Assimilation of ATOVS data in the HIRLAM 3D-VAR System

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1 Background

It was early recognized that radiance measurements from satellites could provide information on atmospheric temperature and moisture profiles through inversion techniques. Several satellite sounding instruments have been launched on operational meteorological satellites during the last 30 years. The VTPR (Vertical Temperature Profile Radiometer) was the first of these operational satellite sounding instruments, measuring radiances in the infrared part of the spectrum only. A new generation instrument, the TOVS (TIROS Operational Vertical Sounder) was launched on American polar orbiting satellites from 1979 and onwards. The TOVS instruments include a High Resolution Infrared Sounder (HIRS), a Microwave Sounding Unit (MSU) as well as a Stratospheric Sounding Unit (SSU). The TOVS instrument was enhanced to the ATOVS instrument with the launch of NOAA-15 in 1998, the Advanced Microwave Sounding Unit (AMSU) with better microwave sounding capabilities replacing the MSU. The ATOVS provides radiance information which is much less affected by cloud contamination than the older TOVS system.

Early attempts to utilize the information from satellite sounding instruments were carried out through two step procedures. Atmospheric profiles of temperature and moisture were determined by a 1-dimensional retrieval from the measured satellite radiances in a first step. These retrieved profiles were then utilized as input to meteorological models by application of meteorological data assimilation. The main component of these (early) data assimilation schemes was a spatial interpolation of observed deviations from a short range forecast of the vertical temperature and moisture profiles. The spatial interpolation was in general linear in the observed deviations.

There were several problems associated with these early simple trials to utilize satellite sounding information for numerical weather prediction. One outstanding problem was the ill-conditioning of the one-dimensional retrieval. Due to the limited vertical resolution of the satellite sounding instruments, many different temperature and moisture profiles may fit the measured radiance data via the radiative transfer equations. In order to obtain a unique solution, a priori information, for example climatological or forecast first guess profiles, was added to the retrieval process. Such a priori information often added further errors to the retrieved profiles, however. For example, too smooth profiles were obtained via the climatological constraint or dependencies on the errors of a particular forecast model were introduced via the forecast first guess. These additional errors turned out to be difficult to handle.

With the introduction of variational data assimilation schemes for initializing NWP forecast models, it has been made possible to directly utilize satellite radiances in the meteorological data assimilation (Andersson et al, 1994), without application of any intermediate retrieval of atmospheric profiles. The extra errors introduced via the a priori information, needed for the 1-dimensional retrieval, are then avoided. This direct variational assimilation of satellite radiances also makes it possible to utilize non-linear relations between the forecast model state variables and the observed quantities.

The international development towards use of sounding data has been driven by forecast centers doing global forecasting, and with the variational assimilation method these data gives a significant impact when assimilated in global models. In regional forecast models the relative influence of the initial state from the assimilation decreases with forecast lead time because of
the forcing of information from a larger-scale model on the lateral boundaries. It is therefore more difficult to find significant impact of new observation systems in regional NWP models than in global ones.

There have been several earlier attempts to introduce TOVS information into regional NWP models in the Nordic countries. Gustafsson (Gustafsson 1979) carried out a TOVS data impact study, where TOVS temperature and moisture profiles, retrieved by the NOAA-NESDIS (the American operational meteorological satellite data producer), were assimilated into a quasi-geostrophic forecast model. Gustafsson found a significant positive impact from the retrieved temperature and moisture profiles. In retrospect it may be argued, however, that this significant positive impact was only made possible through the use a rather poor forecast model. Other researchers at the same time, using more up-to-date forecast models, were not able to prove any impact from TOVS retrievals on Northern hemisphere forecasts. A further effort to assimilate TOVS data at the SMHI was carried out by Gustafsson and Svensson (Gustafsson and Svensson, 1988). A 1-dimensional variational retrieval of temperature and moisture profiles was carried out with forecast profiles as first guess for the retrievals. The retrieved profiles were then inserted into the forecast model via a statistical interpolation data assimilation scheme. A minor impact was found but more seriously, the retrieved profiles were found to be affected by systematic errors. No attempts to adjust for these systematic errors were carried out.

Homleid et al (Claude et al, 1989) and (Homleid 1990) did experiments with assimilation of TOVS retrieved profiles in the weather prediction models of the Norwegian Meteorological Institute. The retrieved profiles were derived using a statistical method with profiles from a radiosonde database as first guesses. A case study was performed and some positive effects were seen in forecasts, but due to the situation dependence of the effects, no clear conclusion on impact could be drawn. Problems were discovered, however, to suggest that the way the observations were used in the assimilation was not optimal. This is in line with the above remarks on the inadequacy of the approach using assimilation of retrievals.

In the 1990's there were several attempts to use a one-dimensional variational scheme (1D-Var (Eyre et al, 1993)) to produce retrievals from TOVS for use in assimilation. These attempts gave positive impacts in several global forecasting centers. Some experiments were also done with HIRLAM at the Finnish Meteorological Institute, but any significant positive impact of TOVS data could not be shown.

With the implementation of the HIRLAM 3D-VAR system and the new generation of instruments in the ATOVS system, there were expectations of obtaining significant positive effects from the assimilation of ATOVS, even in the limited-area setups in HIRLAM. Development projects started at the Norwegian Meteorological Institute (DNMI) and at the Swedish Meteorological and Hydrological Institute (SMHI) at the time when ATOVS was ready for launch. This formed part of a coordinated effort in the HIRLAM community to provide preprocessing and assimilation of AMSU-A data in HIRLAM 3D-VAR. There have also been important contributions from the Danish and Finnish Meteorological Institutes (DMI and FMI). The development had benefit from some of the work that had already taken place at other forecasting centers. For instance, several processing modules developed elsewhere were made available through EUMETSAT.

In this report we describe the developments that have taken place in HIRLAM towards use of AMSU-A data. In the next chapters we give an overview of the preprocessing and the
implementation in 3D-VAR. Then we describe various impact studies undertaken in several of the HIRLAM countries. Finally we give an overview of ongoing work and future developments, before concluding.

2 Processing overview

2.1 AAPP

The American NOAA satellites send out a continuous and non-encrypted signal containing among other observations those made by the on-board ATOVS instruments. This continuous signal is referred to as the HRPT (High Resolution Picture Transmission) string. The HRPT string can be received by any ground station which has the satellite above its horizon. The HRPT string from the NOAA satellites is received at a number of local antennas within the HIRLAM area of interest, and the HIRLAM community acknowledges NOAA for providing this satellite service completely free of charge.

A large and complex software package is needed to extract the calibration information and the observation values from the HRPT string. The “AAPP” (ATOVS and AVHRR Processing Package) software package was developed by some of the EUMETSAT (European Organization for the Exploitation of Meteorological Satellites) member states for this purpose. The AAPP software package is now distributed by EUMETSAT NWP SAF and is made available for free to anyone who signs a license agreement. This software package is in use for interpreting the locally received HRPT string at the HIRLAM centres who have done experimentation with ATOVS assimilation.

For each instrument the HRPT string contains calibration information, time of observation and instrument angles. In addition to the information contained in the HRPT transmission, NOAA also sends out so called TBUS (TIROS Bulletin United States) messages over the meteorological communication network GTS (Global Telecommunications Service) with information necessary for deriving satellite positions. All this information is processed by the AAPP package, and a part of the output is so-called “level 1c” data containing geo-located calibrated radiance values.

2.2 BUFR and CMA

The AMSU-A level 1c files must be converted into BUFR (Binary Universal Format for data Representation) files before they can be processed by 3D-VAR/OBSPROC (MAKECMA). SMHI (tomas.landelius@smhi.se) is currently maintaining the HIRLAM software for converting AAPP level 1c to BUFR. The BUFR files created by this software are slightly different from the corresponding BUFR files generated by ECMWF and Met Office, UK. In the SMHI BUFR files the zenith angle may be negative, indicating that the observation is to the right of the sub satellite track. The ECMWF/Met Office BUFR files have only positive zenith angles. The zenith angle is one of the bias correction predictors (see Section 3.1). It is therefore not recommended to combine BUFR files from these two sources when assimilating AMSU-A in HIRLAM 3D-VAR.
After generation of BUFR observation files, the observations can be read into the HIRLAM 3D-VAR through the OBSPROC interface, which converts the observations from BUFR format into CMA (Comprehensive Memory Array) format, suitable for use in HIRVDA (Lindskog et al, 2001). An overview of the preprocessing flow is given in Fig. 1.
2.3 Cloud mask and thinning in HIRLAM 3D-VAR

The AMSU-A observations are sensitive to the presence of deep cloud and precipitable particles in the atmosphere. This effect is not modeled in the radiative transfer model since it is difficult to determine and forecast the distribution of these quantities with sufficient accuracy. AMSU-A observations that are influenced by deep clouds are therefore not used in the analysis. The procedure for removing cloud contaminated AMSU-A observations is based on an algorithm that was developed at NOAA/NESDIS for estimating total cloud liquid water over ocean (http://orbit-net.nesdis.noaa.gov/arad2/MSPPS/html/day2/algorithmday2.html, see also (Grody, 1993)). This algorithm uses an estimate of the surface skin temperature (here set to a constant reference value) together with observed and calculated AMSU-A channels 1 and 2 (so-called “surface channels”) brightness temperatures. The observation is considered to be contaminated and discarded if the NOAA/NESDIS algorithm suggests that the total cloud liquid water content exceeds a threshold of 0.12 mm. The cloud mask is applied within HIRLAM 3D-VAR, and the amount of data rejected by the cloud mask is reported to the user.

The purpose of data thinning is threefold. First, it alleviates the effects of horizontal observation error correlations in data assimilation. These error correlations are due to the fact that a large number of observations originate from the same instrument. The proper way of dealing with the matter would be to estimate and to model these correlations, but in reality it is very difficult to separate the horizontally correlated observation errors from the horizontally correlated background errors, for instance from innovations (differences between observed and predicted values). Also, such an observation error correlation model is demanding to implement and computationally costly. The second purpose of data thinning is to reduce the data resolution so that it would correspond to the effective resolution of the analysis scheme. This effective resolution is determined by the length scale of the background error correlation model, i.e. by the structure functions. The third purpose of the data thinning is to achieve computational efficiency by assimilating a supposedly optimal set of thinned data.

