

Assimilation of AMSU-A Microwave Radiances with an Ensemble Kalman Filter (EnKF)

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Introduction

The ensemble Kalman filter (EnKF) is a 4D data assimilation method that uses a Monte-Carlo ensemble of short-range forecasts to estimate the covariances of the forecast error (Evensen 1994; Burgers et al. 1998; Houtekamer and Mitchell 1998). It is a close approximation to the standard Kalman filter. The approximation becomes more accurate as the ensemble size increases.

The EnKF is conceptually simple. It does not depend strongly on the validity of hypotheses about the linearity of the model dynamics and requires neither a tangent linear model nor its adjoint. In addition, it parallelizes well.

Like most modern data assimilation methods, the EnKF directly assimilates observed radiance data. This aspect of the EnKF, and in particular the assimilation of AMSU-A microwave radiances, is the focus of this presentation.

First, the EnKF and the experimental environment are briefly described. Then we focus on how the EnKF assimilates the AMSU-A microwave radiances and show some results indicating their impact with the EnKF (including a comparison with similar results from a 3D-Var system). The present text ends with some concluding remarks and a brief outline of our future plans in this area.

The EnKF

For ensemble member i , the EnKF equations can be written as

$$\Psi_i^a = \Psi_i^f + K(o_i - H(\Psi_i^f)) \quad (1)$$

$$\Psi_i^f(t+1) = M(\Psi_i^a) + q_i \quad (2)$$

where

Ψ^a : analysis field,

Ψ^f : first-guess (forecast) field,

- o_i : vector of (perturbed) observations,
- H : interpolation operator (may be nonlinear),
- K : gain matrix,
- $t+1$: the next analysis time,
- M : full (nonlinear) forecast model,
- q_i : representation of model error.

The gain matrix, K , determines how much weight is given to the innovation, $o_i - H(\Psi_i^f)$, vis-a-vis the forecast (or first-guess) field, Ψ^f . As in the standard Kalman filter, the gain matrix is defined as

$$K = P^f H^T (H P^f H^T + R)^{-1}, \quad (3)$$

where R is the observational error covariance matrix.

Unlike the standard Kalman filter, the EnKF uses a random ensemble to estimate error covariances, i.e.,

$$P^f H^T \equiv \frac{1}{N-1} \sum_{i=1}^N [\Psi_i^f - \overline{\Psi^f}] [H(\Psi_i^f) - \overline{H(\Psi^f)}]^T \quad (4)$$

$$H P^f H^T \equiv \frac{1}{N-1} \sum_{i=1}^N [H(\Psi_i^f) - \overline{H(\Psi^f)}] [H(\Psi_i^f) - \overline{H(\Psi^f)}]^T. \quad (5)$$

Note that since H is applied to each background field individually (rather than to the covariance matrix P^f), it is possible to use nonlinear operators. For example, H can be a radiative transfer model if radiance observations are available.

Localization

Correlations associated with remote observations tend to be small and difficult to estimate using small ensembles. To filter covariances at long distances, we use a Schur product (i.e., an elementwise product of two matrices), as described in Houtekamer and Mitchell (2001). That is, instead of directly using covariances calculated from the ensemble, we filter any such covariances using

$$P^f(r_i, r_j) = \rho(r, L) \circ P_{ensemble}^f(r_i, r_j), \quad (6)$$

where ρ is a correlation function with compact support and \circ denotes the Schur product. This leads to a positive definite matrix P^f (Gaspari and Cohn 1999). Here r is the distance between points r_i and r_j and L is the distance beyond which the correlation function, ρ , is zero. Our rationale is that as ensemble sizes increase in the future (for

example, with increases in the available computational power), it will be possible to increase L and thereby relax the localization.

In fact, the EnKF never computes the covariance matrix P^f ; to calculate the gain matrix, K , only $P^f H^T$ and $HP^f H^T$ are required. By applying covariance localization separately in the horizontal and in the vertical, we are effectively using the following modified definition of the gain matrix

$$K = [\rho_V \circ \rho_H \circ (P^f H^T)][\rho_V \circ \rho_H \circ (HP^f H^T) + R]^{-1}. \quad (7)$$

Here ρ_H and ρ_V are the correlation functions used for horizontal and vertical localization, respectively, and $P^f H^T$ and $HP^f H^T$ are computed from the ensemble using eqs. (4) and (5), respectively. Actually, rather than using a single ensemble, we use a configuration consisting of a pair of ensembles, as proposed in Houtekamer and Mitchell (1998). Having two ensembles allows the Kalman gain used for the assimilation of data into one ensemble to be computed from the other ensemble.

