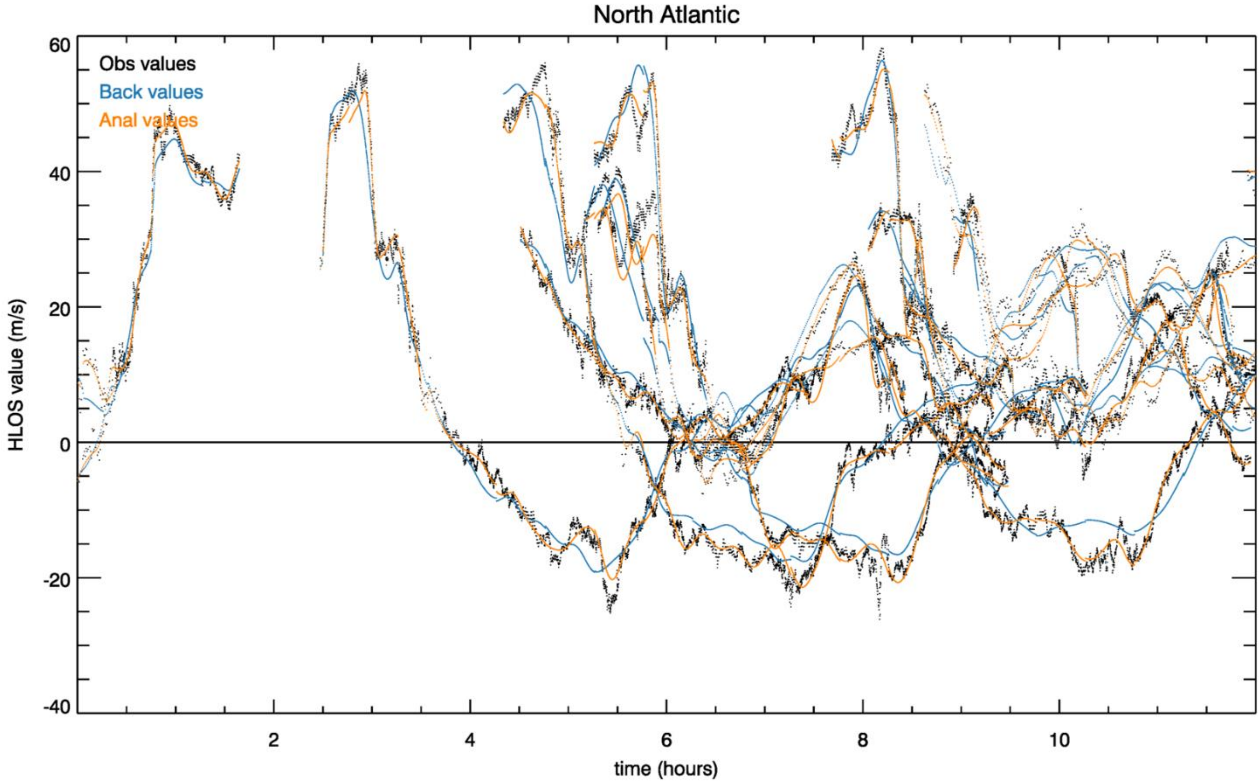


Figure 44. O, B and A values for GADS aircraft (high sampled winds) u-component wind observations in the North Atlantic during a 12 hours data assimilation window. GADS are long-haul British Airways flight data. This is an interesting example of how the atmospheric variability compares to the ECMWF model (T1279) - see also Figure 2**.**

Note that Figure 4 and Figure 9 also show examples of the plots that are produced from this monitoring tool.

6.3.3 Aeolus advanced monitoring: L1B measurement level data

Some plotting of L1B measurement level data (and L2B QC decisions for such data) are also possible; here are some examples.