The data thinning is performed using only purely observational information. One could think of using model background as one thinning criterion, but this would imply support for the model background. In analogy, a bias correction scheme which makes use of model background as a predictor implicitly supports the model biases which the observations might otherwise not support.

The horizontal data thinning implemented to HIRVDA follows the ECMWF data thinning procedure. This makes use of horizontal boxes. All ATOVS reports are assigned with a box index depending on their geographical location. Only the “best” report within each box is retained and passed further to the assimilation. The attribute “best” is determined by sequentially considering the order of preference, which is currently set as follows:

1. difference of observing time to analysis time (in 10 minutes slots)
2. absolute scan angle (look direction relative to nadir)
3. unique sequence number of the report (for reproducibility)

The selection thus retains the nearest-to-nadir observation from the subset of observations with the smallest time difference to the analysis time. If there are more than one observation
with equal preference, the smallest unique sequence number ensures the reproducibility of the thinning procedure.

It often happens with this procedure that two observations very close to each other are retained. These reports are from separate boxes, however. This can happen, for instance, when a divide of two boxes is crossing a set of very good reports. In order to avoid this from happening, and to ensure a minimum distance between nearby reports and thus a geographically homogeneous data distribution, three consecutive scans over the data are performed. The size of thinning boxes of each scan is gradually increased. For the assimilation experiments described in this report, the values of these size parameters are set to 44 km, 99 km and finally 144 km. The sub-satellite track instrument resolution is approximately 50 km. The amount of data rejected owing to the data thinning is among the parameters reported to the user.

2.4 Radiative transfer calculations

To utilize the ATOVS observations, we need a precise description for how the observations relate to the fields in the model which we want to improve by assimilation. In 3D-VAR this is done by using a forward estimation of observed values of ATOVS radiances or brightness temperatures from the model profiles. This is applied both in the prior bias correction processing and in the direct use of the observations in 3D-VAR.

These calculations are performed with the Radiative Transfer Model RTTOV-5 (Eyre, 1991), obtained from EUMETSAT’s SAF for Numerical Weather Prediction (NWP SAF). Below follows an outline of the principles of these calculations.

The ATOVS sensors measure the radiance $L_{\lambda}$ in some zenith angle $\theta$. We introduce $\mu \equiv (\cos \theta)^{-1}$, and the radiance reaching the satellite can be derived from a basic physical law for radiative transfer, also known as Schwarzschild’s equation:

$$\mu \frac{dL_{\lambda}}{d\delta_{\lambda}} = -L_{\lambda} + B_{\lambda}(T).$$

Here the temperature profile enters through the blackbody emission $B_{\lambda}(T)$. $\delta_{\lambda}$ is optical depth increment defined as $d\delta_{\lambda} \equiv k_{\lambda}\rho dz$ which is a measure of the amount of absorption in a path $dz$ for the wavelength $\lambda$. Here $\rho$ is the density of the absorber and $k_{\lambda}$ is the mass absorption coefficient. An integral optical depth can be defined from the top of atmosphere down to some level $z$ in the atmosphere,

$$\delta_{\lambda} = \int_{z}^{\infty} k_{\lambda}\rho dz'.$$

Schwarzschild’s equation can be solved (or “integrated”) to yield the quantity the satellite measures, the radiance $L_{\lambda}$, at the top of the atmosphere

$$L_{\lambda} = \varepsilon_{\lambda}B_{\lambda}(T_s)\tau_{\lambda}^{\frac{1}{2}} + \int_{\tau_s}^{1} B_{\lambda}(T) d\tau_{\lambda}^{\frac{1}{2}}.$$

In this equation a central quantity is the function $\tau_{\lambda}$. This is defined as

$$\tau_{\lambda} \equiv e^{-\delta_{\lambda}} = e^{-\int_{z}^{\infty} k_{\lambda}\rho dz'},$$
and is called transmissivity. It is a function of height, and it is a measure of the fraction of radiation transmitted from some level which reaches the top of atmosphere without being absorbed. The integration domain goes from the earth surface with transmissivity $\tau = \tau_s$ to the top of atmosphere where all of the upward radiation is visible to the satellite and $\tau = 1$.

The determination of the transmissivities is the most important element of a radiative transfer model. The transmissivity varies very strongly with wavelength from absorption lines to non-absorbing parts of the spectrum. The ATOVS observation channels are not able to cover only a fixed frequency, but represents a weighted average of the radiation over some (small) frequency interval. For a realistic estimation of radiances corresponding to the measurements, one must therefore consider not just one frequency, but a part of the spectrum.

The transmissivity not only depends on the concentration of the absorbing gases, but also on their temperature. For application in NWP, very strong constraints with respect to the computational efficiency of the RT model exist. This means that the most advanced line-by-line radiation models can not be used for our purposes. RTTOV has been developed by postulating simplified analytical expressions of the transmissivities. These expressions have been tuned against more complex and accurate transmissivity calculations for a large number of atmospheric temperature and humidity profiles.

The absorption by uniformly mixed gases (like CO$_2$, N$_2$O etc.) is treated separately from that by water vapor. The atmosphere is partitioned up into a number of layers (currently 43) assumed isothermal. The change in optical depth of a layer in the atmosphere from that below is found by a linear regression involving temperature, pressure and zenith angle in various combinations as predictors. From these changes in optical thicknesses from one layer to the next the required transmissivities can be found.

To account for the contribution to the radiances from the ground, the surface emissivity $\varepsilon_s$ is needed. Emissivity shows large variations with surface type. In the microwave region, ice emits almost like a blackbody, so the emissivity is high, but varies according to type of ice. There have been no attempts to assimilate AMSU data over ice surfaces in HIRLAM so far.

Over open ocean the microwave surface emissivity is lower, but varies strongly with wind speed, and is also dependent on the surface temperature. This dependence must be taken into account in the radiative transfer modeling, especially for the AMSU channels which have contributions from the surface. A code for doing such calculations is part of the RTTOV package, the so-called FASTEM microwave emissivity model. This model was developed by Met Office, UK, and is based on both theory and emissivity measurements and is designed to be computationally efficient. Surface wind and temperature as well as satellite incidence angle are input to the FASTEM subroutine.

RTTOV is discretized by dividing the atmosphere vertically into 43 layers which are assumed to be isothermal, and therefore requires the input profiles to be specified as values in these layers, spanning from 1013 to 0.1 hPa. HIRLAM, on the other hand, has in most versions 31 vertical levels spanning from the surface up to 10 hPa. An interpolation step is therefore necessary before the RTTOV calculations to compute the profile values at the RTTOV levels from HIRLAM levels.

Channels with much contribution coming from above the top of HIRLAM were not used, that is channel 11 with peak contribution at about 20 hPa and upwards. The lower channels have smaller contributions from above the model top, and for these it was necessary to add
profile values from the top of HIRLAM at 10hPa up to the uppermost RTTOV level at 0.1 hPa. For this we have used climatological values of temperature and moisture, where the climatology varies with season and latitude band. In an intermediate zone just above the top of HIRLAM, interpolation between the uppermost HIRLAM level and climatology is used.

2.5 Data selection
At present the HIRLAM assimilation system is set up to assimilate AMSU-A over ocean only. There is a significant observation data gap there, while there is decent coverage of upper air data from radiosondes over land in the HIRLAM domains, so the expected effect of added information would be less over land. In addition the observation treatment is more simple over ocean than land, as surface elevation is constant and surface properties are well modelled with FASTEM. Data over sea ice is not used either, even if this would be desirable due to the lack of other observations in the Arctic. For use of surface- and lower troposphere channels over ice, a model of the ice surface emissivity would be desirable. It would probably be quite straightforward to assimilate channels peaking higher up both over land and ice, but this has not yet been implemented. Over ocean we have implemented use of channels 1 to 10. Channels 1 to 3 are surface channels which are not used at several other centres with operational AMSU assimilation. As will be seen later, these channels have relatively high departures from the HIRLAM background modelled values. These channels were retained in some, but not all of the assimilation experiments, but were then given low weight as defined by the specification of the observation error covariance matrix.

3 Bias correction and error statistics
3.1 The need for bias correction
Our understanding of the measurements is expressed in a mathematical function known as the forward model, also referred to as the observation operator. From the forward model a limited amount of information about the atmospheric state is used to reproduce the radiance that the satellite would observe. For ATOVS data it involves radiative transfer calculations, as described in Section 2.4.

In satellite meteorology, the observation operator is usually denoted \( H(\mathbf{x}) \), where \( \mathbf{x} \) is the state of the atmosphere. The observation operator calculates the model counterpart of the observed value for the different instrument channels. For instance, for ATOVS the forward model gives the calculated values for the 15 AMSU-A frequency channels. The term “observation” is here used to denote a set of radiances measured in different channels at virtually the same time and by instrument segments pointing in the same direction.

The NOAA-15 and NOAA-16 ATOVS satellite measurements have gone through a thorough calibration, and empirical calibration coefficients have been applied in the AAPP package described above. Nevertheless, significant biases and scatter is found when comparing the satellite observations with the reference “modeled” measurement values. This is partly because the reference atmospheric temperature and humidity analysis is inaccurate, but also to a large extent...
caused by factors not taken into account in the calibration applied in AAPP as well as factors not taken into account in the observation operator.

Several such effects influence the radiation observed by the satellite. The AMSU-A channels are not much influenced by thin clouds, but there is a significant effect of deep clouds and precipitation particles. Such effects in the observations that are not accounted for in the forward model, are referred to as “contamination” in this context.

3.2 Bias correction method

As a consequence of what was described above, discrepancies between the modeled radiation \((y_{\text{mod}} = H(x))\), and the actual observed radiation \((y_{\text{raw}})\) are observed. We may write this difference as

\[
\delta y_{\text{raw}}^i = y_{\text{raw}}^i - y_{\text{mod}}^i
\]

where the index \(i\) refers to a given observation.

