

Adjoint-based forecast sensitivity applied to observation error variances tuning

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Abstract

This paper deals with the estimation of observation errors for Infrared Atmospheric Sounding Interferometer (IASI) radiances. We investigate the possibility of combining an established method based on diagnosing errors from innovation statistics (so called Desroziers method) with guidance obtained from adjoint sensitivity tools (that aim to minimise short-range forecast error). In a test version of the European Centre for Medium-range Weather Forecasts (ECMWF) 4D-Var assimilation system that uses in situ observations and IASI as the only source of satellite data, it is found that tuning the IASI observation errors with a combined approach is beneficial (compared to using the innovation based method alone). Fits to data within the analysis are improved and forecasts initiated from the retuned analyses also show a moderate increase in skill.

1 Introduction

Accurate Numerical Weather Prediction (NWP) requires a high quality initialising estimate of the atmospheric state commonly produced by a data assimilation system which combines information from a previous short-range forecast with new observations in an optimal way. The successful exploitation of any observation in a data assimilation system requires an accurate description of the observation error covariance (\mathbf{R}) and the background error covariance (\mathbf{B}). Over the years a substantial amount of research effort has been directed towards modeling these error statistics (Hollingsworth and Lönnberg, 1986; Daley, 1991; Parrish and Derber, 1992; Derber and Bouttier, 1999; Lorenc, 2003; Buehner *et al.*, 2005; Desroziers *et al.*, 2005; Chapnik *et al.*, 2006). While significant progress has been made, all of the methods used to date have their difficulties and limitations, such that the estimation of background and observation error covariance matrices remains today a challenging and active problem in state of the art NWP systems.

The operational data assimilation system at European Centre for Medium-Range Weather Forecasts (ECMWF) is based on a 4D-Var algorithm (Rabier *et al.*, 2000) in a hybrid formulation, with flow-dependent background error variances and structure functions estimated from an Ensemble of Data Assimilation (EDA; Bonavita *et al.*, 2012). The system assimilates observations from in situ instruments and satellite observations from more than 50 sensors (English *et al.*, 2013). Recent Observing System Experiments (OSEs) documented in McNally (2014) show that hyperspectral satellite radiance measurements such as those from the Infrared Atmospheric Sounding Instrument (IASI) are one of the main drivers of forecast skill. However, these data are assimilated with a rather crudely specified diagonal error covariance matrix, with errors conditioned by inflation to mitigate the effect of unmodelled inter-channel correlations.

More recently Bormann *et al.* (2010) and Weston *et al.* (2014) have applied the method developed in Desroziers *et al.* (2005) to produce a more comprehensive specification of the IASI error covariance matrix. Under certain assumptions the statistics of observation minus background (innovations) and observation minus analysis (residuals) are decomposed to yield a full description of the IASI error covariance including inter-channel correlations. Unfortunately, these studies have generally found that using the raw output from this approach produces rather poor results when tested in assimilation and an acceptable performance can only be obtained if the error estimates are again conditioned with a condition being an inflation along the diagonal.

Adjoint-based techniques provide tools for the assessment and optimization of data assimilation system performance. Traditionally these have been applied to quantifying the information content of observations and the observation impact on short-range forecasts. The information content provides each observation's contribution to the analysis and the Degrees of Freedom for Signal (*DFS*) is defined

as a measure of the amount of information extracted from the observations (Purser and Huang, 1993; Cardinali *et al.*, 2004; Chapnik *et al.*, 2006; Lupu *et al.*, 2011, 2012; Cardinali, 2013). The forecast sensitivity approach to observation impact (FSOI) is used to estimate the reduction of the forecast error due to the assimilation of the observations and to monitor the observation performance on short-range forecasts (Baker and Daley, 2000; Langland and Baker, 2004; Cardinali and Buizza, 2004; Morneau *et al.*, 2006; Errico, 2007; Gelaro *et al.*, 2007; Zhu and Gelaro, 2008; Cardinali, 2009; Lorenc and Marriott, 2014). The computation of the FSOI involves a metric like total energy moist or dry, over a given area (Rabier *et al.*, 1996; Cardinali, 2009). Moreover, these adjoint techniques are influenced by simplified adjoint model used to carry the forecast error information backwards and therefore limited by the validity of the tangent-linear assumptions to short range forecasts (Janisková and Lopez, 2013).

More recently, the adjoint based methods have been extended (Daescu, 2008) to provide a framework to assess forecast sensitivity with respect to the observation error covariance (**R**-sensitivity) and to the background error covariance (**B**-sensitivity). These essentially provide guidance on how inflating or deflating these errors will impact forecast errors and have been used successfully in Daescu and Todling (2010), Daescu and Langland (2013) and Cardinali and Healy (2014). Unfortunately, these methods do not provide quantitative estimates of what the errors should actually be.

The aim of this study was to evaluate the possibility of combining information from the Desroziers approach based on decomposing innovation statistics with the guidance provided by adjoint sensitivity methods, to hopefully exploit the advantages of both. The new estimate of the IASI error covariance model is tested in a reduced version of the ECMWF 4D-Var assimilation scheme that uses conventional (in situ) observations and IASI radiances on Meteorological Operational satellite-A (MetOp-A) as the only satellite data. This simplified system allows us to attribute any changes directly to the modified IASI observation errors without concerns over potentially complex interactions with other satellite data. The paper is structured as follows. In section 2 details of the adjoint-based diagnostics used to tune the specified covariance matrices by applying scaling factors to the background and the observational error statistics respectively, are described. The method is applied in section 3 to a baseline assimilation system to identify which IASI channels require their error variances to be modified. The details of the Desroziers approach as well as how it is applied to generate new estimates of observation error for those identified IASI channels are also described in section 3. The setup of and results of experiments used to test the new IASI observation error is dealt with in section 4. The paper concludes with a summary and discussion in section 5.