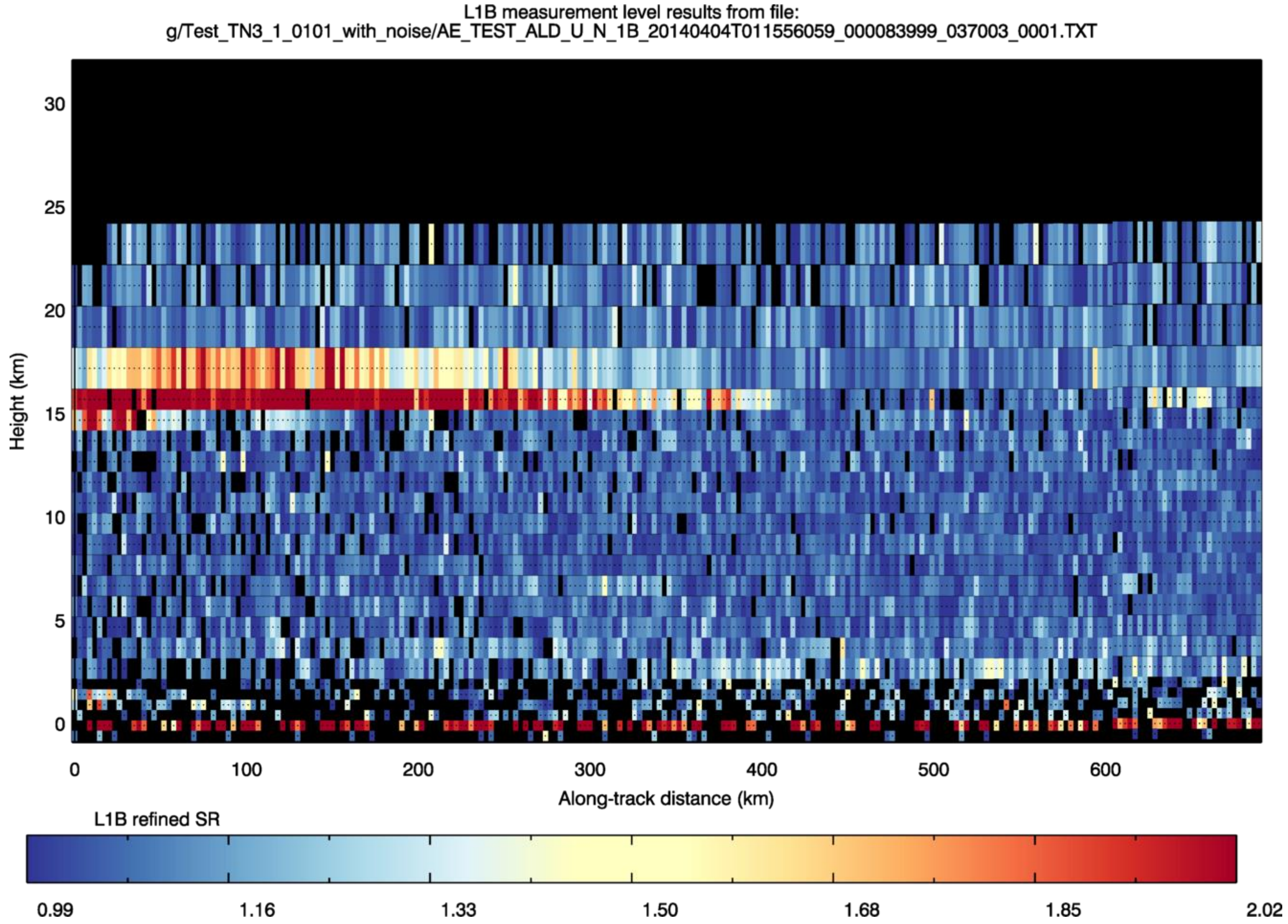


Figure 45. Example of L1B measurement level data: the L1B refined scattering ratio.