In order to compensate for the inadequacy of the forward model, an empirical correction is made to the observations. The corrected observation can be written as

\[
y_{\text{cor}}^i = y_{\text{raw}}^i + b(x_b, y_{\text{raw}}^i)
\]

where \(b\) is the bias correction function, \(x_b\) is the background atmospheric state, i.e. a forecast of the atmospheric state (available at the time when the observation was made). The bias correction regression formula is given by

\[
b(x_b, y_{\text{raw}}^i) = \sum_{j=1}^{N} c_j P_j(x_b, y_{\text{raw}}^i)
\]

where \(c_j\) are constant bias coefficients and \(P_j(x_b, y_{\text{raw}}^i)\) are a set of predictor variables. Our implementation of bias correction uses 7 predictors:

**Pred. 1:** a constant displacement,

**Pred. 2:** a measure (see Eq. 3) of the mean forecast temperature between the 1000 hPa and 300 hPa pressure levels,

**Pred. 3:** a measure (see Eq. 4) of the mean temperature between 200 hPa and 50 hPa,

**Pred. 4:** the surface temperature (here analyzed sea surface temperature values),

**Pred. 5:** the integrated water vapor content per area from the surface up to the top of the atmosphere,

**Pred. 6:** the square of the observation zenith angle and

**Pred. 7:** the observation zenith angle.
Bias correction AMSU-A Channel 5 (Cat 1)

Figure 2: The effect of the bias correction for AMSU-A channel 5.

Predictor 2 is the measure for the mean forecast temperature between the 1000 hPa and 300 hPa pressure levels and is computed given by

\[ P_2 = \sum_{j=b_2}^{e_2} \frac{T_j - T_{j-1}}{\log(p_j/p_{j-1})} \]  

(3)

and similar for predictor 3:

\[ P_3 = \sum_{j=b_3}^{e_3} \frac{T_j - T_{j-1}}{\log(p_j/p_{j-1})} \]  

(4)

In eqs. 3 and 4 \( T_j \) is the temperature at the target pressure \( p_j \) and the summation over \( j \) is determined by the number of target pressures between the given limits. Presently, \( b_2 = 26, e_2 = 40, b_3 = 17 \) and \( e_3 = 24 \). Here the integer numbers refer to the RTTOV pressure levels described in Section 2.4.
The bias coefficients \( \{c_1, \ldots, c_N\} \) are determined by minimizing the cost function

\[
J(c_1, \ldots, c_N) = \sum_i [y_{\text{raw}}^i - y_{\text{mod}}^i + \sum_{j=1}^N c_j P_j(x_b, y_{\text{raw}}^i)]^2
\]

for a large reference data set consisting of data typically from the 30 day time period preceding the time of the observation that is to be bias-corrected. This data set has been screened in advance to take out samples which have been contaminated with deep cloud and which would be removed when assimilating. This is detected by estimating cloud liquid water as described in Section 2.3.

In this way the bias coefficients are allowed to vary depending on the time of year of the reference data set. This has to do with the remaining contamination that is present in the observations and which the bias correction scheme tries to compensate for. Cloud droplet and precipitation radiation physics is believed to be an important source of contamination, and the annual variation in cloud physics will probably influence on the bias correction (for example water droplets in the summer, ice crystals in the winter). The bias coefficients also depend on the type of surface (emissivity). Arctic sea ice has a much larger (microwave) emissivity than open sea, so sea ice appears as bright areas compared to open sea in surface channels. Precipitation water drops absorb radiation, and typically emit radiation with an intensity somewhere in between sea ice surface radiation and open sea surface radiation. Precipitation contamination over sea ice therefore gives rise to a reduction in the observed radiation, while precipitation contamination over open sea gives an increase in the observed radiation.

The algorithm has been designed with flexibility such that the bias correction can be done separately for areas with ice, open sea and mixed ice and sea. Optionally, the bias correction may also be done separately for different latitude bands. Current data suggest that it may be beneficial to use two such bands for the HIRLAM area, one for observation on latitudes lower than that of Iceland, and one for observations with latitudes higher than that of Iceland.

Figure 2 shows how the bias correction may affect an NOAA15 AMSU-A channel (over open sea and for the late summer). It is seen that the data cloud has moved closer to the one-to-one line and that the scatter is slightly reduced.

The potential of a predictor can be found by examining the scatter plot of the uncorrected innovation (i.e. \( \delta y_{\text{raw}}^i \)) for each channel vs the corresponding predictor value. The predictor has potential if the cloud center (bias) shows a linear dependence on the predictor value (i.e. tilts either way).

Figure 3 shows how the uncorrected innovation for channels 4-10 varies with the second predictor (mean forecast temperature between the 1000 hPa and 300 hPa).

Figure 4 shows how the uncorrected innovation for channels 4-10 varies with the third predictor (mean temperature between 200 hPa and 50 hPa).

Figure 5 shows how the uncorrected innovation for channels 4-10 varies with the fourth predictor (surface temperature). Note that the channels 7-10, that “peak” high in the atmosphere, also show a correlation with the surface temperature. This is an indirect correlation. The forward model uses climatological values over the HIRLAM model. The errors in the climatology are probably correlated with latitude, which in turn is correlated with the surface temperature (which decreases with latitude).
Table 1: $\mu$ and $\sigma$ for NOAA16 AMSU-A channels 4 through 10 for December 2001. Rows 2 and 3 are for the raw data and rows 4 and 5 are for bias corrected data.

<table>
<thead>
<tr>
<th>chnl</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu_{\text{raw}}/\text{K}$</td>
<td>0.62</td>
<td>0.30</td>
<td>-0.40</td>
<td>-0.15</td>
<td>-0.27</td>
<td>-0.72</td>
<td>-2.03</td>
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<td>$\sigma_{\text{raw}}/\text{K}$</td>
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<td>0.39</td>
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<td>0.43</td>
<td>0.72</td>
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<tr>
<td>$\mu_{\text{bc}}/\text{K}$</td>
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<td>0.07</td>
<td>0.06</td>
<td>0.08</td>
<td>0.11</td>
<td>0.31</td>
<td>0.66</td>
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<tr>
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<td>0.33</td>
<td>0.45</td>
<td>0.75</td>
<td>1.59</td>
</tr>
</tbody>
</table>

Figure 6 shows how the uncorrected innovation for channels 4-10 varies with the fifth predictor (integrated water vapor content per area from the surface up to the top of the atmosphere).

Figure 7 shows how the uncorrected innovation for channels 4-10 varies with the seventh predictor (observation zenith angle). Note that most of the channels do not show a symmetric behavior around 0. Accordingly, the additional sign of the zenith angle that is included in the HIRLAM BUFR software as mentioned in section 2.2 is very relevant.

Figure 8 shows how the uncorrected innovation for channels 4-10 varies with latitude. Observe how the innovation bias tilt is different on either side of a latitude of 65 degree (Iceland). Figure 9 shows how the bias corrected innovation for channels 4-10 varies with latitude. The bias correction is done separately for three latitude bands: up to 50°N, between 50°N and 65°N, and north of 65°N. The scatter is better distributed around 0 in average as it should be. Note also the change at 50° for channels 10 and 9, and less so for channels 8 caused by the change in bias correction coefficient at 50°N.

Figures 3-9 have been made for data from the run described in section 4.4. This run includes ATOVS data in the assimilation in December 2001 at DMI using locally received data from NOAA-16. The first guess fields (or background fields) used for calculating $H(x_B)$ are three hour forecasts. Thus, the largest time difference between an observation time and the valid time of the background field used for calculating brightness temperatures is 90 min. In each figure the “bias” and “bias plus/minus one standard deviation” values have been plotted as solid lines. The bias and standard deviation have been calculated in bins of one integer increment of the given predictor (or latitude) value and for all available pairs in opposition to the scatter for which every 113th point is plotted (2226 points are plotted).

Figure 10 shows the distribution of the number of innovations within 0.1 K intervals for channels 4 through 10. The “best fit” Gaussian distributions for channels 5 through 10 are also overlaid. The Gaussian distributions are determined by the mean values ($\mu$) and the variances ($\sigma^2$) of the innovations $y_{\text{raw}}^i - y_{\text{mod},\text{an}}^i$:

$$\mu = \frac{1}{N} \sum_{i=1}^{N} (y_{\text{raw}}^i - y_{\text{mod},\text{an}}^i)$$

$$\sigma^2 = \frac{1}{N} \sum_{i=1}^{N} (y_{\text{raw}}^i - y_{\text{mod},\text{an}}^i)^2 - \mu^2$$

where $N$ is the total number of innovations included. The index “an” in $y_{\text{mod},\text{an}}^i$ indicates that for this figure the reference run analyses have been used for the modeled brightness temperature.
The Gaussian distribution overlayed is then given by

\[ \text{Gauss}(\Delta T_{\text{BT}}) = A \exp \left( -\frac{1}{2} \left( \frac{\Delta T_{\text{BT}} - \mu}{\sigma} \right)^2 \right) \]

It is clear from the figure that the distributions are not Gaussians since all channels are asymmetric, in particular channels 4, 9 and 10. Figure 11 show the similar distributions for bias corrected innovations. As expected and in accordance with Figure 9 the bias has been reduced for all channels and the fit to a Gaussian has been improved for the channel 4 data. The distribution of channel 9 and 10 data are still far from being Gaussian. These non-Gaussian innovation distributions might indicate some gross errors or deviations due to unexplained factors, and it could be important to get rid of these data in a first guess check. Table 1 summarizes the Gaussian fit parameters \( \mu \) and \( \sigma \).
Figure 3: Scatterplot of differences between observed brightness temperature ($y$) and the modeled one ($H(x_{FG})$) as function of predictor 2 value ("mean" temperature between 1000 hPa and 300 hPa). The bias and bias plus/minus one standard deviation as function of predictor value are plotted as solid lines. The plot in the lower right corner shows the number of observations per (nearest integer) predictor value. Only every 113th point is plotted.
Figure 4: Scatterplot of differences between observed brightness temperature \( (y) \) and the modeled one \( (H(x_{FG})) \) as function of predictor 3 value (“mean” temperature between 200 hPa and 50 hPa). The bias and bias plus/minus one standard deviation as function of predictor value are plotted as solid lines. The plot in the lower right corner shows the number of observations per (nearest integer) predictor value. Only every 113th point is plotted.
Figure 5: Scatterplot of differences between observed brightness temperature ($y$) and the modeled one ($H(x_{FG})$) as function of predictor 4 value (surface temperature). The bias and bias plus/minus one standard deviation as function of predictor value are plotted as solid lines. The plot in the lower right corner shows the number of observations per (integer part of) predictor value. Only every 113th point is plotted.
Figure 6: Scatterplot of differences between observed brightness temperature ($y$) and the modeled one ($H(x_{FG})$) as function of predictor 5 value (integrated water vapor). The bias and bias plus/minus one standard deviation as function of predictor value are plotted as solid lines. The plot in the lower right corner shows the number of observations per (integer part of) predictor value. Only every 113th point is plotted.
Figure 7: Scatterplot of differences between observed brightness temperature ($y$) and the modeled one ($H(x_{FG})$) as function of predictor 7 value (observation zenith angle). The bias and bias plus/minus one standard deviation as function of predictor value are plotted as solid lines. The plot in the lower right corner shows the number of observations per (integer part of) predictor value. Only every 113th point is plotted.
Figure 8: Scatterplot of differences between observed brightness temperature ($y$) and the modeled one ($H(x_{FG})$) as function of latitude. The bias and bias plus/minus one standard deviation as function of latitude are plotted as solid lines. The plot in the lower right corner shows the number of observations per (integer part of) latitude value. Only every 113th point is plotted.
Figure 9: Scatterplot of differences between bias corrected observed brightness temperature ($y$) and the modeled one ($H(x_{FG})$) as function of latitude. The bias and bias plus/minus one standard deviation as function of latitude are plotted as solid lines. The plot in the lower right corner shows the number of observations per (integer part of) latitude value. Only every 113th point is plotted.
3.3 Background errors in observation space