2 The adjoint observation and background error covariance sensitivities

The ability to perform forecast sensitivity to data assimilation system input parameters relies on relationships established between the forecast sensitivity to observations (**y**), to background (**x_b**) and to the associated error covariances (**R**, **B**). Considering the forecast aspect of interest defined as the norm of energy weighted 24-h forecast error (e_{24}) initialized from an analysis (**x_a**), the forecast **R**- and **B**-sensitivities have been expressed by Daescu (2008) in terms of the forecast sensitivities to observations (**y**) and background (**x_b**) respectively, as:

$$\frac{\partial e_{24}}{\partial \mathbf{R}} = \frac{\partial e_{24}}{\partial \mathbf{y}} (\mathbf{H} \mathbf{x}_a - \mathbf{y})^T \mathbf{R}^{-1}, \quad (1)$$

$$\frac{\partial e_{24}}{\partial \mathbf{B}} = \frac{\partial e_{24}}{\partial \mathbf{x}_b} (\mathbf{x}_a - \mathbf{x}_b)^T \mathbf{B}^{-1}, \quad (2)$$

where H is the nonlinear operator for calculating the equivalent of the state vector in the observation space.

Because of the size of the matrices involved, the evaluation of the error covariance sensitivity matrices from eqs.1-2 is not straightforward in an operational NWP system. In this context, a hypothesis is made that the true covariance matrices can be obtained from the specified ones by applying scaling factors to the observation- and background- error statistics respectively, so that $\mathbf{R}(s^o)=s^o\mathbf{R}$ and $\mathbf{B}(s^b)=s^b\mathbf{B}$, where s^o and s^b are the scaling coefficients. Thus, the specified \mathbf{R} - and \mathbf{B} -covariance matrices correspond to all scaling factors set to 1 ($s^o=s^b=1$).

Different observation types are often assumed to have uncorrelated observation error, so the scaling can be applied to individual sub-components ($i=1:I$) assumed to have the same observation error standard deviation. In this context, instead of using a single scaling factor s^o , one can use multiple scaling factors s_i^o such that $\mathbf{R}_i(s_i^o)=s_i^o\mathbf{R}_i$, $i=1:I$. Following [Daescu and Todling \(2010\)](#), the forecast sensitivities to the scaling factors s_i^o , $i=1:I$ and s^b in the observation- and background-error covariance representations are expressed to be:

$$\frac{\partial e_{24}}{\partial s_i^o} = (H_i\mathbf{x}_a - \mathbf{y}_i)^T \frac{\partial e_{24}}{\partial \mathbf{y}_i}, \quad (3)$$

$$\frac{\partial e_{24}}{\partial s^b} = (\mathbf{x}_a - \mathbf{x}_b)^T \frac{\partial e_{24}}{\partial \mathbf{x}_b}, \quad (4)$$

and the following relationship may be established:

$$\sum_{i=1}^I \frac{\partial e_{24}}{\partial s_i^o} + \frac{\partial e_{24}}{\partial s^b} = 0, \quad (5)$$

For any subset of observations, the sensitivity of 24-h forecast errors to the scaling factor of observation error covariance of that subset can be computed as the observation-minus-analysis residual ($\mathbf{d}_a^o=\mathbf{y} - H\mathbf{x}_a$) multiplied by the observation sensitivity vector to the corresponding observation subset, summed up over all observations in that group (with the sign flipped, eq.3). Furthermore, from eq.5, an observation space s^b -sensitivity can be estimated as the sum of forecast sensitivity to observation error covariance scaling factors (with the sign flipped).

The forecast sensitivity to the scaling factors $s=[s_i^o, s^b]$, $i=1:I$ in the observation- and background-error covariance representations are defined specifically to reduce the 24-h forecast error, as measured by a dry energy norm. A negative sensitivity $\frac{\partial e_{24}}{\partial s} < 0$ identifies those components where error covariance inflation will be of largest forecast benefit, whereas a positive sensitivity ($\frac{\partial e_{24}}{\partial s} > 0$) point towards error covariance deflation. It is proposed here that the forecast s_i^o -sensitivity, $i=1:I$ summarized mathematically in eq.3 provides new insights for tuning the observation-error variance input.

3 Estimates of observation error variances

3.1 Set-up of the experiments

An assimilation experiment subsequently referred to as ‘Baseline’ has been run over a period covering 1 June - 31 July 2012 with a recent version of ECMWF 12-h 4D-Var system model cycle 38R2, with a

spatial model resolution of T511 L137 (~40 km horizontal linear grid and 137 vertical model levels with the model top at 0.01 hPa). The ‘Baseline’ was initialized with the ECMWF operational analysis and the initial fields on the first cycle contain the operational set-up and the bias coefficients from the operational file. Ten-day forecasts were calculated from both the 00 UTC and 12 UTC analysis. The experiment includes a depleted observing system in which only conventional observations and IASI on MetOp-A radiances are assimilated, and no other observations. The conventional observation network consists of near-surface observations (land stations, ships and buoys) and upper-air data. The latter include those from radiosondes, dropsondes, aircraft, wind profilers and PILOTs (high-resolution radiosondes measuring only wind and pilot balloon).

