Reaching far and wide: accounting for spatially correlated errors in an E4DVAR system

Ivo Pasmans[1*], Elias Holm[1], Massimo Bonavita[1], Rishabh Bath[2], Sarah Dance[2]

(1) European Centre for Medium-Range Weather Forecasts (ECMWF); (2) University of Reading; (*) ivo.pasmans@ecmwf.int

Data assimilation (DA) combines prior information with observations to estimate the true state of the atmospheric (the *analysis*). In 4DVAR, the analysis is obtained by minimising a cost function over a time window. The weighting of the prior (the *background*) and the observations is controlled by the background-error covariance **B** and observation-error covariance **R**.

For computational efficiency, **R** is often assumed diagonal in operations. Ignoring spatial observation-error correlations introduces systematic penalties:

- Analyses become too smooth at small scales[1].
- Root-mean square error (RMSE) is higher than when correlations are represented[2,3,4].
- Large-scale corrections are underestimated when observation-error correlation length scales exceed background-error scales[5,6].
- Fewer observations can be assimilated effectively[6,7].

To address this, we are implementing horizontally correlated observation errors in ECMWF's E4DVAR for AMSU-A and SATOB:

- **Phase 1 (this poster): add horizontal correlations to the observation perturbations used to maintain ensemble spread and see how this impacts the ensemble of 4DVARs (E4DVAR) system.**
- Phase 2 (later this year): include correlated-error structure directly in the 4DVAR minimisation through **R**.

Ensemble of 4DVARs (E4DVAR)

- 10 ensemble members with *perturbed observations* and perturbed physics + 1 control run without perturbations.
- Forecasts/backgrounds are produced by the 25-39km global IFS atmosphere-land-ocean model every 12 hours.
- Spatially filtered ensemble members are used to estimate **B**.

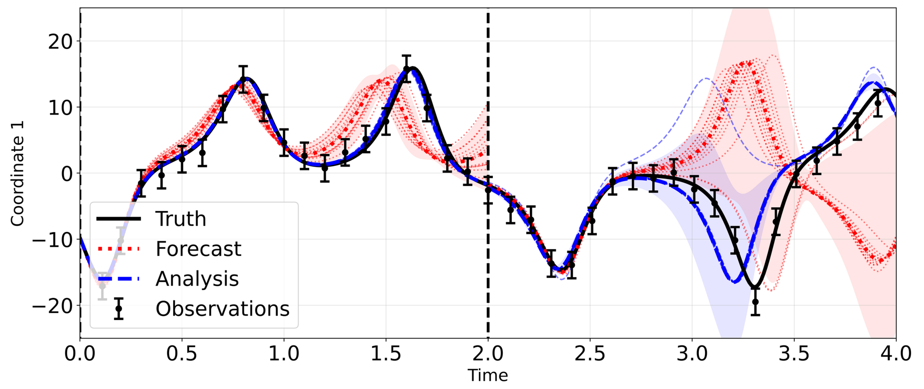

*Figure 1: Schematic of the E4DVAR system. Forecast/background members (red thin lines) are used to estimate the background ensemble covariance (red shade) at time 0. This and their differences with the **(perturbed) observations** (black dots) are used by 4DVAR to calculate the initial conditions for the analyses (blue lines) at time=0. The analyses are propagated forward to time=2 following a path closer to the **truth** (black). They then serve as initial conditions for the forecasts/backgrounds in the next window.*

AMSU-A observations

- Advanced Microwave Sounding Unit-A (AMSU-A) provides brightness temperature measurements that are assimilated in the upper atmosphere (channels 5-14).
- Near global, all-sky cover[8].
- Errors due to calibration and radiative model.
- Errors are dominated by the spatially uncorrelated part (see Fig. 2).