The background error covariance matrix, seen through the observation operator, is given by $\mathbf{HBH}^T$, where $\mathbf{H}$ is the observation operator, $\mathbf{B}$ is the full background error covariance matrix, that is the error covariance matrix for the first guess vector $\mathbf{x}_b$. This is defined as the expectation value $E\{\epsilon_b\epsilon_b^T\}$, where $\epsilon_b \equiv \mathbf{x}_b - \mathbf{x}_t$ is the departure from the "true" state $\mathbf{x}_t$. The $\mathbf{HBH}^T$ matrix is interesting from different perspectives. First of all it is one of the terms that determine the weight given to the observations in the solution to the analysis problem. The rate of convergence in the minimization depends on the condition number of the Hessian of the cost function, which in turn is related to the ratio between the background and observation errors. Secondly, it can be used to diagnose the balance between the background and different observation errors. The background departures $\mathbf{d}$ can be written as

$$\mathbf{d} = \mathbf{y} - \mathbf{Hx}_b = (\mathbf{y} - \mathbf{Hx}_t) + \mathbf{H}(\mathbf{x}_t - \mathbf{x}_b) = \epsilon_o + \mathbf{H}\epsilon_b. \quad (6)$$

Assuming that $\epsilon_b$ and $\epsilon_o$ are independent, the covariance matrix for the departures is then given by

$$E\{\mathbf{dd}^T\} = E\{\epsilon_o\epsilon_o^T\} + \mathbf{HE}\{\epsilon_b\epsilon_b^T\}^T = \mathbf{R} + \mathbf{HBH}^T. \quad (7)$$

Under the assumption that these matrices are diagonal dominant, the background error in observation space should always be smaller than the covariances for the departures.

The focus here is on the background error seen through the AMSU-A observation operator. In HIRLAM 3D-VAR this operator for the raw radiances is based on the radiative transfer model RTTOV-5, described in Section 2.4. Since RTTOV-5 is nonlinear it needs to be linearized around the background field for use in the incremental formulation of the variational analysis. In the experiments presented here, the background is taken as a six hour forecast from the operational SMHI model at 15 UTC, December 15, 1999. Only the oceans are considered in this study, due to a lack of a model for accurate calculation of radiation from land or ice surfaces.

The background error standard-deviations in observation space (the square roots of the diagonal of $\mathbf{HBH}^T$) is studied using a Monte Carlo technique as suggested in Fisher and Courtier (1995). A number of random perturbations $\delta\mathbf{x}$, following the assumed forecast error statistical model, are generated. This is achieved by generating random vectors $\xi$, with Gaussian distribution $N(0,1)$ distributed components in control vector space, followed by a transformation to model space:

$$\delta\mathbf{x} = \mathbf{U}^{-1}\xi. \quad (8)$$

For each such model space perturbation, the tangent linear version of the observation operator is applied to obtain the model perturbation in observation space:

$$\delta\mathbf{y} = \mathbf{H}\delta\mathbf{x}. \quad (9)$$

The perturbation of the surface temperature is handled separately since it is not part of the control vector in HIRLAM. If not stated otherwise, the standard deviation of the surface temperature is set to 1K (only sea points are considered) following Andersson et al. (2000).
Figure 10: Partitioning of NOAA16 data from December 2001 according to the number of data with given differences (innovations) between observed brightness temperature ($y_{\text{raw}}$) and the modeled one ($H(x_{\text{an}})$). Overlaid is the “best fit” Gaussian distribution.
Figure 11: Partitioning of NOAA16 data from December 2001 according to the number of data with given differences (innovations) between bias corrected observed brightness temperature ($y_{raw,bc}$) and the modeled one ($H(x_{an})$). Overlayed is the “best fit” Gaussian distribution.
A sample of perturbed state vectors is then generated and the standard deviation for the AMSU-A channels are estimated as \( \sigma_b = \sqrt{\rho_b} \), where

\[
\rho_b = \text{diag}(\text{HBH}^T) = \text{diag}(E\{H\delta x(H\delta x)^T\}) \approx \text{diag} \left( \frac{1}{N} \sum_{i=1}^{N} \delta y_i (\delta y_i)^T \right).
\] (10)

The error in the estimate of \( \rho_b \) decreases as \( 1/\sqrt{2N} \). In the experiments presented here \( N = 200 \) was used resulting in an error of about 5%.

The study covers the contribution from uncertainties in humidity and temperature profiles, the dependence on scan angle and surface temperature errors. A comparison between statistics for the background departures and the noise equivalent temperatures \( \text{NE} \Delta T \) is also presented. \( \text{NE} \Delta T \) is the uncertainty in brightness temperatures resulting from the noise known to be inherent in the radiometer. The spatial variation of the AMSU-A background error in the northern Atlantic is negligible within the framework of the present study. This is in line with the background error formulation used in the experiments. Development of a spatially varying background error is under way.

In the left panel of Fig. 12, the output from the randomization procedure, simulating AMSU-A on a nadir looking satellite (NOAA-15), is shown as thin white bars. The same figure also presents results from experiments where perturbations are applied to humidity (thick white) and temperature (thick grey) alone. Due to the fact that humidity and temperature are not independent, the sum of these contributions is larger than when both contributions are treated together. Also note that the effect on channels 12-14 is small since they all get large contributions from levels above the top of the atmosphere in HIRLAM.

The effect of varying the satellite zenith angle is described in the right panel of Fig. 12. Here the randomization procedure is applied at six different scan angles from 0 to 50 degrees. An angular dependence can be seen in some of the surface sensitive channels 1-2 and 15 while it is insignificant in the other ones.
Figure 13: Left: Background errors (K) with respect to AMSU-A channel number and surface temperature error, 0-5 K. Right: \( \text{NE} \Delta T \) (1) and standard deviations for the background error (2) and the background departures (3).

Naturally, increasing the prescribed error in the surface temperature results in larger errors in the channels sensitive to the surface. The standard deviation of the surface temperature error is varied from 0 to 5 K which is a value that has been assumed for land areas (Andersson et al., 2000). Comparing Figs. 12 and 13 it can be noted that changing the surface temperature error from 1 to 5 K has a larger effect than changing the scan angle from nadir to 50°.

As described earlier in Eq. 7 the variance of the background error, \( \text{diag}(\text{HH}^T) \), should not be larger than that for the background departures. To the right in Fig. 13 the \( \text{NE} \Delta T \) (1), which can be seen as a lower bound on the observation error, is shown together with the standard deviations in the AMSU-A channels for the background error (2) and the background departures (3). The inequality holds for most of the channels that HIRLAM can model but the background error seems to be a bit too large in channel 8-10.

### 3.4 Estimation of observation error covariance statistics

A proper estimate of the AMSU-A observation error covariance matrix \( R \) is needed to give these observations an optimal weight in the HIRLAM 3D-VAR analysis relative to other available information. If the AMSU-A observation errors are overestimated, the HIRLAM analysis will not use all the information available in the AMSU-A observations and the resulting analysis will be further from the truth than for optimal choice of \( R \) on average. If the AMSU-A observation errors that are used are too small, these observations will dominate over other available information, and the analysis will deteriorate as it tries to agree with the random AMSU-A errors.

The various operational forecasting centers that have been using AMSU data in global NWP have used diagonal observation error covariance matrices with various choices for the actual assumed observation error variances. The HIRLAM AMSU-A assimilation system has been implemented to also allow non-diagonal observation error covariance matrices for flexibility, and the implementation of it is described below. It is not yet clear whether this added feature
actually can improve the AMSU assimilation, but experimentation with this is allowed.

We also present different approaches which have been used to assist the estimation of observation error statistics to be used in HIRLAM 3D-VAR. Firstly, the use of statistics of departures of the observations from an independent analysis, and secondly a randomization technique which allows comparison of observation errors and background errors in observation space.

3.4.1 Rotated channels

The scientific AMSU-A community has not identified the optimal AMSU-A observation error covariance matrix, $R$, for use in data assimilation. The entire AMSU-A observation error covariance matrix is therefore input to HIRLAM 3D-VAR and may be chosen at the users discretion.

When assimilating AMSU-A observations in HIRLAM 3D-VAR, the user may choose to specify an error covariance matrix with non-diagonal elements (i.e. correlations in observation error between the different AMSU-A channels). However, internally the HIRLAM analysis system still requires that observations have uncorrelated observation errors. In order to achieve this, the AMSU-A observations are internally rotated (using the eigenvectors of the specified error covariance matrix) so that the observation error covariance matrix for the rotated channels is diagonal.

The problem of finding an optimal choice of the $R$ matrix, whether it is non-diagonal or not, remains. It would also be of interest to set up an impact study to assess possible benefits from using non-diagonal elements. For such an experiment to make sense, one should compare an experiment with the optimal non-diagonal $R$ with a parallel run with the optimal diagonal $R$. Alternatively one could start with some estimate of the optimal non-diagonal matrix and try to find theoretically the diagonal matrix $R$ which gives the analyses that are closest to those using the optimal non-diagonal one. These two choices could then be compared in a parallel run. However, it is not yet clear how to convert a non-diagonal matrix into such a corresponding diagonal matrix.