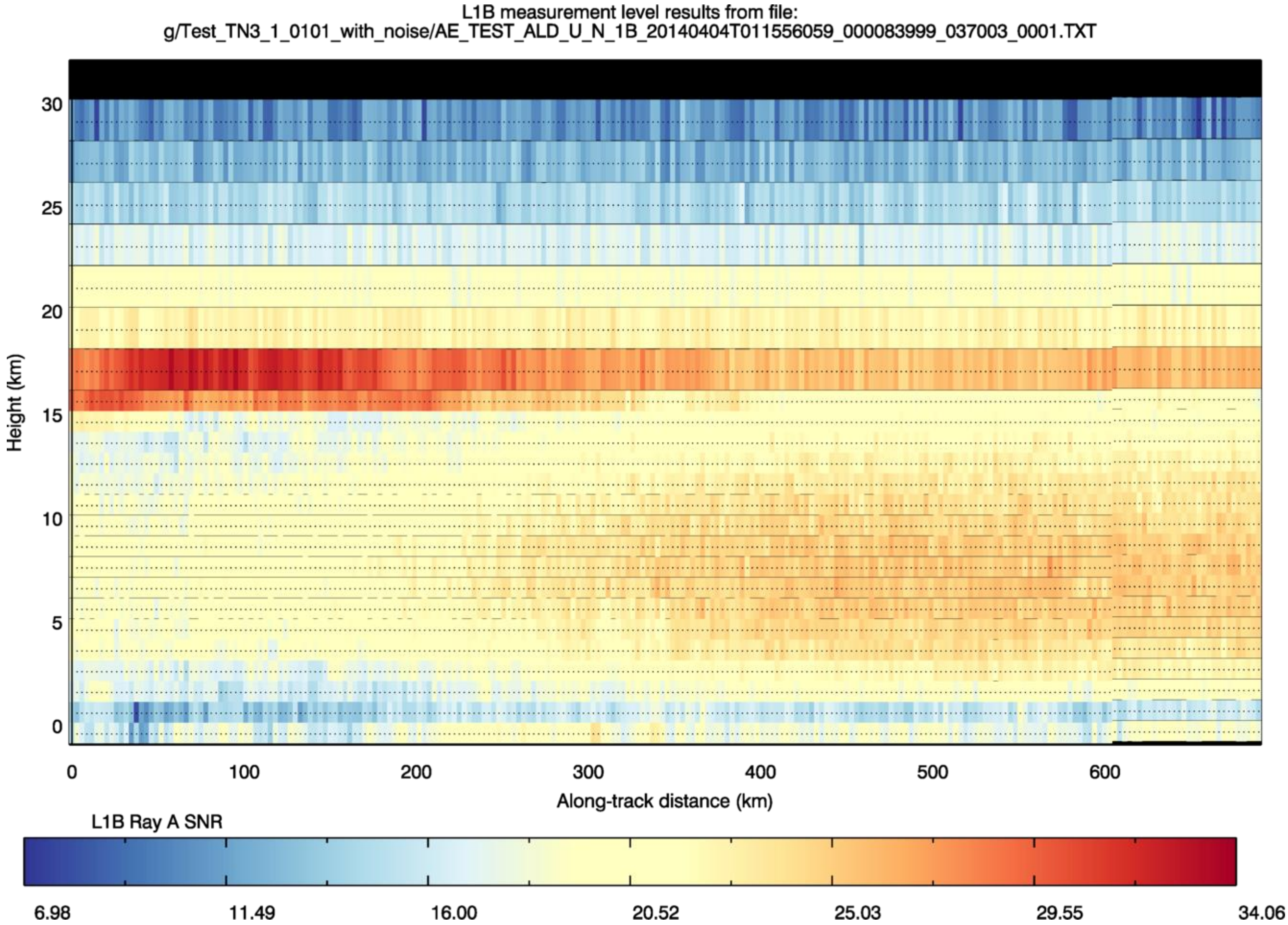


Figure 46. Example of L1B measurement level data: the L1B Rayleigh channel A signal-to-noise ratio.