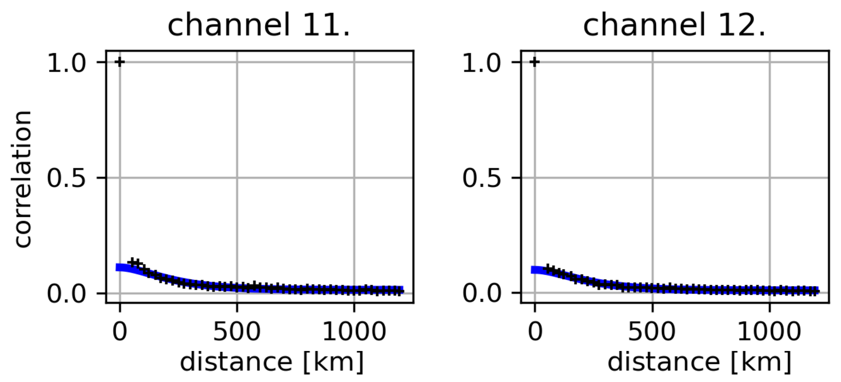

*Figure 2: Estimated observational error correlation as a function of distance for AMSU-A channels 11 and 12 using the Desroziers method[11] (**black crosses**). Also shown is the SOAR-function fit to the correlations (blue).*

SATOB observations

- Satellite observations (SATOB) provide Atmospheric Motion Vectors (AMVs): horizontal wind velocities are estimated by tracking cloud formations over time[9].
- Near complete coverage between 60S-60N.
- Errors due to mistakes in tracking and incorrect height assignment.
- Height errors dominate and give rise to erroneous velocities over large (800 km) areas[10].

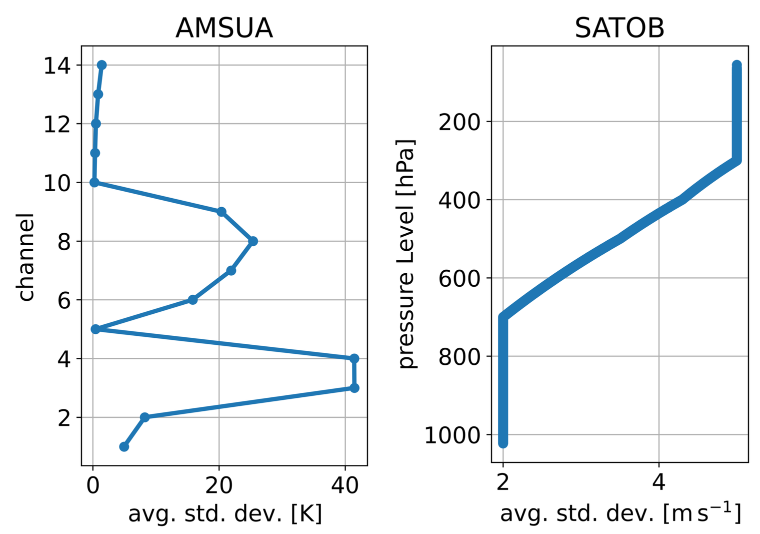

Figure 3: Horizontally averaged observational error standard deviations for AMSU-A (left) and SATOB (right) observations as a function of the vertical coordinate.

Experiments

Experiment	SATOB			AMSU-A		
	α	L [km]	T [h]	α	L [km]	T [h]
Ref	1.0			1.0		
SATOB	0.0	200	1.5	1.0		
AMSUA	1.0			0.85	120	0.75
SATOB+AMSUA	0.0	200	1.5	0.85	120	0.75

Table 1: observational error covariance parameters.

- Initialised from high-resolution, 50-member E4DVAR e-suite.
- Period: 1 June 2024 until 1 July 2024 with 1-6 June serving as spin-up period.
- Observational perturbations are sampled from the covariance

$$\sigma_1\sigma_2\delta(\mathrm{p}_1-\mathrm{p}_2)\left[\alpha+(1-\alpha)\left(1+\frac{\|\mathbf{r}_1-\mathbf{r}_2\|}{\mathrm{L}}\right)e^{-\frac{\|\mathbf{r}_1-\mathbf{r}_2\|}{\mathrm{L}}}\mathrm{e}^{-\frac{|\mathrm{t}_1-\mathrm{t}_2|}{\mathrm{T}}}\right]$$

with σ the observational error standard deviation (see Fig. 3), p the pressure level/channel, δ Dirac delta, $\mathbf{r}$ the horizontal position of the observation, L the horizontal correlation scale, t observation time, T the correlation time-scale and α the spatially uncorrelated fraction of the error variance (see Table 1).
- Other observations are perturbed identically across the different experiments and lack horizontal and temporal correlations.