IASI is a hyperspectral infrared sensor providing high-quality temperature and humidity data in NWP systems (Collard and McNally, 2009; McNally, 2009; Hilton *et al.*, 2009). The assimilation of IASI relies primarily on the use of clear data over sea from a selection of up to 191 channels including temperature sounding channels in the long-wave region of the spectrum and a limited number of ozone and humidity sounding channels (Collard and McNally, 2009; Han and McNally, 2010; Dragani and McNally, 2013). Prior to assimilation, cloud-contaminated channels are identified and rejected in cloud detection (McNally and Watts, 2003; Eresmaa, 2014). Observations are bias-corrected using a variational technique with a standard set of eight predictors to account for scan-angle and air-mass dependent components of the bias (Dee, 2004). The observation error standard deviations for IASI correspond to those assumed in the operational system at ECMWF. They are a step function of spectral bands, giving equal weight to all stratospheric sounding channels (1.0 K), equal weight to all tropospheric sounding channels (0.4 K) and equal weight (2.0 K) for all other channels significantly sensitive to the surface emissivity or to water vapour. While these values overestimate the true ones, currently correlated observation errors are not taken into account and thus some degree of inflation is justified. Background errors are estimated from the operational ECMWF EDA system.

3.2 The s_i^o -sensitivity guidance

An adjoint-based integration has been performed to evaluate the forecast sensitivity to the scaling factors s_i^o , $i=1:I$ of the observation-error variances according to eq.3. Figure 1a, shows the time-averaged forecast error sensitivity to the observations error variance scaling factor for conventional observations and IASI radiances. A positive value indicates that error variance deflation should be beneficial to reduce the 24-h forecast error whilst inflation should be applied on observation error variance with negative sensitivity. The sensitivity guidance in Figure 1a is that the information provided by IASI radiances, aircraft (AIRCRAFT), radiosondes (TEMP) and near-surface observations (DRIBU and SYNOP) is underweighted in the assimilation system and deflation of the assigned observation error variances for these observations is of potential benefit to the forecast. The sensitivity associated with IASI instrument is the highest sensitivity among all the observation types.

In Figure 1b, forecast sensitivities to the scaling factors of the observation-error variances are displayed for each of 191 IASI channels assimilated. It can be seen that, in particular, the long-wave upper temperature-sounding channels and water-vapour channels display positive sensitivities of increased magnitude. This is an indication that an improvement in forecast skill is expected by reducing the observation error variance for selected stratospheric to mid-tropospheric temperature sounding channels between 173 and 254 and selected humidity channels between 2889 and 5480. However, the estimation of how much the observation error variance should be diminished remains with this method problematic (Daescu and Langland, 2013). Other diagnostics should be considered to provide quantitative estimates of what the observation error variance should actually be.

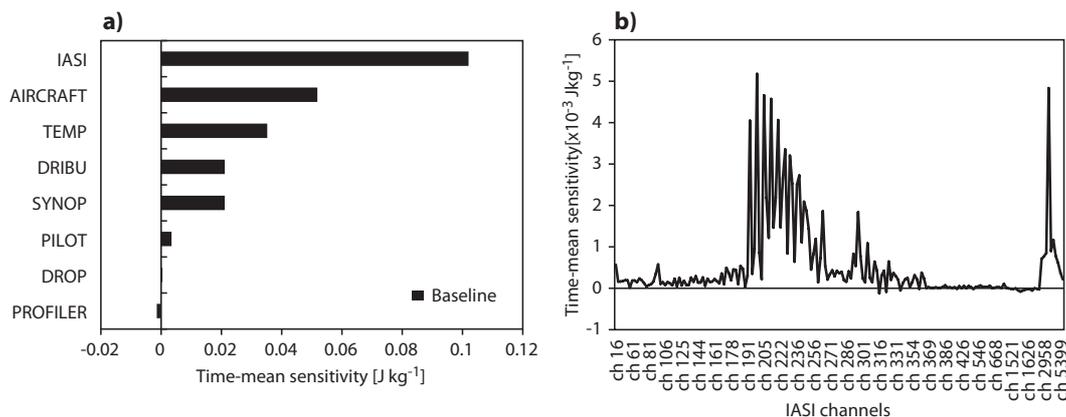


Figure 1: Sensitivity (time-mean value per assimilation cycle, J kg^{-1}) of the 24-h forecast error measure with respect to the observation error variance scaling factor for June-July 2012: a) associated to ‘Baseline’ observing instruments; b) associated to IASI channels.

3.3 Desroziers method

From the statistical analysis of the observation-minus-background (\mathbf{d}_b^o) and observation-minus-analysis (\mathbf{d}_a^o) residuals it is possible to diagnose a posteriori the observation-error covariance matrix as:

$$\mathbf{R} = E[\mathbf{d}_a^o(\mathbf{d}_b^o)^T], \quad (6)$$

where $E[]$ is the statistical expectation operator, \mathbf{d}_a^o and \mathbf{d}_b^o are the analysis and background departures, respectively. Eq.6 is valid if the observation and background errors used to calculate the analysis, are the exact observation and background errors (Desroziers *et al.*, 2005). It has been shown that, provided that the correlation length scales in \mathbf{B} and \mathbf{R} are sufficiently different, a reasonable estimate of \mathbf{R} can be obtained even if the observation and the background errors are not correctly specified. The method can be further iterated to estimate \mathbf{R} , but generally the first iteration provides a good estimate of the result (Desroziers *et al.*, 2009; Menard *et al.*, 2009). However, as highlighted in Todling (2015), in the case where both the observation and background error variances are unknown or mis-specified, the a posteriori observation residual diagnostic may provide poor estimates of the true background error or observation error covariances.

The method of Desroziers *et al.* (2005) is applied to IASI on MetOp-A radiances to assess the consistency of the specified observation-error variances. Estimates of IASI’s observation error variances are calculated over a 30 day period in June 2012 from clear sky and completely overcast observation residuals over oceans only. The diagnosed observation-error standard deviation are significantly lower than the current operational ones, with an averaged ratio of 0.4 for IASI instrument (not shown). These results are consistent with other a posteriori estimates shown in the work of Bormann *et al.* (2010) and Weston *et al.* (2014).