3.4.2 Estimation from analysis departures (DNMI)

The following method has been used at DNMI as a guideline for design of the observation error covariance matrix. First, an error deviation covariance matrix is formed by

$$
\hat{R} = \langle (y - Hx_a)(y - Hx_a)^T \rangle
$$

(11)

where $\langle \ldots \rangle$ gives the average value, $y$ is an ATOVS observation vector, $H$ is the forward model, $x_a$ is the analysis that resulted from using all observations except ATOVS. It can be shown that if the ATOVS observation error is uncorrelated with the non-ATOVS analysis error, we get the following relation between the ATOVS observation error covariance matrix $R$, the error deviation matrix $\hat{R}$ and the non-ATOVS analysis error covariance matrix $A$,

$$
R = \hat{R} - HAH^T .
$$

(12)

If, next, we assume that the analysis covariance matrix in observation space is proportional to the error deviation matrix, i.e. $HAH^T = (1 - \gamma)R$ where $\gamma$ is a constant, we can then find the
observation error covariance matrix as

\[ R = \gamma \hat{R}. \]  

This is probably not a very good assumption, and efforts should be spent in investigating alternative approaches. One possibility one could look at is to use \( y - \tilde{H}(x_b) \) instead of \( y - \tilde{H}(x_a) \) in eq. (11).

For some assimilation experiments at DNMI, this approach was followed, and the value chosen for \( \gamma \) was initially 0.25, since a tuning experiment revealed that this value gave the best impact. It was later agreed that the diagonal values of the observation error covariance matrix should not be smaller than \((0.125 \text{ K})^2\), since the precision of the brightness temperatures that the ATOVS observation consists of is 0.100 K. If the proposed global scaling factor gave a diagonal element that was smaller than the specified limit, then the scaling factor was increased so that the smallest diagonal element in the resulting matrix was equal to the specified limit.

Table 2: Observation error covariance matrix used at DNMI in current ATOVS (NOAA-15, AMSU-A, channels 1 → 10) HIRLAM 3D-VAR impact experiments. The unit is K². This matrix is based on data for April 2001, with a global scaling factor of \( \gamma = 0.289 \).

| \( \text{3.8536} \) | \( 3.3208 \) | \( 1.9177 \) | \( 0.4387 \) | \( 0.1043 \) | \( 0.0215 \) | \( -0.0022 \) | \( -0.0107 \) | \( 0.0005 \) | \( 0.0249 \) | \( \text{3.7165} \) | \( 2.1589 \) | \( 0.4542 \) | \( 0.0736 \) | \( 0.0029 \) | \( -0.0088 \) | \( -0.0056 \) | \( -0.0037 \) | \( -0.0169 \) | \( \text{1.7309} \) | \( 0.4141 \) | \( 0.1443 \) | \( 0.0488 \) | \( 0.0144 \) | \( 0.0060 \) | \( 0.0074 \) | \( 0.0162 \) | \( 0.0268 \) | \( \text{0.4387} \) | \( 0.4542 \) | \( 0.4141 \) | \( 0.1443 \) | \( 0.0488 \) | \( 0.0144 \) | \( 0.0060 \) | \( 0.0074 \) | \( 0.0162 \) | \( 0.0268 \) | \( \text{0.1042} \) | \( 0.0726 \) | \( 0.0869 \) | \( 0.0488 \) | \( 0.0354 \) | \( 0.0138 \) | \( 0.0061 \) | \( 0.0065 \) | \( 0.0138 \) | \( 0.0267 \) | \( \text{0.0215} \) | \( 0.0029 \) | \( 0.0145 \) | \( 0.0144 \) | \( 0.0138 \) | \( 0.0156 \) | \( 0.0118 \) | \( 0.0125 \) | \( 0.0193 \) | \( 0.0297 \) | \( \text{0.0248} \) | \( -0.0037 \) | \( 0.0170 \) | \( 0.0162 \) | \( 0.0138 \) | \( 0.0193 \) | \( 0.0381 \) | \( 0.0569 \) | \( 0.1297 \) | \( 0.1944 \) | \( \text{0.0248} \) | \( -0.0169 \) | \( 0.0124 \) | \( 0.0268 \) | \( 0.0267 \) | \( 0.0297 \) | \( 0.0334 \) | \( 0.0801 \) | \( 0.1944 \) | \( 0.3517 \) | \( \text{0.0005} \) | \( -0.0037 \) | \( 0.0170 \) | \( 0.0162 \) | \( 0.0138 \) | \( 0.0193 \) | \( 0.0381 \) | \( 0.0569 \) | \( 0.1297 \) | \( 0.1944 \) | \( \text{0.0248} \) | \( -0.0169 \) | \( 0.0124 \) | \( 0.0268 \) | \( 0.0267 \) | \( 0.0297 \) | \( 0.0334 \) | \( 0.0801 \) | \( 0.1944 \) | \( 0.3517 \) |

3.4.3 Non-diagonal cost contributions

The user may specify a non-diagonal observation error covariance matrix for AMSU-A, and in this case the cost contribution reported for each channel from a given observation \( J_i(x) \), where the index denotes the selected channel) is defined by:

\[ J_i(x) = \sum_j (y_i - H(x)_i) R^{-1}_{ij} (y_j - H(x)_j) \frac{2w_i}{w_i + w_j} \]

where \( R^{-1}_{ij} \) is the \( ij \) element of the inverse observation error covariance matrix and \( w_j \) is an arbitrary weighting function (HIRLAM 3D-VAR is currently using \( w_j = R^{-1}_{jj} \)). Note that the
The total contribution is independent of the weighting function,

\[ J(x) = \sum_i J_i(x) = \sum_j \sum_i (y_i - H(x)_i) R_{ij}^{-1} (y_j - H(x)_j) \frac{2w_i}{w_i + w_j} \]

\[ = (y - H(x))^T R^{-1} (y - H(x)), \quad (15) \]

since \( R_{ij}^{-1} = R_{ji}^{-1} \).

The purpose of the weighting function, \( w_j \), is to distribute the contributions from the covariances more evenly between the different channels. A poor choice of \( w_i \) may easily result in a negative cost contribution from a channel that has an error that is correlated with another channel with a positive cost contribution. The contributions from all active observations are added together and reported for each iteration in the HIRLAM analysis system (labeled with observation type “RTM”, which is short for “Radiative Transfer Model”).

### 3.4.4 Approach using comparison with background error (SMHI)

In most of the experiments conducted at SMHI so far, the error covariances have been modeled with a scalar value times the identity matrix. This is also the choice made at ECMWF. The scalar is chosen in order to balance the relative weight given to AMSU-A observations with that given to other observation systems. Following ECMWF the scalar value representing the observation error standard deviation has been set be 0.35 K for all the AMSU-A channels in use (5-10).

However, one could utilize the information about the background error in observation space, obtained through the randomization procedure described in section 3.3, to arrive at a model for the observation error covariance matrix. In 3D-VAR the solution for the optimal analysis is influenced by the observation and background errors according to:

\[ x_a = x_b + BH^T (HBH^T + R)^{-1} (y - Hx_b). \quad (16) \]

Assume that the observation and background error covariance matrices, \( R \) and \( HBH^T \), are diagonal and diagonal dominant respectively. Then the ratio between the background and the observation error covariances is what determines the relative weight given to the observation compared to the information in the background:

\[ [Hx_a]_i \approx [Hx_b]_i + [HBH^T]_{ii} ([HBH^T]_{ii} + [R]_{ii})^{-1} (y_i - [Hx_b]_i) \quad (17) \]

\[ = \frac{1}{1 + \frac{[HBH^T]_{ii}}{[R]_{ii}} [Hx_b]_i + \frac{[HBH^T]_{ii}}{[R]_{ii}} y_i} \quad (18) \]

As a guideline when balancing the influence from the AMSU-A observations against other observation systems, the ratio between the background and the observational error variances should be smaller than one. This is the ratio for the radiosonde observations which are considered to be the most reliable ones.

Care should be taken not to assign lower values to the observation errors than those given by the observed noise equivalent temperatures \( NE\Delta T \). This means that the lower bounds for the diagonal elements in the observation error covariance matrix is given by:
Figure 14: Lower bound on the observation error standard deviations is given by the background errors (solid) which are always larger than the NE\Delta T (dashed).

\[ \mathbf{R}_{ii} > \max\{(\text{NE}\Delta T)^2, [\mathbf{H} \mathbf{B} \mathbf{H}^T]_{ii}\} \]  \hspace{1cm} (19)

In Fig. 14 the result for the observation error standard deviations is illustrated for AMSU-A channels 1-10. In this case the lower bound is defined solely by the background errors (solid) since these are larger than the NE\Delta T (dashed) for all channels. The AMSU-A observation operator used in the randomization process was linearized around a background model state from November 15, 1999 and the surface skin temperature error was set to 1 K.

Based on the results from the randomization experiments and information from ECMWF we chose the scalar value representing the observation error to be 0.35 K for the AMSU-A channels in use (ch. 5-10).

One way to determine the observation error matrix is to compare modeled and measured radiances with collocated independent measurements from radiosondes. Since the AMSU-A observations only are accepted over sea the number of possible co-located TEMP (radiosonde) measurements is very limited. However, there is the ship called “Polarfront”, located in the Norwegian Sea at about 66° N, 2° E, that releases radiosondes every 6th hour. In the future these radiosonde measurements could be employed to determine the matrix \( \mathbf{R} \).
4 Impact studies

4.1 Overview

In this chapter we will describe impact studies with AMSU-A data which have been performed in several of the HIRLAM countries. An overview of the experiments undertaken is given in Table 3. Two of the studies (February 2000 and 1–6 May 2000) are reported on earlier (see Gustafsson et al. (2000) and Schyberg et al. (2000)), and will not be further commented on here.

Some of the impact study runs are done online, with ECMWF forecast boundaries, using ATOVS data downlinked from the satellite at a local antenna and processed with AAPP in near-real-time. The coverage of these data is limited by the view of the local antenna.

