A critical comparison of methods to assess observation impact in NWP

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In numerical weather prediction the value of a particular observing system can be assessed both in terms of its impact upon analyses and forecasts. Understanding this impact allows the data assimilation and forecast system to be optimised to make best use of the available observations.

This work aims to provide some references and possible future directions for validating experiments aimed at measuring changes in the forecast system.

Experiments

Metop-A IASI observations with diagonal observation errors were added to a baseline system. Experiments were carried out with the ECMWF Integrated Forecasting System version CY38R2 at T511 resolution (~40 Km), 137 vertical levels and 12 hour 4D-Var for the period 1 June 2012 to 31 July 2012.

- Exp. A: observation errors for IASI as in ECMWF's operations;
- Exp. B: observation errors for IASI from a posteriori consistency diagnosis (*Desroziers et al*., 2005)

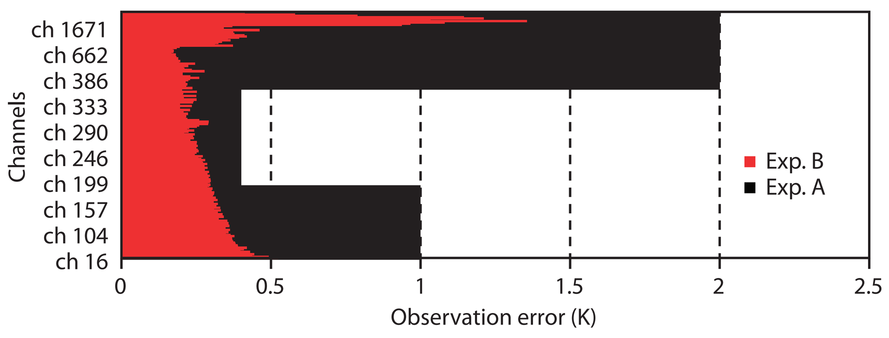

Figure 1 *Estimates of observation errors for Metop-A IASI channels based on the observation error assumed in ECMWF's assimilation system (black) and Desroziers' diagnostic (red).*

Assessing the observation impact in OSEs and adjoint context

1) Traditional metrics in OSEs studies

OSEs evaluation is carried out by means of standard analysis and forecast verification. These comprise for analysis, the comparison of the fit of satellite and conventional data to that from model first-guess and for forecasts, the verification of forecast over short and medium range with observations and analyses.

Compare the fit of observations to that from model-FG

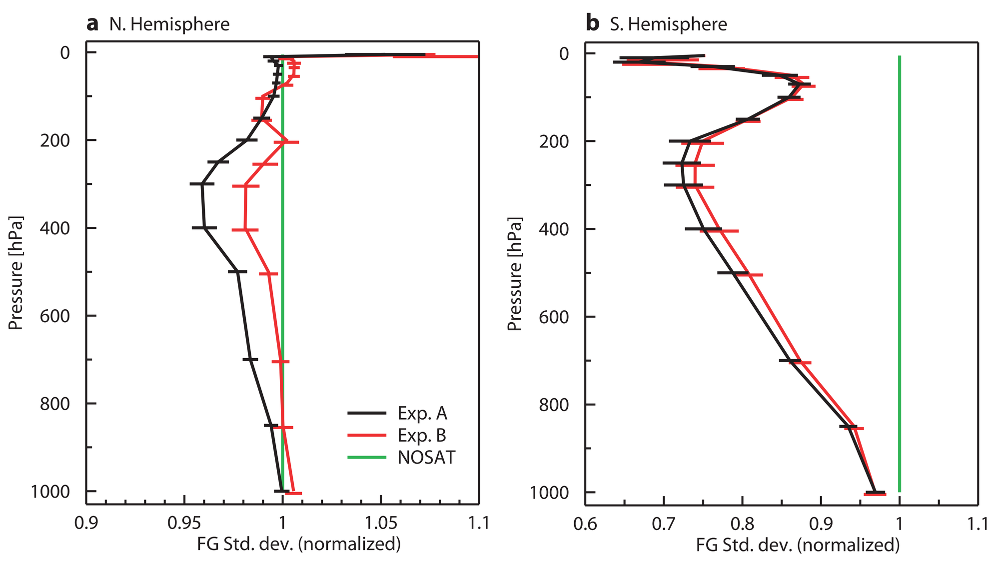

Figure 2 *Normalised standard deviation of background differences from conventional U-wind observations for Exp. A (black) and Exp. B (red) over: a) N.Hemis and b) S.Hemis. Standard deviations have been normalised to the NOSAT experiment (green). Values less than one indicate beneficial impacts from the IASI assimilation.*