Studies performed in recent years to estimate the observation error variances and their correlations for clear-sky IASI radiances suggest a significant degree of correlation between humidity-sounding channels and also between window channels (Bormann *et al.*, 2010; Weston *et al.*, 2014). Mid-tropospheric to stratospheric IASI temperature sounding channels show little or no inter-channel or spatial observation-error correlations, and estimates of the observation error variances are close to the instrument noise. Observation-error variances for humidity channels are generally larger than the instrument noise. More-

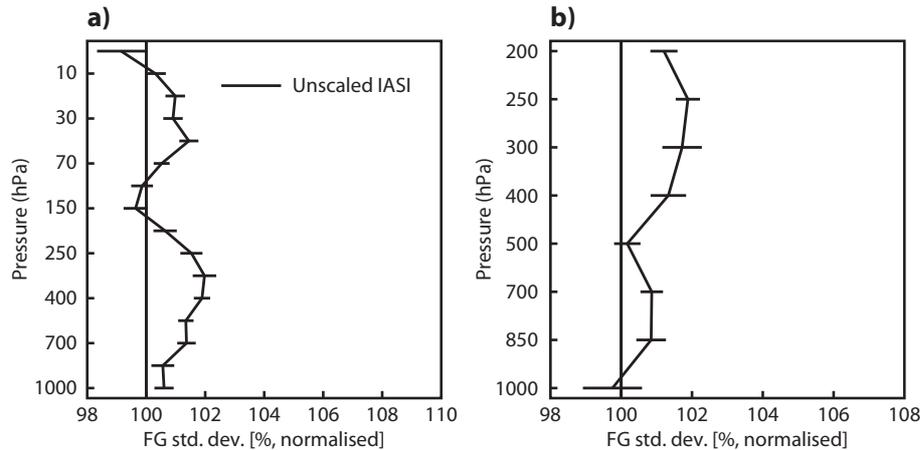


Figure 2: Standard deviation of first-guess departures for temperature-sensitive observations as a percentage relative to the ‘Baseline’: a) temperature observations from radiosondes; b) temperature observation from aircraft. Error bars indicate the 95% confidence range. The ‘Unscaled IASI’ experiment replicates the ‘Baseline’ except that Desroziers estimates of observation errors variances for all assimilated 191 IASI channels have been used. The area is global and the period is from 8 June to 31 July 2012. ‘Baseline’ is equivalent to 100% in these figures and numbers less than 100% indicate beneficial impact.

over, the above results have been confirmed by comparing the error variances diagnosed with the Desroziers technique with those derived using the Hollingsworth and Lönnberg method.

It is worth mentioning that at ECMWF, attempts to use unscaled observation-errors standard deviation estimates from Desroziers approach for all assimilated 191 IASI channels (subsequently referred to as ‘Unscaled IASI’ experiment) resulted in a degradation of the analysis and forecast. This is demonstrated in Figure 2 in terms of the standard deviations of the first-guess departure statistics, given as a percentage relative to the ‘Baseline’, for conventional observations. There is 0.5-2% degradation in the fits to radiosondes (Figure 2a) and aircraft temperature observations (Figure 2b) and 1-2% degradation in the fit to wind observations (not shown). All diagnostics exclude the first week because of possible spin-up effects caused by lack of realistic initial bias correction coefficients. Each experiment run is verified against a control run, which is based on the full operational set-up in terms of conventional and non-conventional data usage and T511 L137 resolution. The forecast impact on headline scores (root-mean-square of 500 hPa geopotential forecast errors) displays strong degradations at both shorter and medium ranges in the midlatitudes (Figure 3).

4 Tuning IASI observation errors: a combined approach

With these considerations in mind, in this article we study the possibility of combining information from the Desroziers diagnostic with the guidance provided by the adjoint-based sensitivity tool to re-estimate the observation error variances for IASI channels. In section 3.2, the adjoint-based forecast sensitivity tool provided guidance on the IASI channels where the observation error variances should be decreased to reduce the norm of energy-weighted 24-h forecast error. Among 191 IASI channels, 33 IASI channels displaying the largest sensitivity values have been selected, as illustrated in Figure 4a. These include 25 temperature sounding channels in the range 173-254 and 8 humidity sounding channels in the range 2889-5480. The Desroziers approach is then used to provide estimates of the observation-error standard deviation for these selected channels. Figure 4b illustrates the results of Desroziers estimates of the

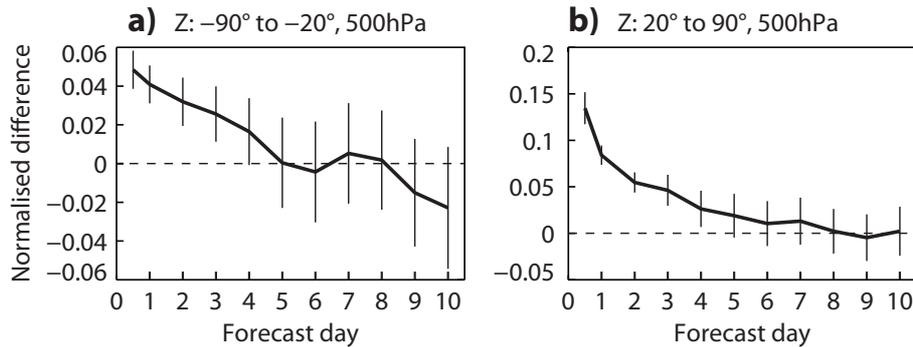


Figure 3: Normalised change in root-mean-square (RMS) geopotential error at 500 hPa between ‘Unscaled IASI’ and ‘Baseline’ experiments for: a) Southern and b) Northern extratropics, based on a maximum of 107 forecasts (8 June - 31 July 2012). Error bars indicate the 95% confidence range. Verification is against the control run.