Currently, the vertical localization forces covariances to zero in 2 units of \ln (pressure). Thus, for example, the covariances associated with a 1000-hPa observation fall to zero at 135 hPa, while those associated with a 10-hPa observation fall to zero at 74 hPa.

The Experimental Environment

The EnKF used here has been developed in a series of studies in increasingly realistic environments starting with the 3-level quasigeostrophic model used by Houtekamer and Mitchell (1998) and Mitchell and Houtekamer (2000). For the past few years, we have been using the Canadian Global Environmental Multiscale (GEM) primitive equation model (Côté et al. 1998): initially, a dry 21-level version to assimilate simulated observations (Mitchell et al. 2002) and, more recently, a 28-level version that includes a complete set of physical parameterizations to assimilate real observations (Houtekamer et al. 2003).

Our approach with the EnKF has been to use those observations accepted by the Canadian operational global 3D-Var. As discussed in Houtekamer et al. (2003), this facilitates comparisons with the operational system and allows the EnKF to make use of the operational: (i) “background check” and QCVAR, (ii) TOVS monitoring and bias correction, and (iii) horizontal thinning of TOVS observations.

Currently, of the observations assimilated by the 3D-Var, the EnKF assimilates the following:

- from radiosondes: $u, v, T, q, p_{surface}$;
- from aircraft: u, v, T ;
- from satellites: cloud track winds u, v , and AMSU-A microwave radiances;
- surface observations: $T, p_{surface}$.

The EnKF uses the same observational error statistics as the operational 3D-Var. This, too, facilitates comparisons with the operational system.

Assimilation of AMSU-A Microwave Radiances

For the calculation of simulated radiances from a model state vector, the EnKF (like the Canadian operational 3D-Var procedure) uses the RTTOV radiative transfer model. RTTOV-6 (Saunders et al. 1999, Saunders 2000) was used for the experiments presented here, although we have subsequently converted to RTTOV-7. Our implementation of RTTOV is very much based on its use in the operational 3D-Var (Chouinard et al. 2002). Since it uses eqs. (1), (4), (5), and (7) to assimilate observations, the EnKF requires neither the tangent linear nor the adjoint of the radiative transfer model.

Using only observations accepted by the operational 3D-Var, the EnKF assimilates AMSU-A channels 3–10 over open ocean and from three to five of these channels over land and ice depending on the height of the topography, as described by Chouinard et al. (2002). In addition, the AMSU-A observations used operationally are thinned to a horizontal resolution of ~ 250 km.

The results shown below are from data assimilation cycles over a 2-week period in May - June 2002. During this period, AMSU-A observations were available from two polar orbiters, NOAA-15 and NOAA-16. Due to the horizontal thinning of the AMSU-A observations, approximately 3000 profiles were available for assimilation every 6 h from each of these two satellites.

Results from Two Experiments

The first experiment is a TOVS/NOTOVS experiment. Results are evaluated by verifying 6-h forecasts against radiosonde observations. The evaluation is performed over a 5-day period, after a 5-day spin-up. In this experiment, the horizontal grid is 144×72 , the EnKF uses a total of 96 ensemble members, and the correlation function used for localization in the horizontal falls to zero at 2300 km.

Results show a neutral to modest improvement in the Northern Hemisphere (not shown). A more substantial positive impact of the AMSU-A observations is observed in the tropics and in the Southern Hemisphere. The Southern Hemisphere results are presented in Fig. 1. It can be seen that assimilation of the AMSU-A profiles results in generally smaller biases and standard deviations (std dev) for all five variables.

The second experiment is a 3D-Var/EnKF comparison. Both methods have been used to assimilate exactly the same set of observations, using the same observational error statistics. The same forecast model (resolution, physical parameterizations, etc.) has been used for both methods. For this experiment, the horizontal grid is 240×120 ;

the EnKF uses a total of 128 ensemble members; and the correlation function used for horizontal localization in the EnKF falls to zero at 2800 km. Houtekamer et al. (2003) present verifications of 6-h forecasts and analyses against radiosonde observations for this experiment. Here we examine verifications against the AMSU-A data.