Compare forecast against observations

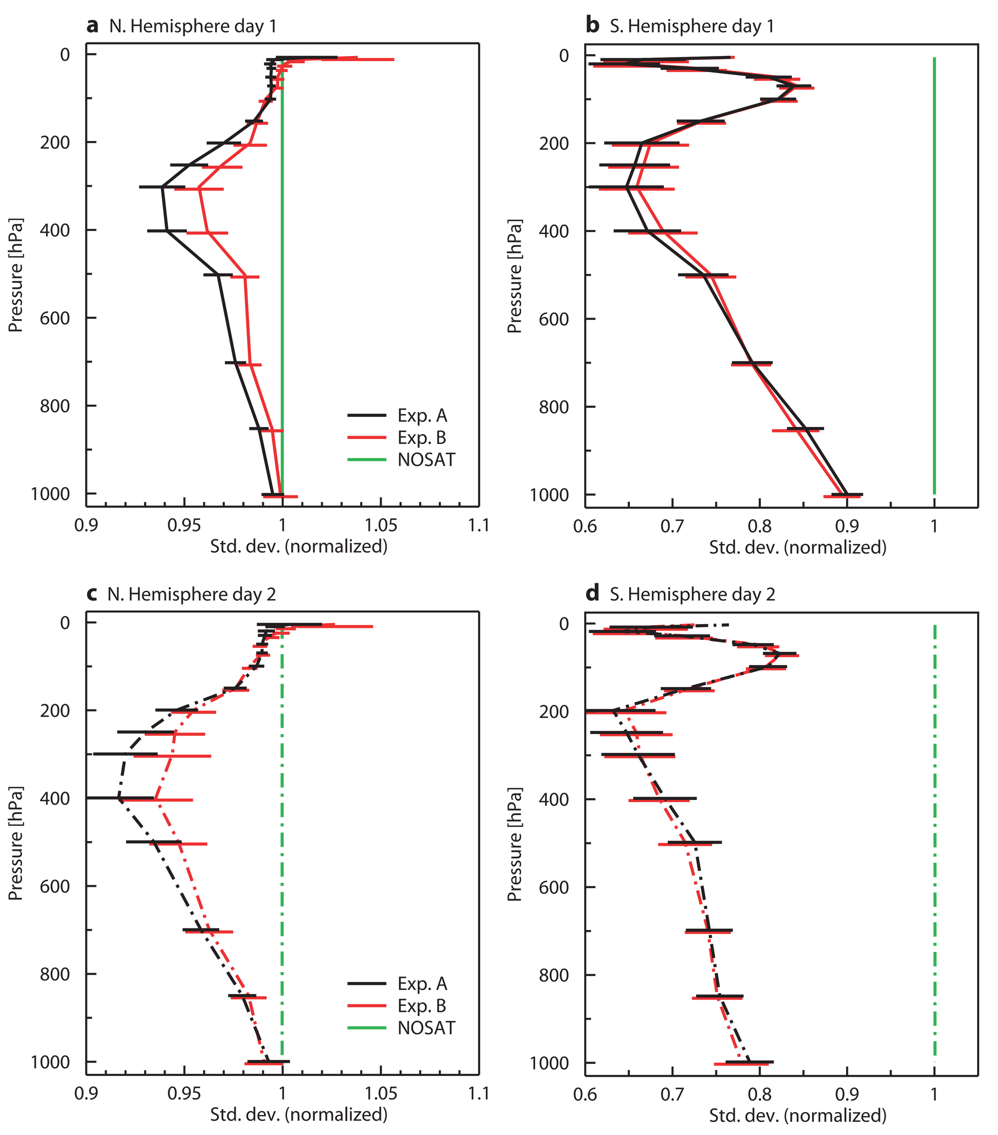

Figure 3 *As Fig.2 but for 24-h (top) and 48-h (bottom) forecast departures differences from conventional U-wind observations over the N. Hemisphere (left) and the S. Hemisphere (right).*