Changes in background variance

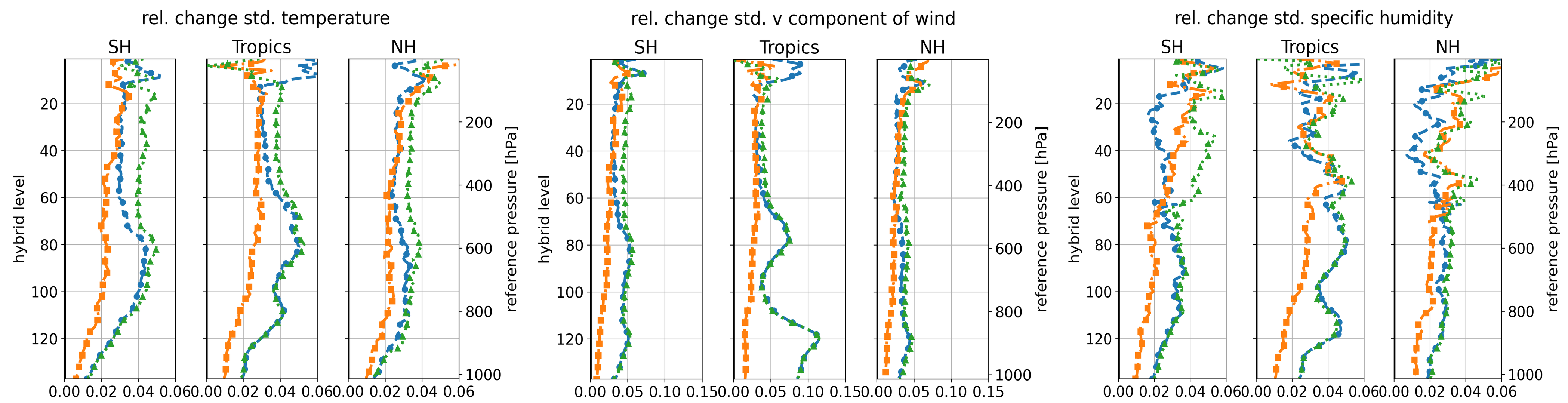

*Figure 4: Relative change of the ensemble background variance **B** compared to experiment REF as a function of the vertical coordinate averaged over experimental period for different variables.*

- Inclusion of spatial correlations generally increases background variance by 2-4% (Fig. 4).
- Increase predominantly caused by correlations in the SATOB perturbations as a large fraction of the AMSU-A perturbations is uncorrelated (Fig. 4).
- Increase due to AMSU-A correlations uniformly distributed over the atmosphere (Fig 4,5).
- Increase due to SATOB correlations largest over the ocean, especially in the tropics where ample clouds are available to track (Fig. 5, centre column).