Other runs are done off-line and use archived ATOVS data from the ECMWF MARS archive and “perfect” (analysis) ECMWF boundary data. The coverage of these data is not limited by the view of the local antenna or the timeliness constraints in an online run, and thus have a much better data coverage.

Table 3: Overview of impact studies.

<table>
<thead>
<tr>
<th>Period</th>
<th>Model</th>
<th>Data sources</th>
<th>Analysis window</th>
<th>Other information</th>
</tr>
</thead>
<tbody>
<tr>
<td>December 1999</td>
<td>SMHI 44 km HIRLAM</td>
<td>ECMWF global archive BUFR data, NOAA-15</td>
<td>3 hours</td>
<td>Diag. O (Cloud mask bug)</td>
</tr>
<tr>
<td>February 2000</td>
<td>DNMI 50 km HIRLAM</td>
<td>DNMI Oslo antenna, NOAA-15</td>
<td>6 hours</td>
<td>Non-diag. O</td>
</tr>
<tr>
<td>1–6 May 2000</td>
<td>SMHI 22 km HIRLAM</td>
<td>ECMWF global archive BUFR data, NOAA-15</td>
<td>3 hours</td>
<td>(Cloud mask bug)</td>
</tr>
<tr>
<td>21 May - 7 June 2001</td>
<td>DNMI 50 km HIRLAM</td>
<td>DNMI Oslo antenna, NOAA-15</td>
<td>6 hours</td>
<td>Non-diag. O</td>
</tr>
<tr>
<td>December 2001</td>
<td>DMI 0.45° HIRLAM-G</td>
<td>DMI Denmark and Greenland antennae, NOAA-16</td>
<td>3 hours</td>
<td>Non-diag. O</td>
</tr>
<tr>
<td>January 2002</td>
<td>DMI 0.45° HIRLAM-G</td>
<td>DMI Denmark and Greenland antennae, NOAA-16</td>
<td>3 hours</td>
<td>Revised non-diag. O</td>
</tr>
</tbody>
</table>

Some of the runs (indicated in the table) were affected by a cloud mask bug, which caused the deep cloud check not to be applied before assimilation, which will cause cloud contaminated data to be entered into 3D-VAR. This probably had a detrimental effect on the results of AMSU assimilation, but to what extent is unknown. The background check and variational quality control could partly compensate for that by rejecting parts of the contaminated observation sets.
4.2 The May 2001 impact study at DNMI

The experiment used data from NOAA-15 from 21st of May 2001 until 7th of June 2001. There was relatively little ATOVS data available in this period, and in some cases there was no ATOVS data available at all for several days in a row (this was probably caused by a failure in the ATOVS data preprocessing system). Table 2 shows the ATOVS observation error covariance matrix that was used in this impact study.

Figures 15, 16 and 17 show the bias, rms and standard deviation between the HIRLAM model +0, +06, +12, +24, +36 and +48 hour forecast and independent observations, for two trials. One trial where only conventional observations were assimilated (labeled “REF”), and one trial where conventional and ATOVS data were assimilated (labeled “ATOVS”). Only observations from the EWGLAM stations are used for the verification. We see from Figures 15, 16 and 17 that assimilating ATOVS gives a small positive effect on the geopotential. Note that it is the improvement in the surface pressure that is the main cause of the improvement in the geopotential.

Figures 18, 19 and 20 show corresponding figures for the wind speed. We see that assimilating ATOVS gives a neutral effect on the wind speed.

Figure 21 shows the RMS and bias in the difference between observations and the two trials for the mean sea level pressure, 2m temperature and 10m winds. We observe that assimilating ATOVS gives an improvement in the mean sea level pressure, while the effect on the other parameters is neutral.
Figure 15: Impact of assimilating ATOVS on geopotential Bias in the May 2001 DNMI experiment.
Figure 16: Impact of assimilating ATOVS on geopotential RMS in the May 2001 DNMI experiment.
Figure 17: Impact of assimilating ATOVS on geopotential StdErr in the May 2001 DNMI experiment.
Figure 18: Impact of assimilating ATOVS on wind speed Bias in the May 2001 DNMI experiment.
Figure 19: Impact of assimilating ATOVS on wind speed RMS in the May 2001 DNMI experiment.
Figure 20: Impact of assimilating ATOVS on wind speed StdErr in the May 2001 DNMI experiment.
Figure 21: Impact of assimilating ATOVS on ground pressure, ground temperature and ground wind speed in the May 2001 DNMI experiment.
Figure 22: The integration area (left) and temporal distribution of AMSU-A observations at the forecast starting points (00, 06, 12 and 18 UTC) using 3 h assimilation windows (right).

4.3 December 1999 SMHI experiment

Here we present an impact study for the month of December 1999, including the three severe low pressure storms over Europe. The data assimilation is performed with and without archived AMSU-A radiances from the entire Atlantic to verify our suspicions that the inclusion of AMSU-A data will result in positive effects on the forecasts for the entire Europe. There were four December storms, which hit land in Denmark (named “Anatol”), north east of Scotland 25th, 06 UTC, Brittany 26th 06 UTC, (named “Lothar”) and France 27th, 18 UTC (named “Martin”). The first and the last two were extreme events which caused severe damage over central Europe, and in total these claimed more than 130 lives.

4.3.1 Data coverage and model area

Only AMSU-A data over the oceans were used for the impact study, since we have no model for accurate calculation of radiation from land or ice surfaces. Also, today’s observation operators are not capable of dealing with data contaminated by deep clouds, so such observations were discarded from further processing.

The integration area used for the impact study is shown to the left in Fig. 22. An illustration of the temporal data distribution at the forecast starting point 00, 06, 12 and 18 UTC, using a 3 h assimilation window (i.e. 00±1.5 h, 06±1.5 h, 12±1.5 h and 18±1.5 h), is given by the heights of the columns to the right in the same figure, showing fractions of all the available observations in the experiment period.

The impact experiment at SMHI used the following setup:

- Time period from 1st December 1999 through 31st December 1999,
- SMHI area, 44 km, 31 levels, perfect ECMWF boundaries,
- 44 km increments,
- 3 h analysis window,
- AMSU-A MARS data from ECMWF covering the entire Atlantic region,
- latitude independent bias correction coefficients, based on data from 30 days in November 1999,
- observation error covariance matrix based on 30 days of data from November 1999 and a gridpoint forecast model with semi-Lagrangian advection.

4.3.2 Verification
The largest impact of assimilating Atlantic AMSU-A data in HIRLAM is found in the Atlantic area, where the AMSU-A data density is the highest and where the analysis is not dominated by conventional observations.

We have verified the forecasts both against EWGLAM stations and against forecast fields from a reference run covering the entire integration area. Verification results for the EWGLAM stations are presented for temperature, surface pressure, geopotential and wind speed since the AMSU-A data mainly contains information about temperature. Field verifications are presented for temperature and surface pressure since these parameters are directly available from the forecast model fields. All differences are calculated as modeled values minus observed values if not stated otherwise.

Experiments are numbered starting with the forecast made at the 1st of December, 00 UTC, then the one made at 06 UTC the same day and so on. The last experiment is the forecast made at the 29th December 18 UTC. This means that three storms appear with number 10 (Denmark), 96 (east of Scotland) and 106 (France) in the +12 h forecast series and with number 8 (Denmark), 94 (east of Scotland) and 104 (France) in the +24 h series.

4.3.3 Results
The time evolution of RMS and bias errors for different forecast lengths and parameters are shown in Figs. 23 - 24. The verified parameters are the temperature at 300 hPa (Fig. 23), the surface pressure (Fig. 24) and the geopotential and wind at 300 hPa (Fig. 25).

Mean RMS and bias errors for the differences between each of the two forecast cycles and EWGLAM stations are shown in Fig. 26. The results are shown for the analysis and forecasts of eight different lengths (06, 12, 18, 24, 30, 36, 42 and 48 h) started at 0, 6, 12, and 18 UTC, where "REF" uses conventional observations only, and "TVS" also assimilates AMSU-A observations.

Note that the differences between the forecast fields in the two runs are smaller and different than errors obtained when verifying against observations. The effect on the French storm is for example hard to find in the field verification. This is probably due to the fact that the locations of the stations in the EWGLAM list are biased towards the European continent while the field verifications also are based on lots of information from the Atlantic region. Mean differences between fields from the two runs with respect to forecast length are not presented since they are negligible.
Figure 23: Verification of temperature (K) at 300 hPa with (TVS) and without (REF) AMSU-A data. Top row: +12 h forecasts. Bottom row: +24 h forecasts. Left column: Against EWGLAM station list. Right row: Against reference fields.
In this winter case AMSU-A data in HIRLAM 3D-VAR gives generally a positive or neutral impact on the forecasts of temperature, geopotential and wind in the upper atmosphere while it is neutral for other parameters and levels. Note, however, the clear positive impact by using AMSU-A radiances for predicting the French storm, especially in the +12 h forecast of surface pressure.

After the experiments were conducted a bug was found that had put the cloud mask algorithm out of play. Some of the cloudy radiances are probably rejected in the background check, but this bug may have affected the results by decreasing the possibility of showing a positive impact of the AMSU-A data.

4.3.4 The “French storm”

The above results show that the impact of AMSU is highly variable in space and time, and that average statistics does not give a full description of the effects obtained. Another aspect of statistical assessments of impacts, is that the statistics is not in any way weighted with the
Figure 25: Verification against EWGLAM list stations at 300 hPa with (TVS) and without (REF) AMSU-A data. Left column: geopotential (dm). Right column: wind speed (m/s). Top row: +12 h forecasts. Bottom row: +24 h forecasts.

Figure 26: Verification of temperature (left), geopotential (middle) and wind speed (right) at 300 hPa against EWGLAM station list for different forecast lengths with (TVS) and without (REF) AMSU-A data.
importance of each situation. One would for instance like the forecast improvements to occur in situations of rapid change and extreme weather rather than in cases of “uninteresting” weather.

Figure 24 shows that most of the statistical improvement found over the period studied, came from one situation, which coincided with the so called “French storm” of 27 December 1999 (named “Martin”). This was a storm which caused severe damage over the European continent, and it should thus be of great importance to forecast accurately. Figure 27 shows how badly this storm was forecasted using conventional observations only, even on a 12 hours forecast.