Compare forecast with verifying analyses

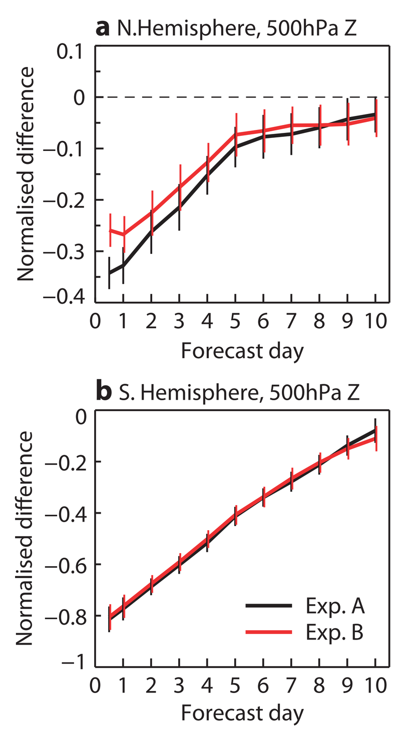

Figure 4 *Normalized differences in the root-mean-square forecast error between the Exp. A and the NOSAT (black) and between the Exp.B and the NOSAT (red) for the 0Z forecast of the 500 hPa geopotential. Verification is against the ECMWF control experiment (all operational assimilated observations) and the sample size is 54. Negative values indicate that the Exp. A and Exp.B have smaller RMS errors than the NOSAT experiment.*

The difference between observation and background (Fig. 2), the comparison of observations with forecast departures (Fig. 3) and the forecast scores (Fig. 4) show that Exp. A outperforms Exp. B.

2) Adjoint-based forecast sensitivity to observations

The adjoint provides forecast sensitivity to initial conditions so that it can be inferred how much an individual observation could contribute to the reduction in forecast error.

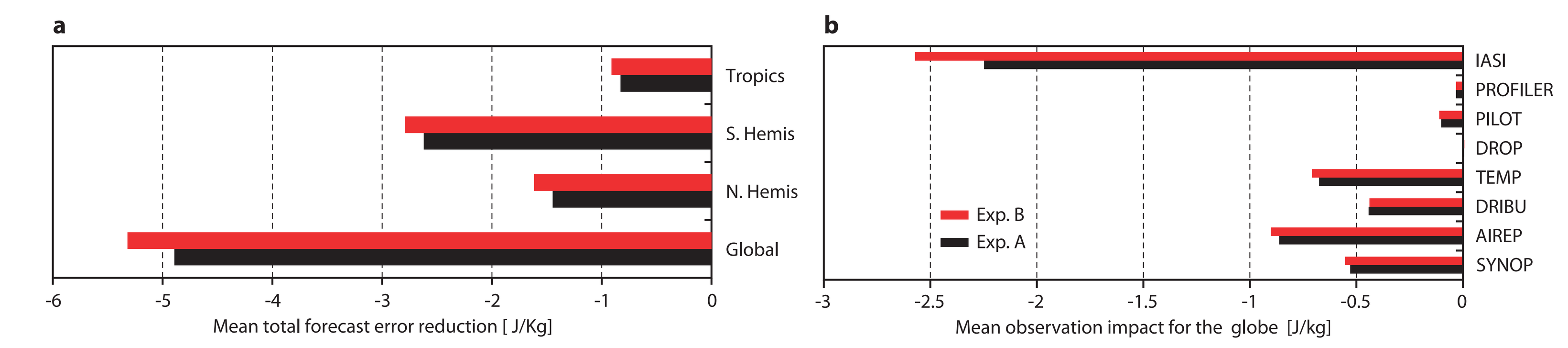

Figure 5 *Contribution of various observation types to the total forecast reduction in terms of dry energy norm for 8 June to 31 July 2012.*

Large 24-hr forecast error reduction from Exp. B, show that Exp. B outperforms Exp. A.

How do the observation impacts results compare?

1) Traditional metrics (OSEs studies)

- Comprehensive analysis of the observation impact on meteorological fields;
- **Exp. A outperforms Exp. B.**

2) Adjoint-based forecast sensitivity to observations

- Observation impact assessment for a particular target metric (e.g., 24-h dry total energy norm);
- **Exp. B outperforms Exp. A!?**

Should we expect such differences?
We need to fully understand the relationship between OSEs and adjoint methods!

Forecast sensitivity to error covariance weighting

- The adjoint methodology can be used to estimate the sensitivity of the forecast with respect to the main input parameters of the assimilation system: observation, background, observation and background error covariance matrices.
- In this study, the forecast sensitivity to the observation and background error variance has been computed following *Daescu* (2008) and *Daescu and Langland* (2013).
- The observation sensitivity vector is a key component to R- and B-sensitivity and impact estimation.