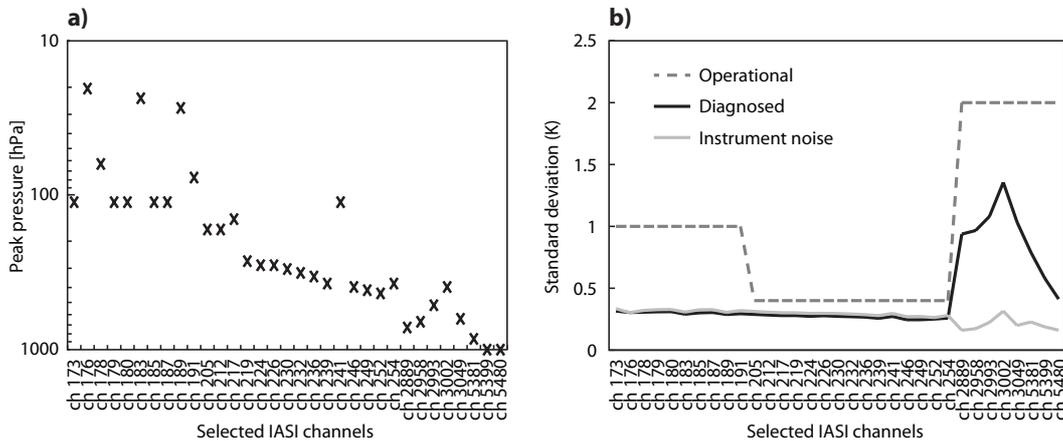


Figure 4: a) Pressure [hPa] of the Jacobian peak for a subset of 33 IASI channels (25 long wave CO_2 temperature sounding channels in the range 173-254 and 8 water-vapor channels in the range 2889-5480). b) Diagnosed IASI error standard deviations from ‘Baseline’, IASI instrument noise and operational values for a subset of 33 IASI channels.

observation-error standard deviation together with IASI instrument noise and the assigned operational values for each of the 33 selected IASI channels. For the long wave CO_2 temperature sounding channels in the range 173-254 the size of the Desroziers diagnosed observation-error standard deviation is close to the instrument noise, while for IASI water-vapour channels is considerably larger than the instrument noise. However, the Desroziers diagnosed observation-error standard deviation for all 33 selected IASI channels were found to be lower than the corresponding values assigned in the ‘Baseline’ assimilation.

A new experiment (subsequently referred to as ‘Retuned-IASI’) was then run for the same period to investigate the performance of the modified observation-error standard deviation in selected IASI channels and to evaluate the analysis and forecast system performance. The usage of observations is kept similar to the ‘Baseline’, except for the 33 selected IASI channels where unscaled observation-error standard deviation relative to the Desroziers diagnosed ones are used.

Exp.	Observation number (p)	DFS	OI
Baseline	2411956	222015	0.092
Retuned-IASI	2418318	250104	0.103

Table 1: DFS and mean observation influence.

4.1 Analysis impact

An indication of the impact of ‘Retuned-IASI’ experiment on the quality of analyses and short-range forecasts is provided by the first-guess departures. Figure 5 shows the normalised standard deviations of first guess (FG) departures statistics for temperature observations from radiosondes, and aircraft, and in-situ wind observations (from aircraft, radiosondes, pilots and profilers) and IASI observations. The standard deviations are normalised with respect to the standard deviations used in the ‘Baseline’ experiment. Globally, retuning the observation error variances for selected IASI channels marginally improves the temperature, humidity and wind fits to conventional observations in the troposphere. In the stratosphere around 30 hPa statistically significant degradations are noticed in the temperature fit (from radiosondes, Figure 5a) and in the winds fit (from conventional wind data, Figure 5c). The fit to IASI observations is analysed through Figure 5d). Consistent reductions of standard deviation of the FG departures were confirmed globally across the channels spanning the troposphere and to a lesser extent the stratosphere (e.g., O_3 band channels). We found approximately up to 2% significant improvements in the standard deviation of FG departures for several temperature sounding channels, significant improvements of about 3% in the FG fit to humidity IASI channels and significant degradations by around 2% in the FG fit to ozone sensitive channels.

The analysis impact of the individual observation types can be illustrated using the observation influence (OI: defined as the degrees of freedom of signal DFS normalized by the total observation number). OI varies between 0 and 1: OI=0 would imply that there has been no contribution from the observations in the analysis, with the analysis equal to the background, whilst OI=1 would imply that there has been no contribution from the background in the analysis. Table 1 shows the globally averaged OI for ‘Baseline’ and ‘Retuned-IASI’ experiments. The mean observation influence estimated over the globe in ‘Baseline’ is 0.092, which implies that the analysis extracts 9.2% of its information from the observations and 90.8% from the background, which contains also observation information from the previous analysis cycles. In the ‘Retuned-IASI’ experiment, the total number of assimilated observation increase, the total DFS increase and the global OI per assimilation cycle has been found to be 0.103. Thus, on average the information in the analysis that comes from the observation is larger in ‘Retuned-IASI’ experiment compared to ‘Baseline’. The contribution to the global observation influence for each observation type is shown in Figure 6a for both experiments. IASI provides the largest contribution to the mean observation influence among the different observation types, followed by aircraft, radiosondes and SYNOP observations. OI is proportional to the analysis error variance and inversely proportional to the observation error variance. Therefore, IASI’s OI is larger in ‘Retuned-IASI’ experiment than in ‘Baseline’ because of the variance deflation of 33 selected IASI channels (Figure 6b).

It is worth noting that the conventional OI is unchanged, which provides a consistency check on the robustness of the IASI applied variance tuning. In fact when the variances are tuned by applying Desroziers method on all channels, that is the adjoint-based sensitivity guidance is not jointly used for channel selection, the increased IASI OI is detrimental to conventional OI (decreased conventional OI, not shown).

