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Diagnosing observation error statistics for atmospheric motion vectors

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Introduction

Data assimilation techniques combine observations, $\boldsymbol{y}$, with a model prediction of the state, the background, $\boldsymbol{x}^b$, to provide a best estimate of the state, known as the analysis, $\boldsymbol{x}^a$. To obtain an accurate analysis the errors associated with the background and observations must be correctly specified and well understood.

Motivation

The errors associated with the observations, $\boldsymbol{\varepsilon}^o = \boldsymbol{y} - \boldsymbol{H}\boldsymbol{x}^t$, where $\boldsymbol{H}$ is the observation operator and $\boldsymbol{x}^t$ is the true state, can be attributed to four sources; instrument error, representativity error, error in the observation operator and pre-processing error [1]. For many instruments these errors will be correlated with error $\boldsymbol{\varepsilon}^o \sim N(0, \boldsymbol{R})$.

Currently many observation errors are assumed uncorrelated; to avoid violating this assumption the observation density is severely reduced. To improve the quantity of observations used and the impact that they have on the forecast requires the introduction of the full, potentially correlated, error statistics [2,3].

Aim

Estimate the observation error covariance matrix, $\boldsymbol{R}$, for atmospheric motion vectors (AMVs) using the diagnostic of Desroziers et al. [4].

The diagnostic of Desroziers et al. [2005]

Desroziers et al. [4] show that R can be estimated using the diagnostic,

$$\boldsymbol{R} \approx E[(\boldsymbol{y} - \boldsymbol{H}(\boldsymbol{x}^b))(\boldsymbol{y} - \boldsymbol{H}(\boldsymbol{x}^a))^T]. \quad (1)$$

Equation (1) is valid if $\boldsymbol{B}$ and $\boldsymbol{R}$ used in the assimilation are exact. It has been used successfully to estimate $\boldsymbol{R}$ and produced good results even when $\boldsymbol{R}$ and $\boldsymbol{B}$ used in the assimilation are not correct [5].

Atmospheric motion vectors

AMVs are wind observations derived by tracking water vapour or cloud features over consecutive satellite images. The derivation of AMVs is complex and has some inherent assumptions and limitations which may become sources of errors for the AMVs. The two main contributors to the total AMV error are the tracking error and height assignment. The magnitude of the error is influenced by specific atmospheric situations including wind shear, temperature inversions, the jet stream. Mid-level features are hard to track as they are difficult to distinguish from features above and below.

Currently the Met Office assimilate AMVs derived using images from four channels of the SEVIRI instrument. Observations are thinned to 5km before assimilation. We estimate error statistics for these AMVs.

Results

Variance

The estimated variances are generally smaller than those used in the assimilation; they also vary significantly with height (Fig. 1). The maximum value occurs at the mid-levels and this is likely to be a result of high wind shear or features being contaminated from above or below. The variances are also large at high levels. This may be due to the very large assigned variances affecting the results of the diagnostic [5]. An alternative explanation relates to high wind shear at these levels due to the presence of the Polar Front Jet Stream.