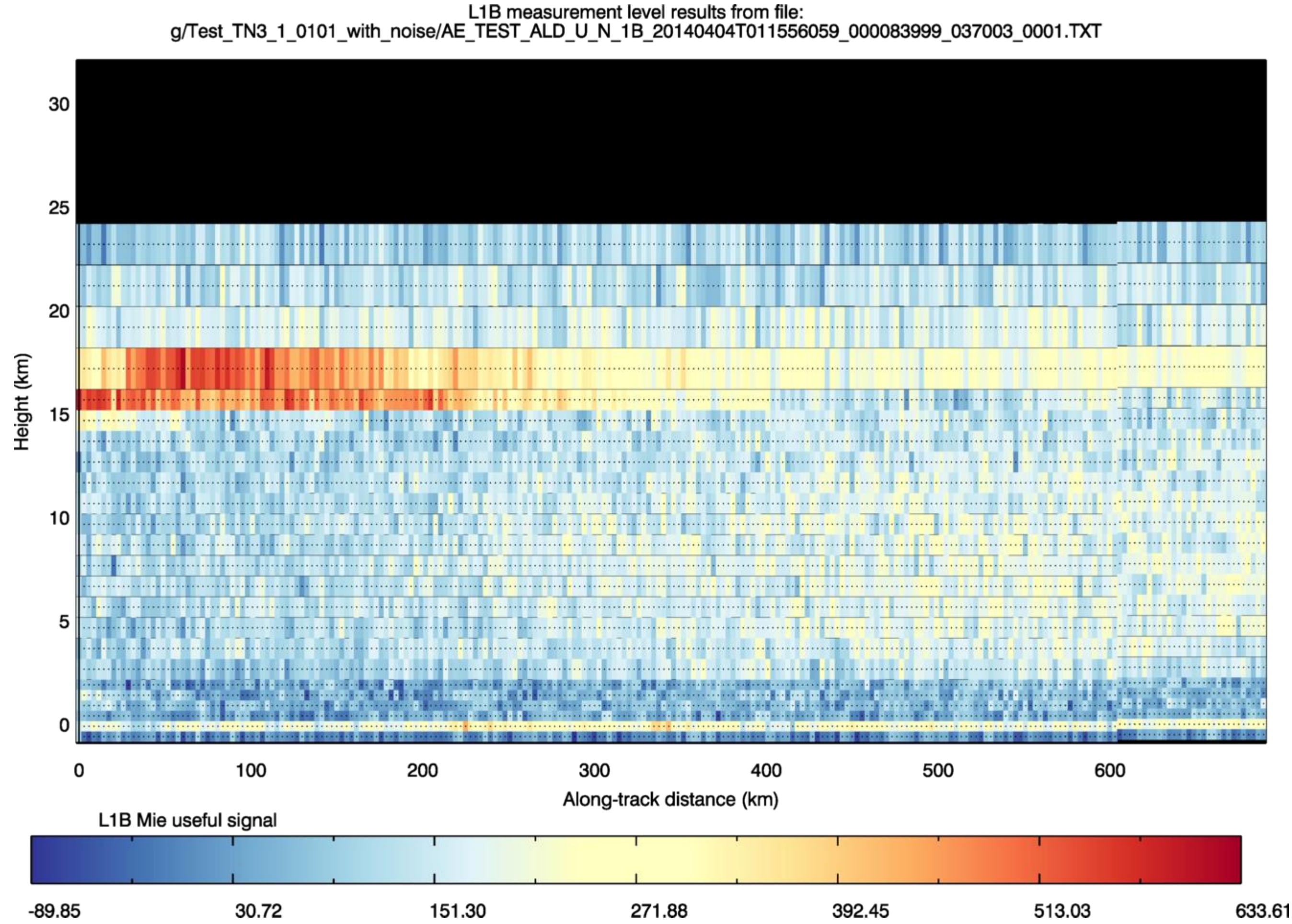


Figure 47. Example of L1B measurement level data: the L1B Mie channel useful signal.

6.4 Automating the advanced monitoring after launch

Note that the advanced monitoring described above will be run regularly by RD, but will not be an operational system like the L2/Met PF. Any operational monitoring that is required will be implemented with OBSTAT and controlled by FD, as is the normal procedure at ECMWF.

7 Summary

This technical note has provided evidence that the ECMWF high resolution global model will provide winds which will be suitable as a geophysical reference in most circumstances for assessing (via advanced monitoring) the Aeolus L2B winds. However, the model winds should be treated with caution for certain conditions e.g.:

- Upper troposphere winds in the tropics.
- Stratosphere winds more generally.
- Winds at the outflow levels of strong convection.

An assessment of which variables are predicted to be useful for Aeolus monitoring was made and some example plots using tools developed for the assessments of simulation Aeolus L2B winds have been presented.

Some of the suggested monitoring plots/tools will continue to be developed in preparation for the launch.

8 Acknowledgements

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9 Appendix

9.1 A1. Definition of orbit phase angle

If we assume Aeolus' orbit eccentricity is zero (i.e. it is a circular orbit (TBC if appropriate)) then orbit phase angle (from the centre of the Earth) in radians is:

$$\theta = \frac{2\pi t}{P_0}$$

Where t is the time from the ascending node crossing (ANX) time and P_0 is the period of the orbital motion. N.B. θ is also known as "argument of latitude" in the Harmonic Bias Estimation algorithm. P_0 is planned for Aeolus to be 92 minutes 29 seconds (although this may alter during the mission, TBC).

To find the time since ANX, the observations will be searched for the one closest to ANX, i.e. when the latitude changes from a negative value to a positive value (i.e. crosses zero latitude). The time t will then be calculated relative to that observation. *Need to take into account that latitude of off-nadir ground-track is not the same as nadir. Alternatively just use time t relative to the first observation, so the phase is measured compared to the first observation of the monitored period. Expect 7.785 orbits per 12 hour data assimilation cycle.*

The angle θ will be expressed as modulus 2π, hence allowing the statistics to be partitioned with the repeating nature of the orbit in terms of phase relative to the centre of the Earth.