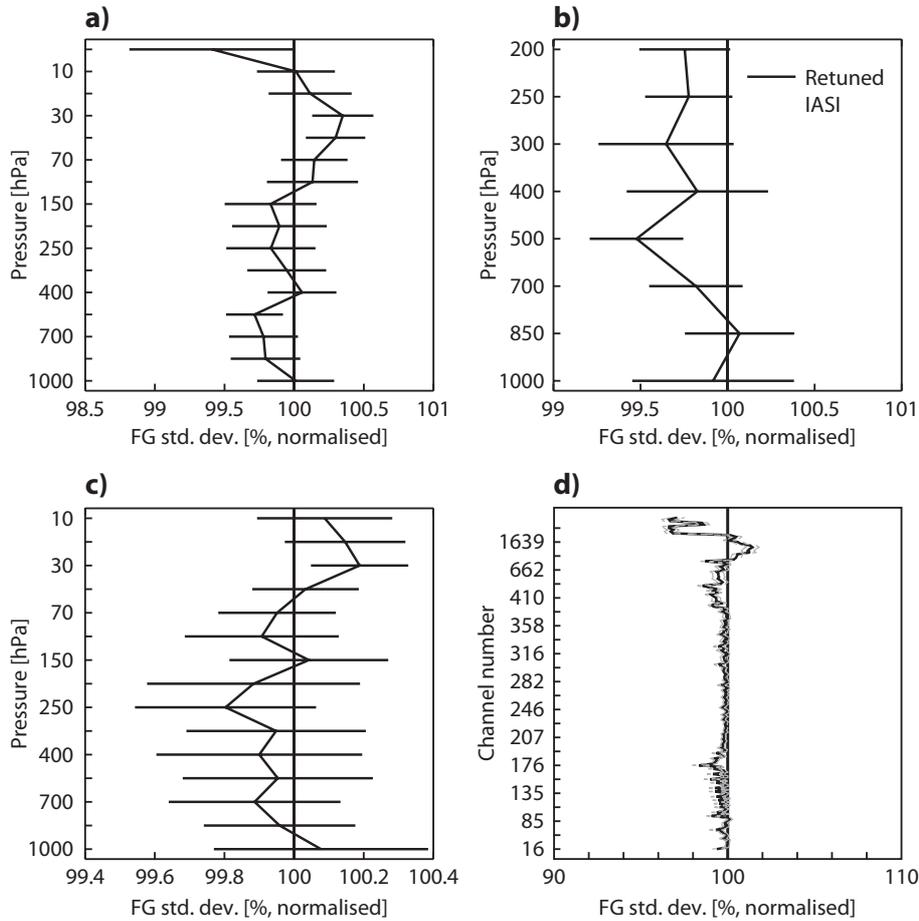


Figure 5: Normalised standard deviation of first-guess departures for: a) temperature observations from radiosondes (top left); b) temperature observation from aircraft (top right); c) conventional meridional and zonal winds from aircraft, profilers, pilot and radiosondes (bottom left); d) IASI observations on the Metop-A satellite. Only IASI assimilated channels are shown and there are eight channels per division on the y-axis. Standard deviations are normalised by those of the ‘Baseline’. The area is global and the period is from 8 June to 31 July 2012. Error bars indicate the 95% confidence interval. Numbers less than 100% indicate beneficial impact.

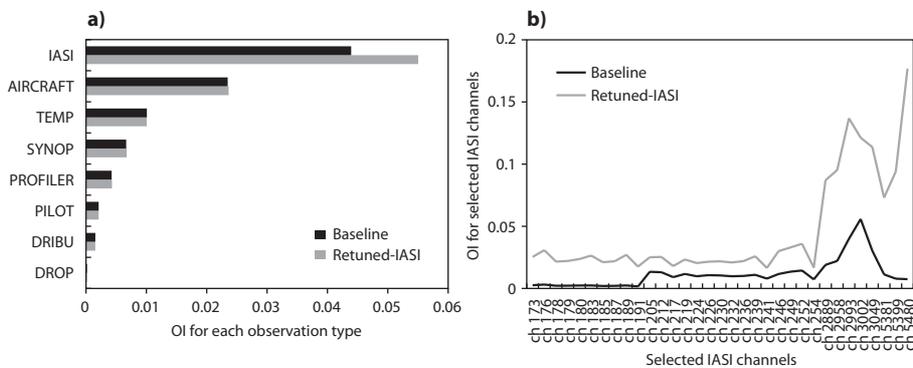


Figure 6: Contribution to the global observation influence (OI) of: a) each observing instruments; b) each of 33 selected IASI channels.

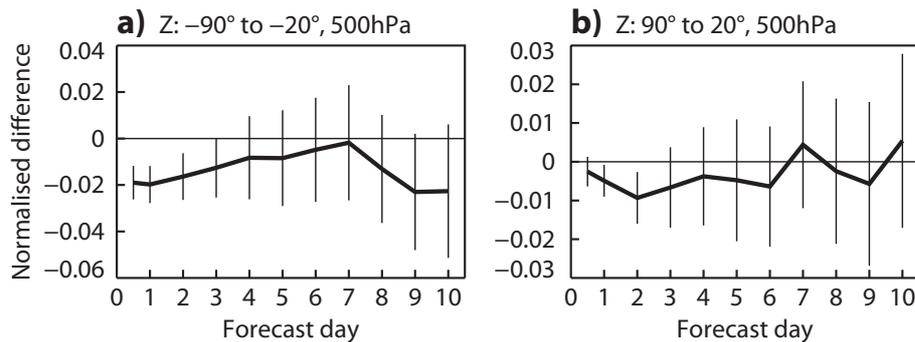


Figure 7: Normalised change in RMS geopotential error at 500 hPa between ‘Retuned-IASI’ and ‘Baseline’ experiments for: a) Southern and b) Northern extratropics, based on a maximum of 107 forecasts (8 June - 31 July 2012). Error bars indicate the 95% confidence range. Verification is against the control run.