Figs. 2 and 3 show O - P and O - A statistics for each AMSU-A radiance channel for the 3D-Var and EnKF assimilation cycles, respectively. A comparison of corresponding panels from the two figures indicates that the current version of the EnKF yields larger std dev values than the 3D-Var, especially for channels 3, 9, and 10. The EnKF also produces larger biases than the 3D-Var system, perhaps because the AMSU-A data is bias corrected using the latter system. The results, while encouraging, indicate that there is considerable room for improvement with respect to the EnKF assimilation of the AMSU-A data.

Conclusions

An EnKF has been developed for atmospheric data assimilation. It is to be used as the data assimilation component of the Canadian operational medium-range Ensemble Prediction System. Results with real observations indicate that the EnKF can be used to assimilate AMSU-A microwave radiances.

Work is continuing aimed at improving the assimilation of the AMSU-A microwave radiances in the EnKF. Among the aspects that we intend to examine are: the effect of the vertical/horizontal localization; the necessity for EnKF-specific (a) QC, (b) monitoring, and (c) bias correction procedures; the desirability of adjusting the observational error specification, including the possible inclusion of observational error correlations. We also intend to assimilate other types of radiance data, e.g., AMSU-B, with the EnKF.

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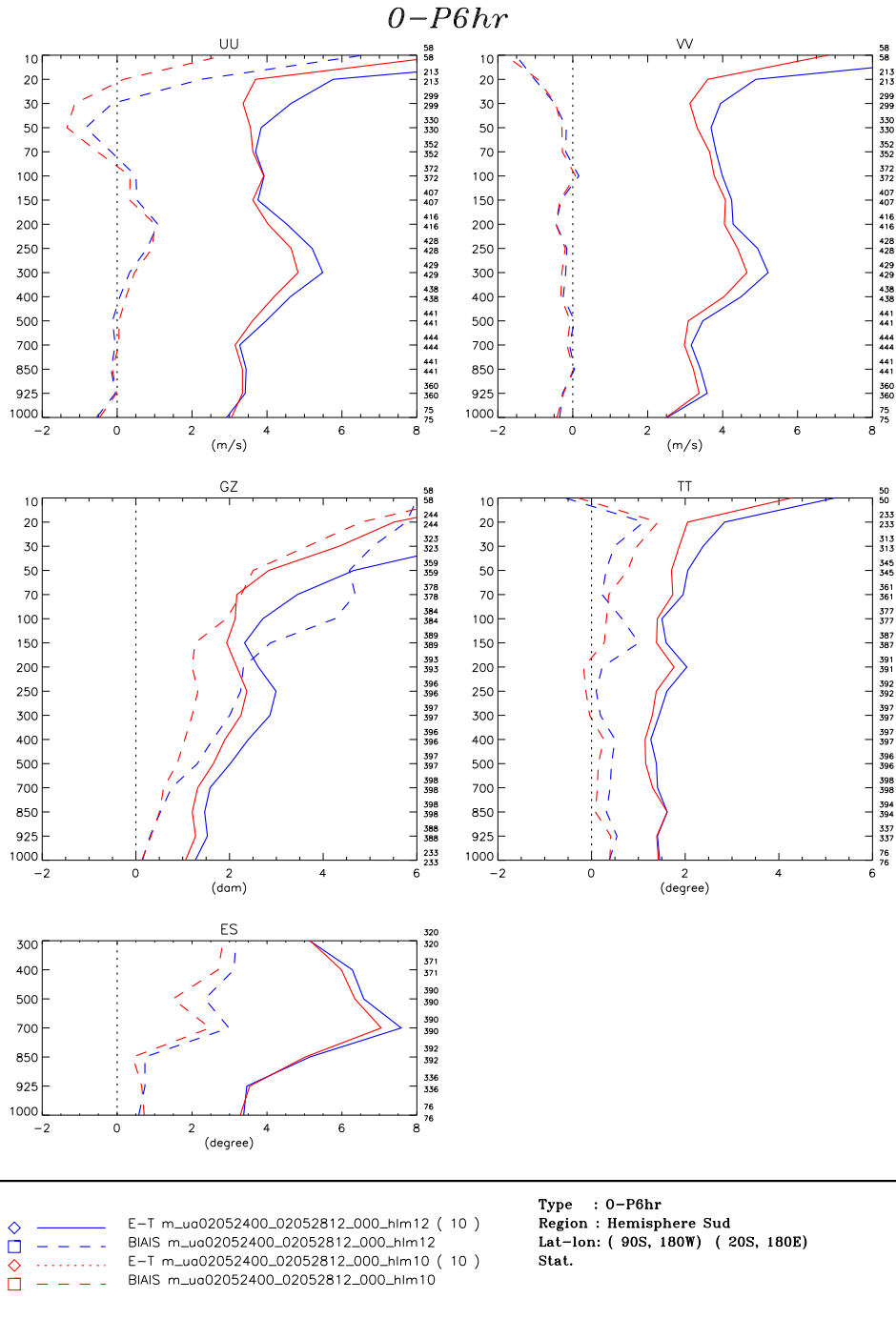