9.2 A2. Observation bias effect on data assimilation analysis

The following derivation indicates how a biased observation affects the analysis. This is done using the simplest form of the linear analysis equation to provide a more intuitive answer.

When assimilating one observation into a scalar linear analysis (bias unaware assimilation) we have a scalar problem, and the analysis (a) error variance can be shown to be a function of the observation (o) and background (b) forecast variances:

$$\sigma_a^2 = \frac{\sigma_o^2 \sigma_b^2}{\sigma_b^2 + \sigma_o^2}$$

The mean analysis error in linear data assimilation theory can be shown to be (where < > indicates the expectation operator i.e. mean, see [RD2]):

$$\langle e_a \rangle = \langle K e_o \rangle + \langle (I - KH) e_b \rangle$$

Assuming the observation operator H is the identity operator (i.e. the observation is in the same space as the model variable), then the Kalman gain factor (which determines the influence of the observation mean error on the analysis mean error) is simply given by:

$$K = \frac{\sigma_b^2}{\sigma_b^2 + \sigma_o^2}$$

If we assume the background forecast has a mean error of zero then the mean analysis error is:

$$\langle e_a \rangle = \frac{\sigma_b^2}{\sigma_b^2 + \sigma_o^2} \langle e_o \rangle$$

To indicate the importance of the observation bias upon the analysis error, consider the ratio of the squared value of mean analysis error to the analysis error variance (hence this is a unit-less ratio) i.e.

mean error relative to random error. Using the definition of analysis error variance above the ratio is:

$$r_a = \frac{\langle e_a \rangle^2}{\langle (e_a - \langle e_a \rangle)^2 \rangle} = \frac{\left(\frac{\sigma_b^2}{\sigma_b^2 + \sigma_o^2} \langle e_o \rangle \right)^2}{\frac{\sigma_o^2 \sigma_b^2}{\sigma_b^2 + \sigma_o^2}} = \frac{\sigma_b^2}{\sigma_b^2 + \sigma_o^2} \left(\frac{\langle e_o \rangle^2}{\sigma_o^2} \right) = K \frac{\langle e_o \rangle^2}{\sigma_o^2}$$

Assuming that the observation bias becomes a problem if this ratio r_a is greater than some value α^2, then this leads to the following condition for the observation bias being a problem:

$$\langle e_o \rangle_{crit} > \alpha \sigma_o \sqrt{1 + \left(\frac{\sigma_o}{\sigma_b} \right)^2} = \frac{\alpha \sigma_o}{\sqrt{K}}$$

Therefore, a given observation mean error level is more damaging if the observation error variance (random error) is small and the background error variance is large (making the above condition more likely to be met).

Assuming that an analysis mean error greater than half the standard deviation of analysis error is likely to be problematic, i.e. $\alpha = 0.5$. Given some expected error levels: an observation error standard deviation of 2.5 m/s, an ECMWF model background error of 2.0 m/s (which are reasonable values given the expected random errors). **This suggests an observation bias greater than 2 m/s is problematic**. This level of bias is well within the range of possibility for Aeolus based on the ADS' error budget.

Note that if our background forecast is less accurate, say background error is 4 m/s (hence the observation is given more weight in the data assimilation) then an observation bias greater than 1.5 m/s is problematic. That is, the observation bias affects the analysis bias more, unsurprisingly, when given more weight in the analysis. However areas where background wind errors are large (random error) tend to be where the model winds are fairly biased (see section 3.1), so Aeolus may still reduce the bias of the analysis.

This derivation gives a rough impression of what affects the acceptable level of analysis bias, but the actual figures from this scalar data assimilation cannot be taken too literally to apply to the 4D-Var system which has the complication of many observations distributed in space and time with background error correlations in space. Also we do not know what an acceptable value for α is such that forecasts are not degraded. For example, how does the bias interact with different meteorological situations? A practical example of the effect of bias on the real ECMWF system using in situ wind observations was given in the NWP impact study (see [RD1]); there it was found that biases exceeding 1 m/s (for observations of 2 m/s error standard deviation) were particularly damaging — which is not too far from the simplistic model estimate.