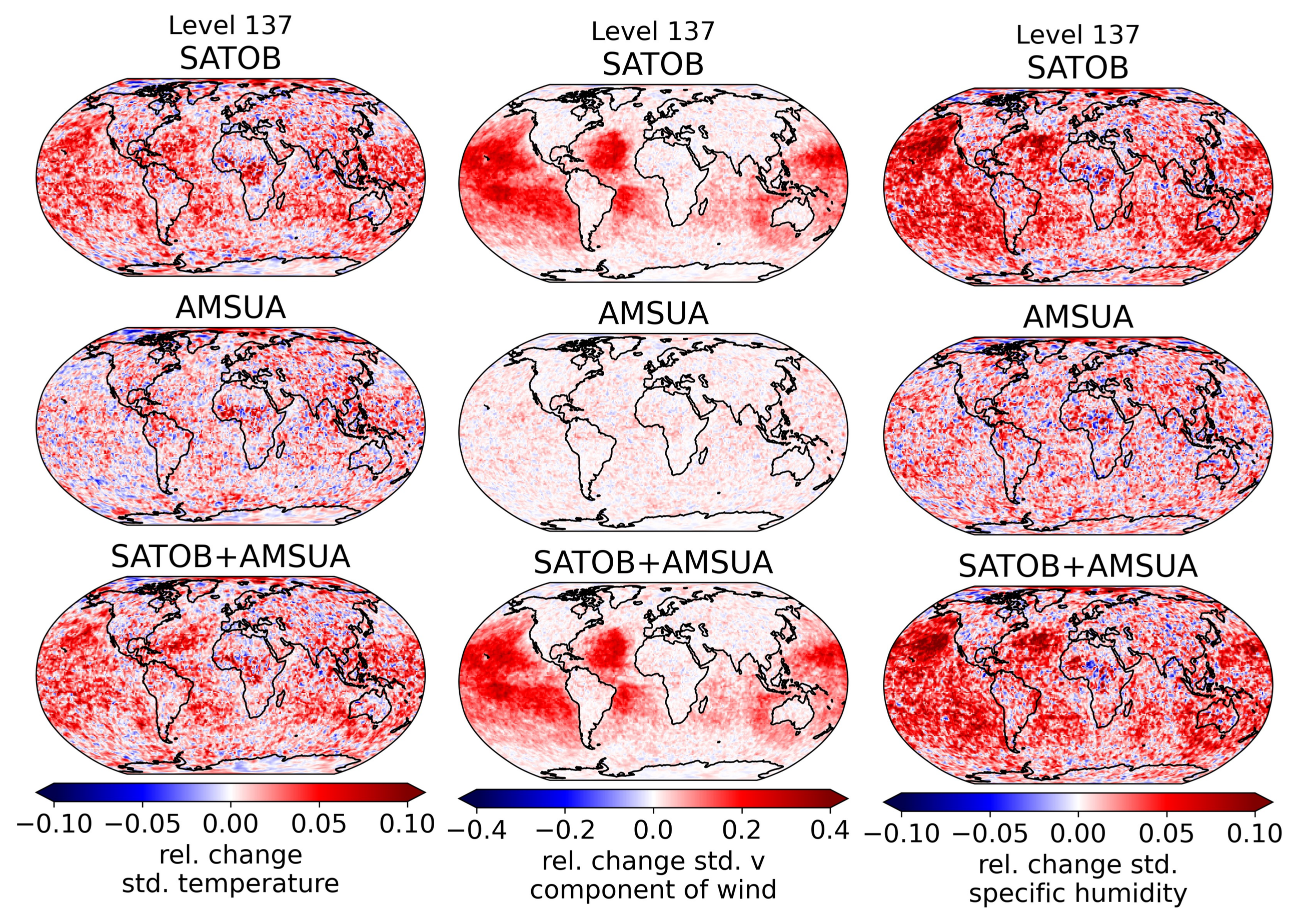

*Figure 5: Relative change of the ensemble background variance **B** compared to experiment REF near the surface for different variables and experiments.*