Figure 1: Verification scores for the ensemble mean for the first experiment. The mean value, i.e., bias, (dashed) and std dev (solid) of the observed minus interpolated 6-h forecasts are shown for the assimilation cycle with AMSU-A data (in red) and without AMSU-A data (in blue) for the region south of 20° South.

Brightness Temperature 3DVAR NOAA 16 globe

O-A O-P

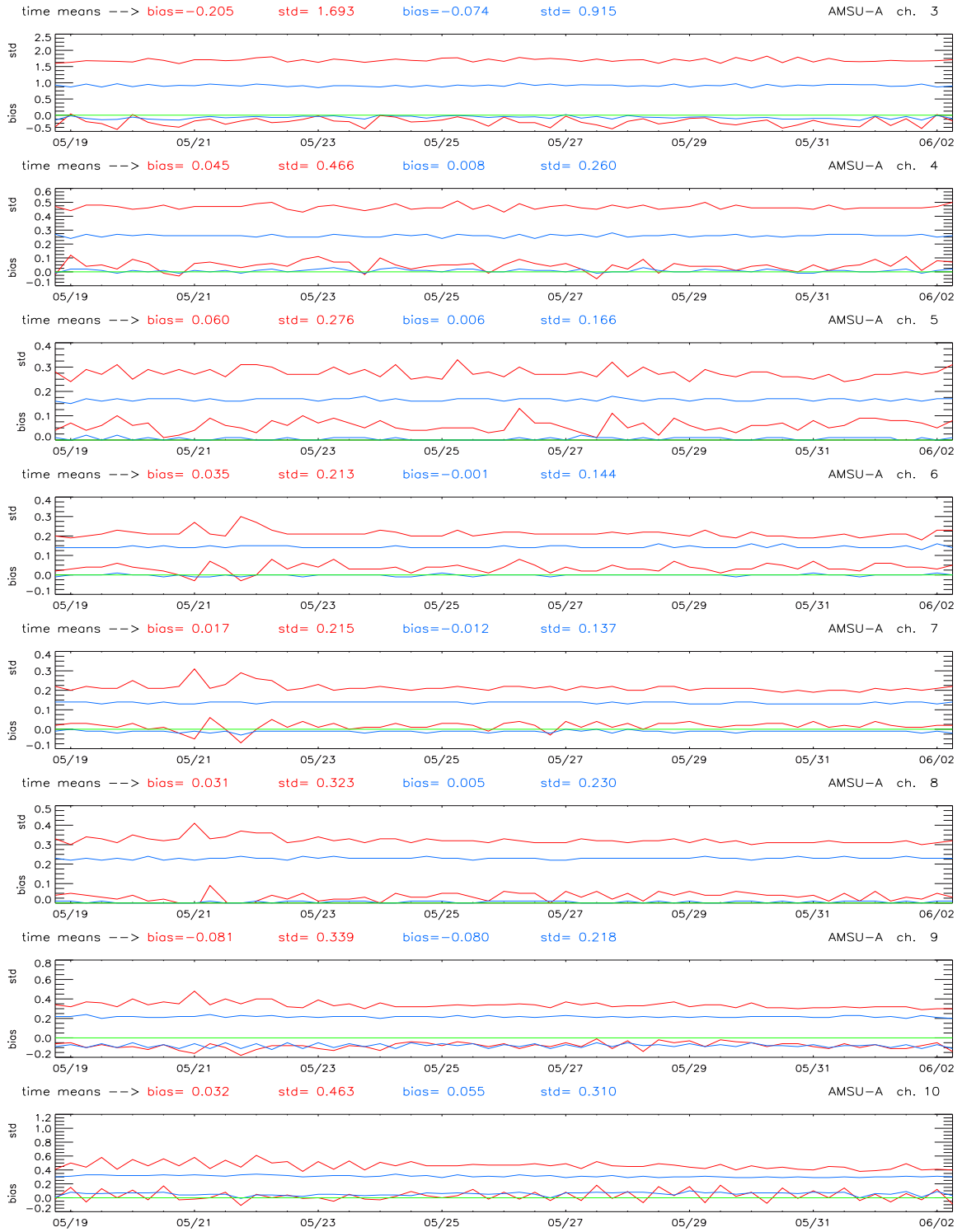


Figure 2: Observed minus analysis (O - A, blue) and observed minus 6-h forecast (O - P, red) for AMSU-A channels 3–10 for the 3D-Var assimilation cycle.