9.3 A3. Detecting bias from O-B sample statistics

Here we assess the sample size of O-Bs that is necessary in order to be confident that the bias estimate value is correct. The population mean of O-B is:

$$\langle O - B \rangle = \langle O - T - B + T \rangle = \langle O - T \rangle - \langle B - T \rangle = \langle \varepsilon_o \rangle - \langle \varepsilon_b \rangle$$

Where T=truth value. That is, mean departure is the mean observation error minus the mean background error (assuming the observation and background errors are somehow stationary).

However in practice we obtain the sample (rather than population) mean (subscript s for sample), which has a standard error on the mean of:

$$\langle O-B\rangle_s = \langle O-B\rangle \pm \sqrt{\frac{var(O-B)_s}{n}} = \langle \varepsilon_o\rangle - \langle \varepsilon_b\rangle \pm \sqrt{\frac{\sigma_o^2+\sigma_b^2}{n}}$$

Where the σ^2 values are the variances of observation (o) and background (b) error. If the determination of O-B mean is required with a standard error of x, then the sample size required to achieve this is:

$$n = \frac{\sigma_o^2+\sigma_b^2}{x^2}$$

Which with typical values of Aeolus HLOS wind observation standard error (2.5 m/s) and background standard error (2 m/s), and choosing x=0.1 m/s (a fairly small uncertainty on the bias) gives n=1025.

If Aeolus has a constant bias then for the Rayleigh winds, given ~6000 good observations per orbit are expected, we need roughly 15% of an orbit to determine the constant bias with a standard error of 0.1 m/s. This also assumes any background forecast bias is constant, which may not be a good assumption. If the observation bias e.g. varies with altitude, then at any particular altitude (range-bin) we get ~462 observations (BRCs) per orbit, therefore we need around 2 orbits to determine the bias to 0.1 m/s.

These rough estimates are promising for the ability to detect an Aeolus bias (given a sufficiently unbiased background forecast) with relatively small samples of data i.e. during which the observation bias should not drift too much.

In practice the variations in bias along the orbit and with meteorological scenarios may mean this calculation is too simplistic. TBC after launch!

9.4 A4. ECMWF model estimates of wind velocity vertical component

The magnitude of the error in HLOS wind speed that could result from non-zero wind velocity vertical component is investigated, by using the ECMWF model's prediction of this. Vertical wind component is a diagnostic variable (derived from the equation of continuity) in the hydrostatic ECMWF model and is output as the partial derivative of pressure with respect to time. The relationship to the more traditional definition of vertical wind component w (in spatial coordinates) is given (assuming hydrostatic equilibrium) by:

$$\frac{\partial p}{\partial t} = -\rho g \frac{\partial z}{\partial t} = -\rho g w$$

w was calculated assuming g=9.81 ms^{-2} and that the density of air ρ varies exponentially with height with a typical 7 km scale height and a surface density of 1.25 kg/m^3. Figure 48 shows w from an arbitrary ECMWF model forecast date. The largest vertical wind components where found around model level 80 (~9.4 km), the level shown in the figure.

The ECMWF model vertical velocities should be reasonably accurate for horizontal scales greater than 100 km (roughly the model effective resolution); but the model cannot resolve the small scale and fastest vertical velocities which are present in convective cells or associated with small-scale gravity waves and turbulence. With the Aeolus horizontally (~80 km) and vertically (~1 km) averaged Rayleigh observations, then perhaps small-scale convective plumes can safely be ignored.