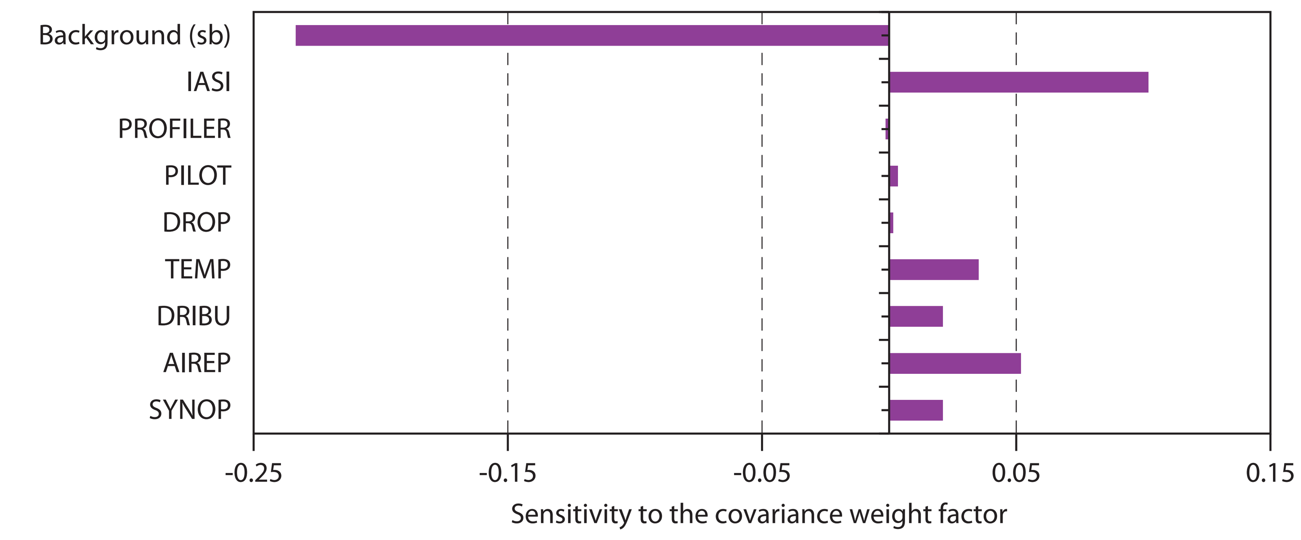

Figure 6 *Sensitivity (J/kg) of the 24-h forecast error with respect to the observations error covariance weight factor associated with a) various data types; b) each IASI channels. The positive sensitivities indicate that error variance deflation should be beneficial to reduce the 24-h forecast error.*

The forecast R- and B-sensitivity guidance to covariance weight adjustments show that:

- **Background error covariance inflation is of potential benefit to the forecast;**
- **Observation error covariance deflation for various observation types is of potential benefit to the forecast;**