Brightness Temperature EnKF NOAA 16 globe

O-A O-P

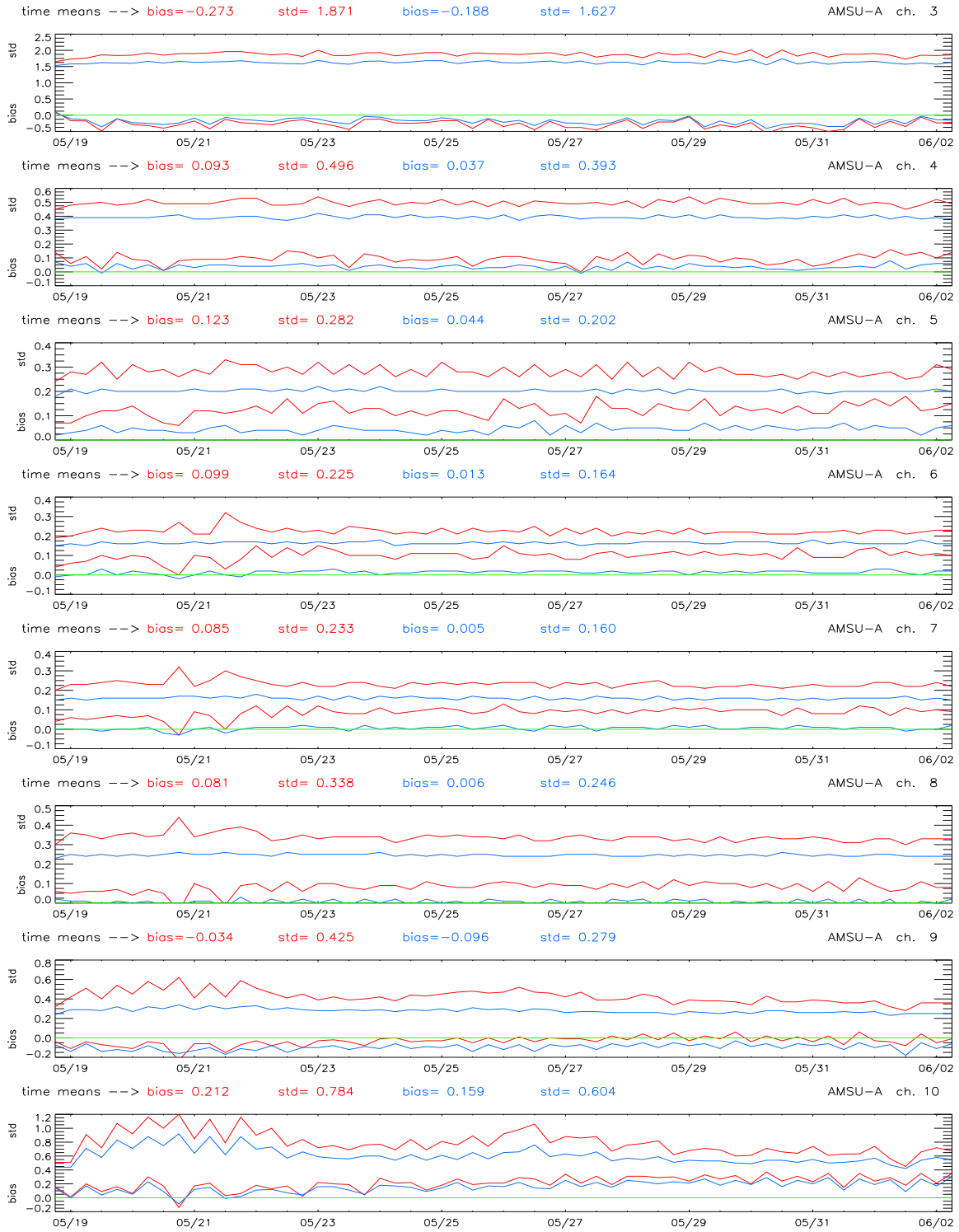


Figure 3: As in Fig. 2, but for the ensemble mean of the EnKF assimilation cycle.

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