The figure shows winds in the lowest model level (approximately 30 m above ground) for the “REF” run, verified against the corresponding analysis from the same cycle. The model does not at all capture the strong winds above 50 knots over Bay of Biscay and Central France at this time. The “TVS” run shown in Fig. 28, has a significantly better 12 h forecast. Even if this forecast does not quite capture the actual magnitude of the analyzed winds, it is dramatically better than the “REF” run for this situation, giving higher wind speeds and a better idea of the strength of the low pressure system. This is what must have given the main contribution to the improvement in the verification against the EWGLAM stations presented in Fig. 24, since
many of these stations are located over Central Europe.

We have not performed a detailed analysis on exactly which AMSU-A observations played largest role in creating this improvement. It is probably the additional upper-air information provided by ATOVS in the Central North-Atlantic, that is important here. In addition ATOVS data could play a role by adding information which causes conventional observations which would otherwise be too extreme and rejected, to pass the quality control.
4.4 December 2001 NOAA 16 impact study at DMI

In this section results from December 2001 using locally retrieved data from the two Danish antennas located in Smidsbjerg and Sdr. Strømfjord/Kangerhussuaq (Greenland), respectively, are presented. Results from July/August and September 2001 can be found in Amstrup (2001).

The model applied is DMI-HIRLAM-G (see Sass et al., (2000, 2002) for details), based on HIRLAM reference version 4.5/4.6. The horizontal resolution is 0.45°, the number of vertical levels 31, the number of grid points is 190 x 202, the time step is 240 s and the lateral boundary values are updated every 6 hours from ECMWF 00 UTC or 12 UTC forecasts. However, in the last part of December the so called “frames” boundaries were used and in these runs the lateral boundary values were updated every 3 hours from ECMWF 00 UTC, 06 UTC, 12 UTC or 18 UTC forecasts. The model area is shown in Fig. 29 together with the other DMI-HIRLAM operational areas. DMI-HIRLAM-G is denoted “G”. 48 hour forecasts are made at t00, 06, 12 and 18 UTC. Version 4.9 of the HIRLAM 3D-VAR system was used for the 3D-VAR analyses.

Twice a day (at 00 UTC and 12 UTC reassimilation cycles) the DMI-HIRLAM-G model is restarted from fresh ECMWF analyses using an analysis increment method. The available analysis for the model is interpolated to the grid used for ECMWF data. The difference between interpolation and the new ECMWF analysis is an increment (“large scale increment”) which is interpolated to the HIRLAM grid and added to get an updated HIRLAM analysis. Normal HIRLAM cycles then follow (03 UTC, 06 UTC, 09 UTC) in the morning to produce an “up-to-date” state of the atmosphere. In the evening normal analyses cycles subsequent to the insertion of ECMWF analysis increments give analyses valid at 15 UTC, 18 UTC and 21 UTC, respectively. Using this method ATOVS data are implicitly used even if they are not assimilated into the HIRLAM model since ECMWF uses these data in their analysis system. This also means that some of the AMSU-A data used in the ECMWF analysis may be used once more in the HIRVDA ATOVS assimilation, and the weighting of the AMSU-A in this cycling of HIRVDA is therefore probably not optimal.

The observation window covers a 3h span around the analysis time (00, 03, 06, 09, 12, 15, 18 and 21 UTC) except for a 6 h span around the analysis times 06 UTC and 18 UTC before the long forecasts starting from these. For AMDAR/ACARS (Aircraft Meteorological Data Reporting/Aircraft Communication Addressing and Reporting System) aircraft observation data a ±1.5 h observation time window is used to reduce along track analysis increments leading to spurious effects in the following forecast. A standard observation set is used, including synoptic observations, ship observations, (drifting and moored) buoys, pilot balloons, radiosonde data and aircraft data. The run with these observation types is denoted REF and the run denoted WIA (With ATOVS) also uses NOAA16 AMSU-A brightness temperature data. The first guess field is a 3 h forecast from the preceding data assimilation cycle except for a 6 h forecast for the analyses at 06 UTC and 18 UTC.

The observation error covariance matrix used in the present assimilation study is is equivalent to the DNMI observation covariance matrix in Table 2 for NOAA15, however, the scaling is different. Here, the matrix elements for the first three channels are such that the diagonal elements are 10 to avoid use of these channels. For the rest, the scaling is made so that the lowest diagonal element (channel 7 in this case) is 0.016 K² and the scaling for channel 4 is 4 times the scaling for channels 5 through 10.
The data used for the December 20, 09 UTC analysis cycle is shown in Figure 30 as an example of a good coverage of locally received NOAA16 AMSU-A data. Note that only data over open water are used and the data shown are after “cloud clearing” and subsequent data thinning.

Figure 31 shows the number of active ATOVS data in December for the given data assimilation cycles. The assimilation cycles having the largest number of data are 03 UTC, 06 UTC and 15 UTC. The small drift in position of the satellite track from day to day can also be seen as a slowly varying number of active data from day to day.

Figures 32 and 33 show observation verification scores (bias and rms) for December 2001 using the standard EWGLAM (European Working Group on Limited Area Modeling) station list. It is clear that the impact from using ATOVS brightness temperatures is very small for these parameters. However, there is a tendency towards REF having marginally better rms-scores for upper level geopotential height and 500 hPa temperature and for WIA having marginally better rms-scores for 850 hPa temperature. WIA has better bias-scores for mslp. The daily differences in the scores are also very small as can be seen in Figure 34 where daily errors in terms of bias and standard deviation are shown for 48 h forecasts for a number of surface and upper level parameters.

Field verification, in which forecasts are compared with initialized analyses from their own data assimilation suite, results of mslp and 850 hPa temperature are shown in Figure 35. The effect of including ATOVS is basically neutral over large parts of Europe using this measure. Larger deviations are seen north of 70° and in small parts of the Atlantic.

4.5 January 2002 NOAA 16 impact study at DMI

In this section results from January 2002 from the ongoing assimilation experiments are presented. The setup is similar to the setup used for the impact study with NOAA-16 AMSU-A presented in section 4.4 with some minor differences: 1) the runs used only “frames” from ECMWF for the lateral boundaries, 2) no data were available from Sdr. Strømfjord for the first 14 days of January, and 3) a modified observation error covariance matrix was used from January 9 onwards.

The reason for the use of a modified observation error covariance matrix is the rather large off-diagonal elements for channels 1 through 3 in the matrix used in the December 2001 runs. These are inaccurate surface channels that are left out from the assimilation at several other forecasting centres. The assumed error cross covariances means that background departures in these channels (1–3) affect the weighting of other channels in the analysis as well, and it was feared that these channels thus would have a negative effect on the use of the others. In addition, the revised matrix is also based on a longer period with statistics, namely December 2001. In the revised matrix the cross correlations between channels 1 through 3 and the other channels have been set to zero.

Figures 36 and 37 show observation verification scores (bias and rms) for January 2002 using the standard EWGLAM station list. In contrast to the observation verification for December there is now a positive impact from the use of ATOVS data on the rms-score for mean sea level pressure, geopotential height and temperature at 250 hPa, 500 hPa and 850 hPa and also a minor positive impact on wind speed at 850 hPa and 500 hPa. With respect to bias, the impact
Figure 29: DMI-HIRLAM operational model areas.

Figure 30: Positions (with dots) of data used (after data thinning and “cloud clearing”) in the December 20, 09 UTC data assimilation cycle.
Figure 31: Number of active rtm ATOVS during December for the given analysis cycles (00 UTC and 03 UTC upper, 06 UTC and 09 UTC upper middle, 12 UTC and 15 UTC lower middle, and 18 UTC and 21 UTC bottom).
Figure 32: Verification result for WIA and REF of surface and upper level parameters as specified in the plot. EWGLAM station list.
Figure 33: Verification result for WIA and REF of upper level parameters as specified in the plot. EWGLAM station list.
Figure 34: Daily obs-verification (bias and standard deviation, EWGLAM station list) results of 48 h forecasts for December 2001 of surface and upper level parameters specified in the plot.
Figure 35: Difference of standard deviation between the WIA (analyses including AMSU-A brightness temperatures) and the REF (analyses not including AMSU-A brightness temperatures) for 36 h forecasts of 850 hPa temperature (upper) and mslp (lower) for December 2001. Full lines/dark shaded for areas where REF is better and dashed lines/light shaded for areas where WIA has better standard deviation scores. Contour lines are for every 0.25 K and 0.25 hPa, respectively.
is basically neutral. The daily observation verification for 48 h forecasts is shown in Figure 38. The daily differences in both bias and standard deviation scores are fairly small. However, it should be noted that the lower rms-score in mslp seen in Figure 36 is from a generally lower daily bias-score as well as from a generally lower daily standard deviation score.

Field verification results of mslp and 850 hPa temperature are shown in Figure 39. The effect of including ATOVS is basically neutral on average for 850 hPa temperature. For mean sea level pressure the areas where WIA has better scores are much larger than the areas for which REF has better scores. This is consistent with the observation verification results. Similar results (not shown) are found for 500 hPa geopotential height.

Contingency tables of precipitation accumulated over 12 hours (from 6 to 18 hour forecasts and from 18 to 30 hours) are shown in Table 4. The numbers in these tables are obtained by counting the number of observed and predicted precipitation amounts in each of five classes for 25 Danish stations (as in the quarterly DMI verification reports). The five precipitation classes are (precipitation amounts in mm): $P1 < 0.2$, $0.2 \leq P2 < 1.0$, $1.0 \leq P3 < 5$, $5 \leq P4 < 10$ and $P5 \geq 10$. $P$ is either F (forecast) or O (observation) in Table 4. The “sum” row and column are the sum of numbers in the given observation class or forecast class, respectively. The line labelled “%FO” gives the percentage of observed occurrences in each class which was correctly forecasted in that class. The table clearly shows that the forecast model has a tendency to predict weak to moderate precipitation too frequently. For the shortest range (6–18 h forecasts) WIA and REF have very similar scores but for the longer range (18–30 h forecasts) WIA has clearly better scores than REF. This difference was not seen in the December impact study.