4.2 Forecast impact

Forecast scores have been calculated in terms of normalised difference of root mean square errors between ‘Retuned-IASI’ experiment and ‘Baseline’, verified using a control run. Headline forecast scores are shown in Figure 7. It can be seen that ‘Retuned-IASI’ experiment improves by 2% the standard 500 hPa geopotential height forecast scores up to day 3 in the Southern extratropics. In the Northern extratropics the impact is positive but smaller. Overall, the forecast performance of the ‘Retuned-IASI’ assimilation scheme is encouraging, essentially showing a consistent positive impact in the geopotential height at different tropospheric levels (not shown). The verification of temperature and wind forecasts from the two systems is generally consistent with the height results and shows improved forecast scores as compared with the ‘Baseline’ run (not shown). These changes are statistically significant in many areas, meaning that, tuning IASI observation error makes an improvement to the quality of geopotential height, temperature and wind forecasts at different tropospheric levels, areas and range forecast. A negative impact of retuning IASI observations, is noticed in layers higher in the stratosphere. Though in the Southern extratropics between 10 hPa and 50 hPa, the root mean square errors in temperature and vector wind between ‘Retuned-IASI’ experiment and ‘Baseline’ increase by up to 2% with statistical significance out to day 3. The signal was present also on Figure 5.

To summarize the results, the integrated total dry energy norm (Rabier *et al.*, 1996) over the entire model atmosphere has been examined. The normalized difference of the integrated total dry energy of the forecast error (verified against the control run) between ‘Retuned-IASI’ experiment and ‘Baseline’ for forecast days 1-5 for the Northern Hemisphere extratropics and Southern Hemisphere extratropics is shown in Figure 8. A beneficial impact is one that results in a reduction of forecast error (negative normalised difference). It is found that ‘Retuned-IASI’ experiment has smaller forecast error up to day 5.

4.3 Sensitivity guidance and observation impact

It was found earlier that re-estimating the observation error variances for 33 IASI channels in ‘Retuned-IASI’ experiment yields an overall positive impact on both analyses and forecasts. The adjoint-based integration has been again performed to assess the forecast sensitivity to the scaling factors of the observation-error variances of the ‘Retuned-IASI’ experiment.

It is worth noting that if the error statistics are perfectly specified then each of the values of the forecast

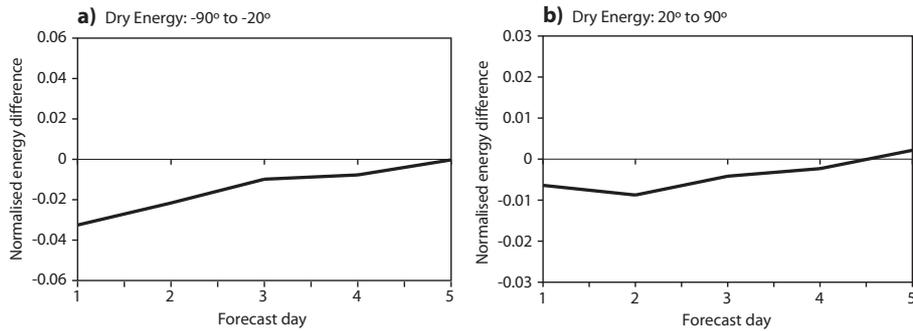


Figure 8: Normalised change in dry energy forecast error between ‘Retuned-IASI’ and ‘Baseline’ experiments in the a) Southern and b) Northern extratropics, based on a maximum of 107 forecasts from summer (8 June - 31 July 2012). Verification is against the control run.

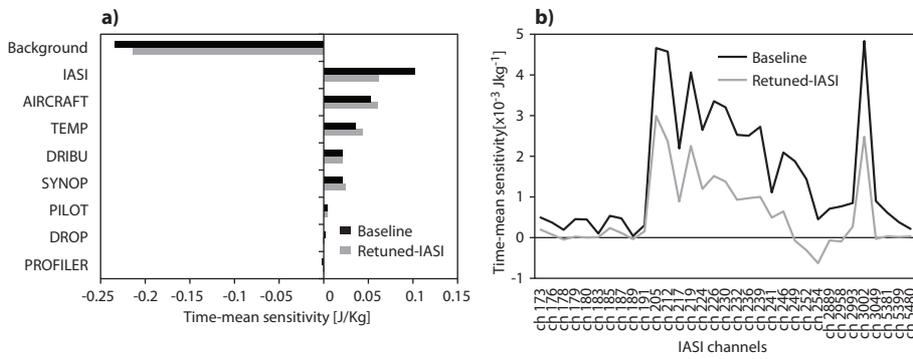


Figure 9: Sensitivity (time-mean value per assimilation cycle, $J kg^{-1}$) of the 24-h forecast error measure with respect to the observation error variance scaling factor and background error covariance weight factor in June-July 2012: a) associated with various observation type; b) per instrument channel for IASI.

sensitivity to the observation-error variances scaling factors associated to various observing instruments and the complementary value of the sensitivity to the background error statistics are expected to be zero.