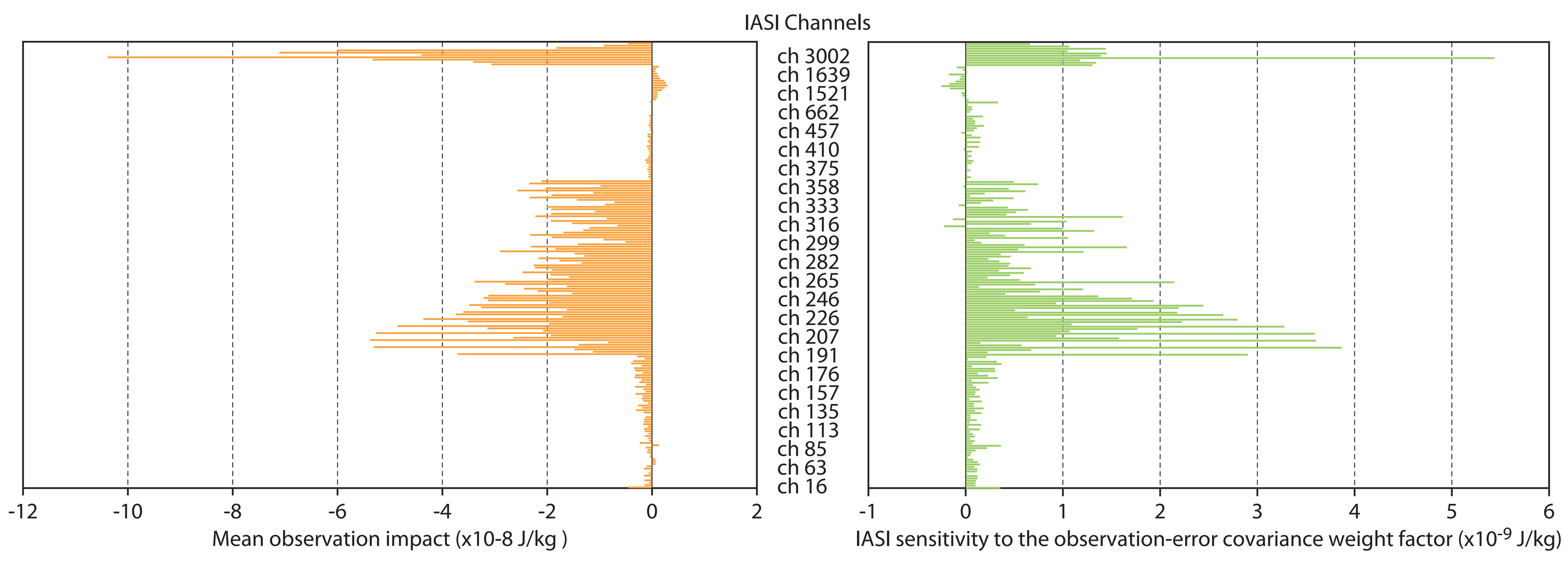

Figure 7 *a) Average forecast impact per observation and b) Sensitivity of the 24-h forecast error with respect to the observations error covariance weight factor of the IASI channels. The positive sensitivities indicate that error variance deflation should be beneficial to reduce the 24-h forecast error.*

IASI sensitivity guidance

- **The information provided by IASI is under-weighted and deflation of the assigned observation-error variances for IASI should be beneficial for the short-range forecast.**

Assess the benefit of adjusting the observation error variances associated with all IASI channels to the diagnosis estimate

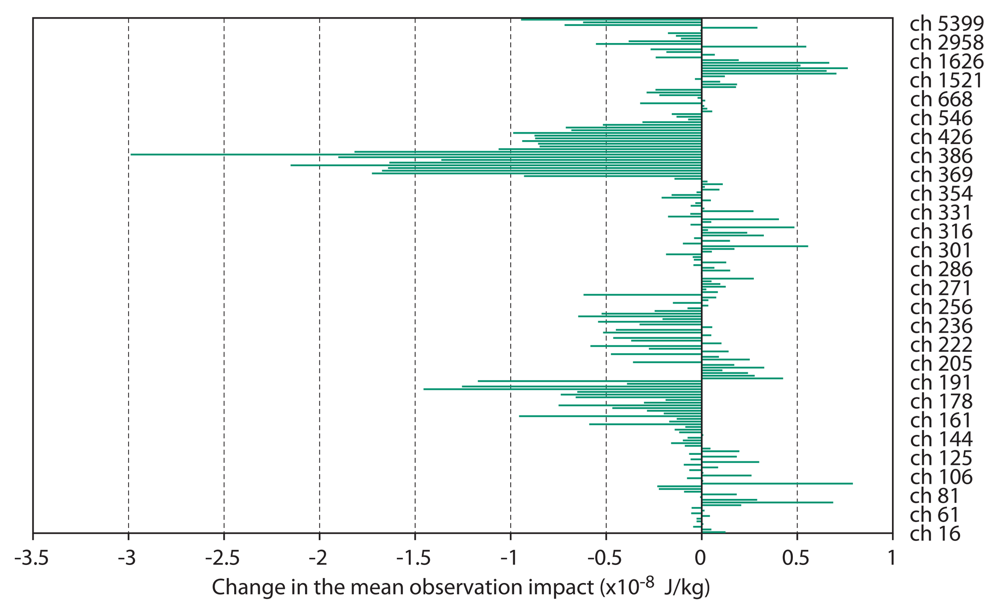

Figure 8 *Change in the forecast-error reduction from tuning the observation-error variances associated with all IASI channels to the diagnosis estimate. Negative forecast error variation is synonymous of forecast improvement.*

- **The additional forecast error reduction achieved by adjusting the observation error variance associated with all IASI channels to the diagnosis values was estimated to be 14.8%, suggesting that Exp. B outperforms Exp. A**
- **This outcome is not in agreement with the OSEs results (see Fig. 2-4) !?**

Steps to determine how much the observation-error variances for IASI channels should be deflated (inflated)?

- identify those instrument channels whose reduced (increased) observation-error values will have a beneficial forecast impact.
- estimate of how much the observation-error variances should be changed (the sensitivity analysis does not provide an optimal value).
- validation through OSEs is needed to assess the data assimilation system performance!

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Acknowledgements

Discussions with Carla Cardinali and Alan Geer are gratefully acknowledged.
Authors thanks to Anabel Bowen for designing the poster.