<table>
<thead>
<tr>
<th>Table 4: Contingency tables of precipitation at Danish stations for January 2002. For details, see text.</th>
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<tr>
<td><strong>WIA 200201 6-18 h</strong></td>
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<td>----------------------</td>
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<tr>
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</tr>
<tr>
<td>F1</td>
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<tr>
<td>F2</td>
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<td>F3</td>
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<table>
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<th><strong>REF 200201 18-30 h</strong></th>
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</tr>
<tr>
<td><strong>%FO</strong></td>
<td>33</td>
</tr>
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</table>
Figure 36: Obs-verification results for January 2002 for WIA and REF of surface and upper level parameters as specified in the plot. EWGLAM station list.
Figure 37: Obs-verification result for January 2002 for WIA and REF of upper level parameters as specified in the plot. EWGLAM station list.
Figure 38: Daily obs-verification (bias and standard deviation, EWGLAM station list) results of 48 h forecasts for January 2002 of surface and upper level parameters specified in the plot.
Figure 39: Difference of standard deviation between the WIA (analyses including AMSU-A brightness temperatures) and the REF (analyses not including AMSU-A brightness temperatures) for 36 h forecasts of 850 hPa temperature (upper) and mslp (lower) for January 2002. Full lines/dark shaded for areas where REF is better and dashed lines/light shaded for areas where WIA has better standard deviation scores. Contour lines are for every 0.25 K and 0.25 hPa, respectively.
Thus, for January 2002 the impact of NOAA16 AMSU-A data is positive in the DMI-HIRLAM-G data assimilation system. The main difference from the neutral impact in December 2001 is the modified observation error covariance matrix. This is probably the main reason for the improved impact since the large off-diagonal elements in the observation covariance matrix between the surface channels 1 through 3 and the other channels used in the December runs could cause unwanted side effects.

5 Ongoing and future work

5.1 Overview

As already described in this report, HIRLAM is presently using only the AMSU-A channels of ATOVS, and we only use data over ocean areas. Other NWP centers (such as ECMWF and Met Office, UK) use more channels and also some data over land and sea ice surfaces. There is therefore a potential for extending the ATOVS data use to the same level as these centers.

Some work has been undertaken to investigate possible strategies for applying AMSU-A channels over sea ice, which will be described below.

5.2 Use of observations over ice

For HIRLAM countries with model domains covering the Arctic, it is highly interesting to be able to use AMSU data over ice covered surfaces. These regions have a very low coverage of conventional observations, which would make the potential impact of adding AMSU data in these areas high.

The application of AMSU channels for the lower troposphere requires accounting for the surface contribution to the signal. Over sea ice the emissivity cannot be estimated a priori from the NWP model like over ocean. Information on surface emissivity must either be derived from the sounding channels themselves or from other measurements.

Global NWP centers have used upper-tropospheric AMSU channels over ice, and have recently also extended their use of surface channels. ECMWF has used an approach where they have estimated the surface emissivity from the AMSU channels themselves and have retuned the variational quality control over ice. Schyberg and English (Schyberg and English, 2001) undertook an investigation to assess the usefulness of SSM/I based ice charts to derive surface emissivity information for AMSU. Such charts are for instance available from the EUMETSAT Ocean and Sea Ice SAF (Satellite Application Facility), and this type of information was shown to help in determining the surface emissivity.

A natural basis for emissivity modeling is to split the detected radiance into contributions from open water and various surface types in the footprint. Assuming a constant surface temperature, if the surface is divided into three types, water with concentration $c_W$, first-year ice with concentration $c_F$ and multi-year ice with concentration $c_M$, we can estimate the emissivity as a sum of the emissivities characteristic of the three types as

$$\varepsilon = c_W\varepsilon_W + c_F\varepsilon_F + c_M\varepsilon_M,$$  (20)
where we have
\[ c_W + c_F + c_M = 1. \]
This formulation is also used in the derivation of SSM/I ice concentration algorithms such as for instance the NASA/Team algorithm. If we have estimates of the three concentrations from SSM/I data and we can determine a typical emissivity for each of the three surface types for the desired AMSU microwave frequencies, this gives a simple method for emissivity estimation.

Eq. 20 can be rewritten as
\[ \varepsilon = \varepsilon_W + \Delta \varepsilon \]
with
\[ \Delta \varepsilon \equiv c_T(\varepsilon_F - \varepsilon_W) + c_M(\varepsilon_M - \varepsilon_F) \]
where we have introduced the total ice concentration \( c_T = c_F + c_M \). From this we see that keeping \( c_M \) constant and varying \( c_T \) should give a linear relation between emissivity and the total concentration with the constant of proportionality equal to \( \varepsilon_F - \varepsilon_W \).

Schyberg and English (Schyberg and English, 2001) compared background departures for the surface channels with estimates of total ice concentration as well as multi-year ice fraction from the Ocean and Sea Ice SAF. Areas with complete ice cover (\( c_T = 1 \)) showed a linear dependence of background departures on \( c_M \), and areas with mixture of water and first-year ice (\( c_M \) small) showed a linear dependence on \( c_T \).

This shows that such an emissivity model would allow a much more precise forward modeling of AMSU radiances over ice than for instance assuming a constant ice emissivity over all the ice cap. Further work in HIRLAM will probably take benefit of this approach by interfacing the AMSU surface emissivity calculation over ice to the Ocean and Sea Ice SAF ice products.

5.3 Moisture channels

There is also ongoing work at DNMI to use HIRS moisture channels. The infrared data from HIRS are much more sensitive to clouds than AMSU-A data, and present activities focus on finding a good cloud masking strategy for high-resolution modeling purposes. There are plans at SMHI to develop methods for assimilating AMSU-B moisture information as well.

Obtaining impact from the assimilation of moisture data is not as straightforward as for temperature sounding channels. Moisture is to a high extent governed by precipitation and evaporation processes, which are parameterized in the NWP model. The initial moisture field in HIRLAM is usually altered by parameterized moist processes in a short spinup period to yield a new moisture field which is more compatible with the model parameterizations than the initial state. One might hope that assimilation schemes which also includes model time evolution such as 4D-Var could alleviate this problem.

The available observations typically describes total moisture in a deep layer, while the real vertical moisture variability is very high. Experiences at ECMWF shows that observation increments for moisture sounding channels are typically of the same magnitude as the moisture variability itself. In this respect improvements in assimilation methods, model physics for moist processes as well as in the observations themselves seem necessary.
5.4 Future sensors

The methods developed and experiences gained in assimilation of ATOVS can also be of use in exploiting future satellite sensors applying similar measurement principles.

Several future sensors will provide sounding data with high horizontal resolution, and this increased observation resolution will be of particular interest for limited-area modeling. Such sensors include infrared sensors with several thousand channels such as AIRS and IASI. Another sensor of particular interest is the MODIS, which includes channels similar to HIRS, but with higher horizontal resolution. There will also be new microwave sensors with increased sounding capability, such as the SSMIS which will be available in 2002, and which will eventually replace the present SSM/I sensors on the DMSP satellites. For all those sensors, however, data delivery and timeliness issues are not yet resolved, and they may not necessarily meet the requirements of high resolution modeling.

6 Conclusions and outlook for the future

The HIRLAM 3D-VAR system has been adapted to use locally received AMSU-A data processed with the AAPP package. The system has been set up with bias correction, data quality control and data thinning, and all necessary modules for assimilation of AMSU-A have been included in 3D-VAR.

Several impact studies on the effect of assimilation of AMSU-A data in HIRLAM 3D-VAR on different setups of the HIRLAM model have been performed. It is generally considered more difficult to obtain positive impact in limited-area models than in global models due to the continuous forcing from the lateral boundaries. The impact have been studied both in terms of verification statistics and by detailed study of weather events of particular interest.

A positive impact has been obtained in several of the experiments. It is found that the impact of AMSU-A varies in space and time as seen in any observation system experiment. In general the number of cases with positive impact should outweigh the cases with negative impact, and this seems the case here. It is particularly encouraging that the forecast of the so-called French storm was improved by use of AMSU-data, as this was a severe weather situation of great impact for which the operational forecasts were bad.

Decent statistics in terms of background and observations errors is necessary for good results in the variational data assimilation. Ongoing research and development includes improved quality control and improved tuning of the assimilation scheme by estimation of forecast error standard deviations in AMSU-A radiance space as well as estimation of observation error standard deviations for the AMSU-A measurements.

The three HIRLAM weather services which have performed the impact studies applied somewhat different approaches for tuning of the observation error statistics assumed. The HIRLAM system is set up to allow various options for ATOVS such as non-diagonal or diagonal observation error covariance matrix as well as different values for the observation error variances. The impact experiments were not set up in a way that enabled direct comparison of the impact of the various assumptions. It seems, though, that several of the approaches can make beneficial use of AMSU-A in 3D-VAR, but it is still not clear which approach gives the best impact. Some work therefore still remains on defining optimal error statistics.
We conclude, nevertheless, that AMSU-A radiances can improve the forecast scores since they contribute with observations over sea where observations otherwise are scarce. It is believed that the HIRLAM ATOVS assimilation has reached a stage where it is recommendable to use the AMSU-A data operationally.

In addition to remaining work on tuning, there is ongoing work to extend the ATOVS dataset that is assimilated. In particular there is work on taking HIRS moisture channels into use and to use the observations over sea ice. There are also plans on developing use of AMSU-B moisture data.

The use of ATOVS radiances for operational numerical weather prediction is presently limited by the restricted coverage of data from local satellite data reception stations at European weather services and by the time delay for receiving data with global coverage from NOAA/NESDIS in Washington. A joint European effort for collection and distribution of ATOVS data from several downlink stations (including reception stations in Canary Islands, Greece, Northern Norway, Greenland, Canada and Alaska) is being set up by EUMETSAT, the European meteorological satellite organization. The observations are planned to be available in calibrated and geolocalized form within 30 minutes, which should meet the requirements for operational data assimilation in limited-area models at the HIRLAM forecasting centers. The geographical coverage of ATOVS data available at each forecast center will then be dramatically extended, and the number of observations in sensitive and important regions will increase.

It is therefore envisaged that the positive effects of ATOVS found so far will become more significant in the near future.
Acknowledgment

Kristian Mogensen did valuable work on improving the ATOVS processing in the HIRLAM 3D-VAR code. Erik Andersson, ECMWF, is acknowledged for useful advices on tuning of error statistics.

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