Comparison with observations

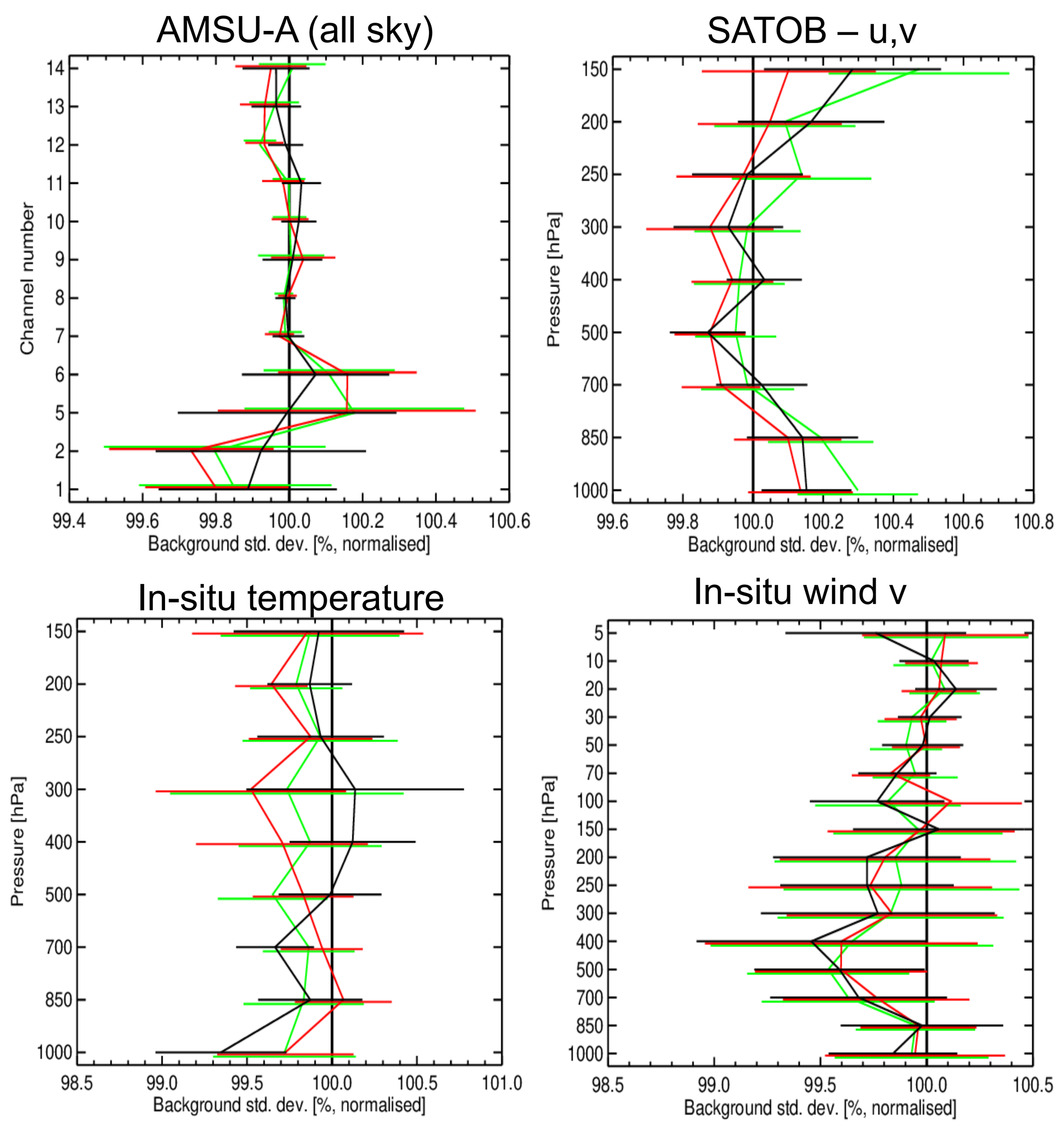

Figure 6: Relative change in RMSE between background and observations as a function of vertical coordinate for the different experiments and different observation types.

- No statistically significant improvement (at 95% confidence) against the observations with horizontally correlated perturbations (Fig. 6, top row).
- Addition of horizontal correlations does improve the background compared to some other observations like aircraft/ballon/radiosonde/profiler observations of velocity and temperature (Fig. 6, bottom row).
- No significant change for other observations without horizontal correlations (not shown).

Conclusions

- Perturbations are added to the observations in the E4DVAR ensemble members prior to assimilation to account for uncertainty introduced by observational errors. The E4DVAR system has been modified to add physically realistic horizontally correlated perturbations for AMSU-A and SATOB observations.
- Inclusion of the correlations increases background ensemble spread due to horizontal correlations with 2% (AMSU-A) to 4% (SATOB) with the latter dominating.
- The increased ensemble spread has no or a small positive impact on the quality of the background/forecast.

Future plans

- Extend experiment period to obtain statistically significant results.
- Incorporate horizontal observational error correlations in **R** as used in the 4DVAR cost-function.
- Revisit need for observation thinning and observation inflation.

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