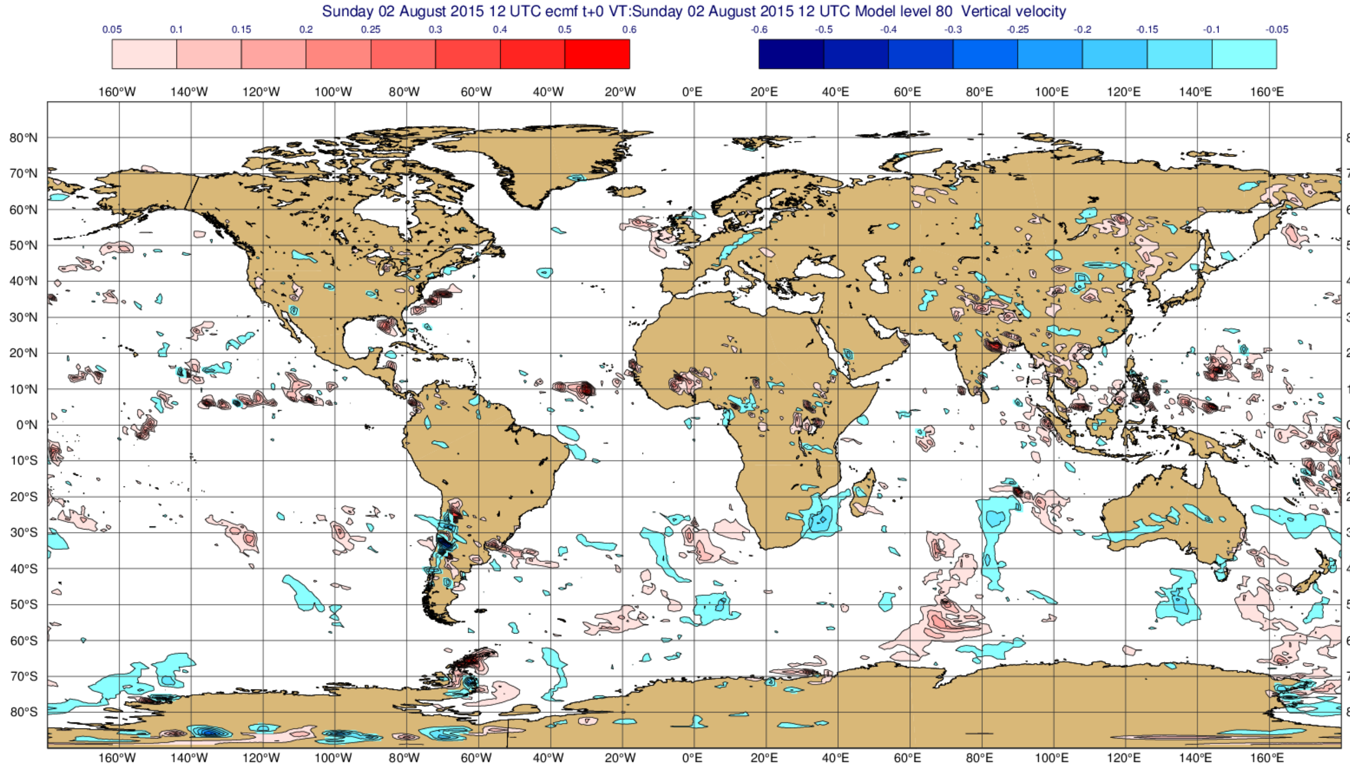

Figure 48. ECMWF model (T1279, i.e., about 16 km model grid size) vertical velocity (m/s) at model level 80 (~9.4 km) for an arbitrary forecast day (12 UTC on 2/8/2015).

Figure 48 shows large areas of ascent (pink) and descent (blue) which are more prevalent in the winter hemisphere (Southern in this case) associated with extratropical cyclones with *w* reaching ~0.2-0.3 m/s on synoptic horizontal scales. However 99% of the global *w* distribution lies between ± 0.15 m/s. There are small areas of strong ascent (reaching ~1 m/s) associated with convection along the ITCZ and there is a persistent patch of ascent/descent associated with the Andes Mountains (gravity waves generated with the strong zonal flow over the mountains).

By assuming vertical velocity to be zero in the L2Bp HLOS wind retrieval, this introduces a systematic error of around $sin(52.5°)w$~$0.79w$ i.e. with w=0.2 m/s a bias of 0.16 m/s. This is a fairly small bias compared to other potential sources, but may be noticeable in extreme cases where the non-zero *w* persists over long stretches of the orbit ground-track. However such conditions may be obscured by frontal clouds, in which case this is less of a problem. Note that the ECMWF model most probably underestimates the magnitude of wind vertical velocity (TBC).

Vertical winds are potentially detrimental during the calibration IRC mode when pointing near-nadir (with the assumption of zero wind induced Doppler shift), if they are persistent over 1 frequency step (2 BRCs, ~180 km). Imperfect RRC due to non-zero vertical winds will affect the AUX_CSR update step and hence will affect the AUX_RBC and hence L2B Rayleigh winds (at test not yet considered in simulation studies). The MRC will be done using the ground return and hence should not be affected by non-zero vertical winds.

Vertical velocity is not available as an input to the observation operators in the ECMWF data assimilation as yet. If it was then we could consider assimilating the LOS wind rather than the HLOS wind.