Compared to ‘Baseline’ assessment (Figure 9a), the forecast sensitivity to observation error variance scaling factor for IASI instrument has been halved. The information provided by the observing system as a whole is under-weighted in ‘Retuned-IASI’ runs with still positive sensitivities for IASI and aircraft data. This points also to a suboptimal assimilation of these data and suggests further deflation of the observation error variances, in particular, for the IASI channels shown in Figure 9b and for temperature and wind measurements from aircraft observations between 200-300 hPa (not shown). Similarly, a reduced negative background error sensitivity is noticed, suggesting that the EDA based background error variances are less overweighting the background in ‘Retuned-IASI’ experiment. The combined forecast sensitivity results indicate that ‘Retuned-IASI’ consistently outperforms the ‘Baseline’ run. Nevertheless, the sensitivity guidance applied to ‘Retuned-IASI’ identifies further forecast error reduction which may be obtained either by decreasing some observation-error variances or by increasing the background-error variances. One can use these diagnostics to further tune the specified covariance matrices, so that zero sensitivity gradients will be obtained with respect to the new error statistics.

The forecast sensitivity approach to observation impact (FSOI) of all the observing system components has been evaluated for both ‘Baseline’ and ‘Retuned-IASI’ experiments and are shown in Figure 10a. In both experiments all observation types are estimated to reduce the 24-h forecast error on average over the global domain, with the largest contribution provided by IASI observations. In fact, most of the

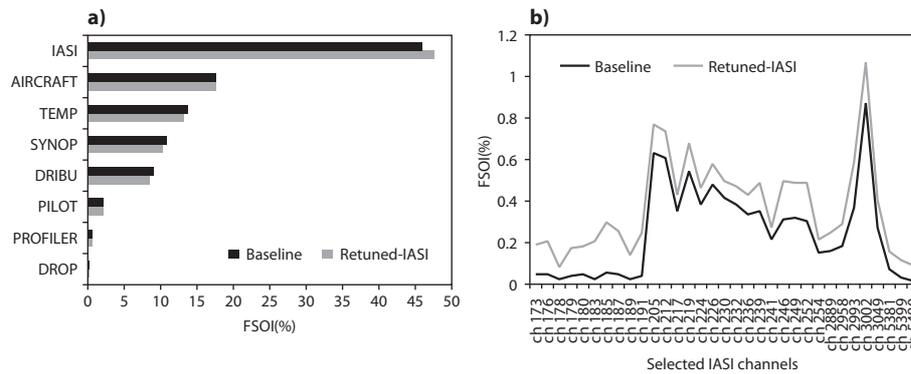


Figure 10: Average observation impact relative to: a) each subset of observations; b) each of 33 selected IASI channels.

IASI channels have positive impact on the forecast and contribute to the total forecast error reduction. In particular, the subset of channels from 193 to 232, primarily located in the long-wave CO_2 band has a relatively large positive impact, while channels in the O_3 band (1574 to 1626) show a very small but negative impact (not shown). Overall, the average impact of the observations as a whole in the data assimilation scheme is beneficial in both experiments and the 24-h forecast error is reduced by an average of 23.06% in ‘Baseline’ and by an average of 23.12% in ‘Retuned-IASI’ experiment. Tuning of the observation error in selected IASI channels will produce a forecast improvement as shown in Figure 10b.

5 Conclusions

In a test version of the ECMWF 4D-Var assimilation system that uses in situ observations and IASI as the only source of satellite data the possibility of tuning the IASI observation error variances using combined information from the adjoint-based sensitivity tools and from the Desroziers approach has been studied. For each observation type, the adjoint forecast sensitivity with respect to the observation error variances tool provides guidance on how inflating or deflating these errors will impact the 24-h forecast error, but does not provide a quantitative estimate of what the errors should actually be. Other diagnostics, such as Desroziers method based on diagnosing errors from innovation statistics might be used in addition to provide new estimates of the observation error variance.

It is found that tuning the IASI observation errors in selected IASI channels with a combined approach yields a positive impact on both analyses and forecasts. First-guess fits to conventional observations within the analysis are improved and forecasts launched from the retuned analyses also show a moderate increase in skill in the geopotential height, temperature and wind at different tropospheric levels, areas and range forecast. Assessing the information content of observations before and after tuning we demonstrated that the information content in the analysis attributable to the assimilated observations increased from 9.2% to 10.3%, whereas the complementary background information decreased from 90.8% to 89.7%. The ‘Retuned-IASI’ experiment has been constructed specifically to reduce the 24-h forecast error as measured by a dry energy norm and we did find that the improvements in the dry energy norm are propagated up to day 5. The average impact of the observations as a whole was beneficial in each analysis cycle and reduced the 24-h forecast error. Both, the observation influence and the FSOI are proportional to error variance reduction and inversely proportional to the observation accuracy, and so a large observation influence in selected IASI channels produced a large FSOI.

The evaluation of adjoint-based forecast sensitivities to error covariance parameters provides new insights for tuning the observation-error variance input. Systematic non-zero forecast sensitivities in the observation- and background-error covariance representations point towards mis-specification of the errors. The approach in this article was to optimise mostly the estimation of the error statistics of the IASI observations. IASI channels were identified where reducing the observation error variances yielded an overall positive impact in both analyses and forecasts, without accounting for observation error correlations. The results also suggest that the EDA generated background errors are too small. The reason lies in the representation of the model error in the ensemble data assimilation, which is not able to characterise the model uncertainties, especially in the extratropics at any atmospheric level and in the tropics in the mid-troposphere (Cardinali *et al.*, 2014). This study encourages further investigation on the 50-10 hPa background error variances provided by the EDA, as well as the observations sensitive at that atmospheric pressure.

Although this study was performed with a reduced observation network, it tested a process for observation error variances tuning, that could be applied in the operational ECMWF context. Given the various components of the observing system assimilated in the ECMWF operational run, it is anticipated that it might be hard to tune the observation error variances in a much larger parameter space. However, this study does support further effort to better specify the observation error statistics and to take the error correlations into account in the assimilation. An interesting area of future development could be to estimate the off-diagonal terms in the observation error covariance using this approach to assess whether modeling the observation error correlations in the data assimilation system will entail substantial improvements in the model forecast skill.

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