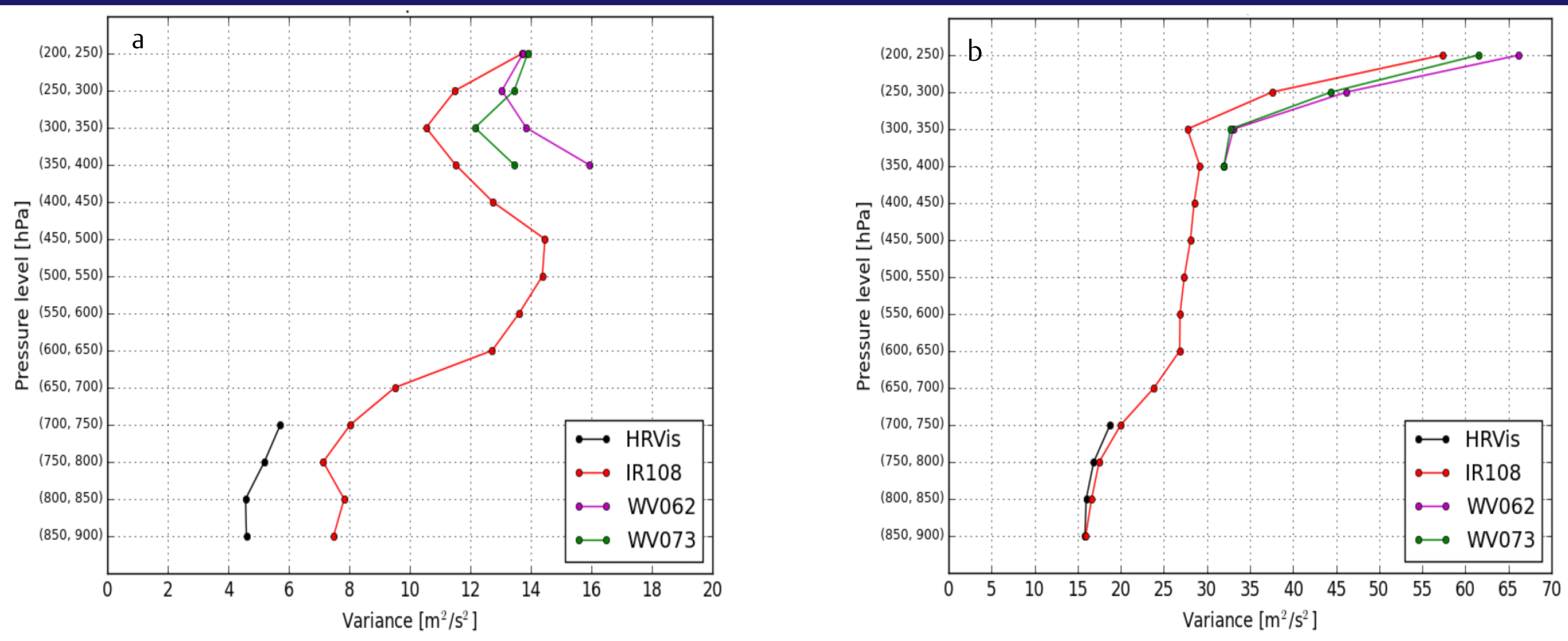

Figure 1: Estimated (a) and assigned (b) AMV observation error variance profiles

Horizontal correlations

The estimated horizontal correlation length scales range between 120km and 360km (Table 1) and are longer than the current thinning distance. Comparing the correlations for IR108 at high, medium and low levels suggests that the correlation length scales also vary with height, with larger length scales in the mid-levels. The estimated correlation for the three high level channels have similar length scales suggesting that the error sources for each channel are similar (Fig. 2). HRVis is not strictly comparable with the other channels as the AMVs derived from the HRVis channel are only available during the day. The error correlation length scale for the HRVis AMVs is longer than those for other channels (Fig.3). This suggests that at least one source of error has larger length scale during daytime than at night.

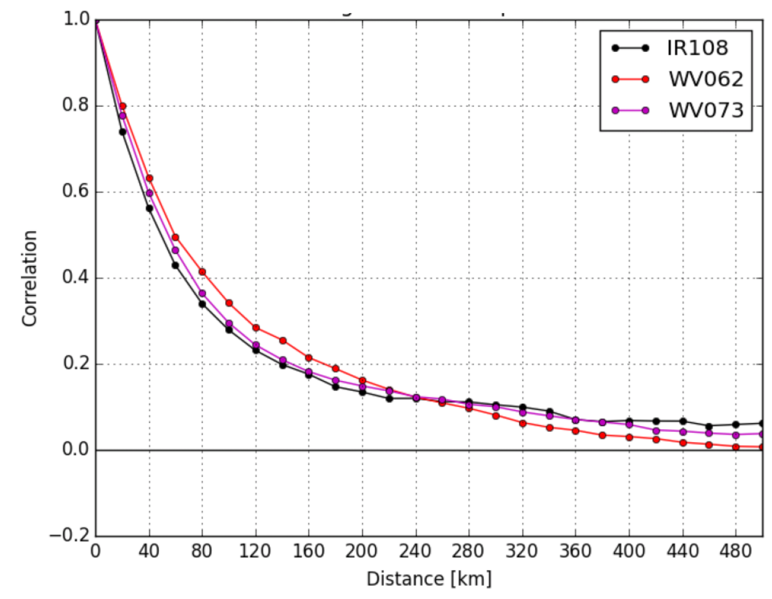

Figure2: Horizontal AMV observation error correlation estimates at high levels.

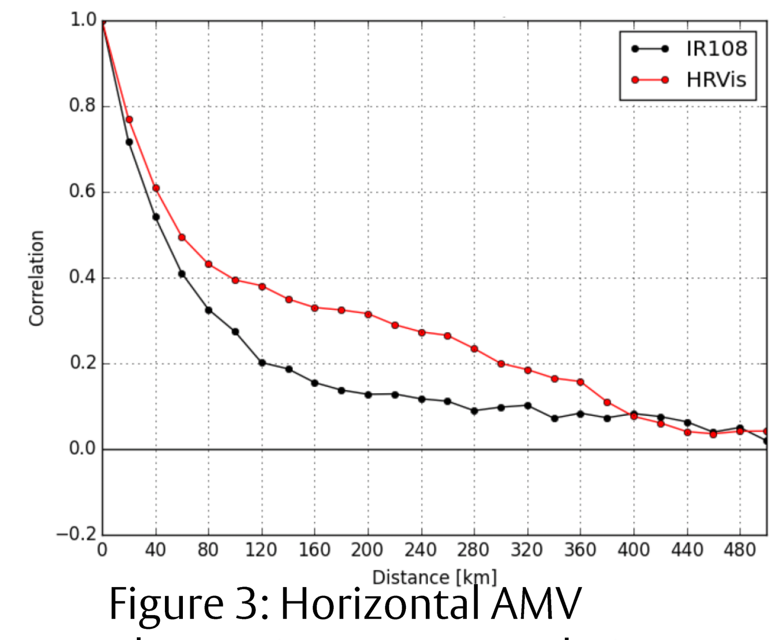

Figure 3: Horizontal AMV observation error correlation estimates at low levels.

	High level			Medium Level			Low level		
	U	V	S	U	V	S	U	V	S
IR108	120	140	140	200	200	210	140	150	140
WV062	160	200	180	-	-	-	-	-	-
WV073	150	170	160	-	-	-	-	-	-
HRVis	-	-	-	-	-	-	320	220	360

Table 1: AMV wind speed (U, V and S components) observation error horizontal correlation length scale [km] for the 4 SEVIRI channels at high, medium and low level

Conclusions

- The estimated variances vary significantly with height and are smaller than those used in the assimilation.
- Variances are largest between 400hPa and 700hPa where wind shear is large and the tracked features are most likely to be contaminated.
- The horizontal length scales found are significantly larger than the current thinning distance of 20km.
- At least one source of error has longer correlation length scales during day than at night.

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