Characterizing AMV Height-Assignment Error by Comparing Best-Fit Pressure Statistics from the Met Office and ECMWF Data Assimilation Systems

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(Manuscript received 17 December 2013, in final form 3 September 2014)

ABSTRACT

To ensure realistic use of atmospheric motion vector (AMV) observations in data assimilation, the error characteristics of the observation type need to be known and carefully taken into account. Assigning a height to the tracked feature is one of the most significant error sources for AMV observations. In this article, the characteristics of the AMV height-assignment error are studied by comparing model best-fit pressure statistics between the Met Office and ECMWF data assimilation systems. The aim is to provide detailed uncertainty estimates for the assigned pressure and to demonstrate that the best-fit pressure enables reliable estimation of the uncertainties in the AMV height assignment. Typical values for the standard deviation of the difference between the assigned pressure and the best-fit pressure are 50–80 hPa at high levels, 115–165 hPa at midlevels, and 60–125 hPa at low levels, depending on satellite, channel, and height-assignment method. Observed minus best-fit pressure biases are mostly within the range of 650 hPa. The results are very similar for the Met Office and ECMWF systems, suggesting that the pressure differences are not strongly dependent on the data assimilation system. Furthermore, the findings are in good agreement with the expected characteristics of the height-assignment methods and quality of the observations. Thus, best-fit pressure statistics give reliable information about the uncertainties in the AMV height assignment.

1. Introduction

This article provides a detailed characterization of the height-assignment errors from atmospheric motion vectors (AMVs). AMVs are wind observations generated by tracking clouds, or water vapor features, in consecutive satellite images. It is assumed that the tracked features act as passive tracers of the atmospheric flow. A representative pressure level is assigned during the derivation, and typically this is an estimate of the cloud top or the cloud base. AMVs are obtained both from geostationary and polar-orbiting satellites. They have very good spatial (horizontal) and temporal coverage over the globe, particularly over the ocean. Further information on AMV derivation can be found in Velden et al. (2005), Menzel (2001), Nieman et al. (1997), and Schmetz et al. (1993). AMV observations are operationally used in various global and limited-area NWP systems (e.g., Bormann et al. 2012; Cotton and Forsythe 2012; Cress 2012; Pauley et al. 2012; Su et al. 2012). They are typically interpreted as single-level wind observations that are assigned to a representative pressure level that is provided by the AMV producers.

One of the most significant error sources for AMVs is the height assignment of the tracers (e.g., Nieman et al. 1997). The height assignment introduces uncertainties in the wind observations, which propagate into the atmospheric forecasting system through data assimilation. It is important to understand and quantify these uncertainties in order to improve the accuracy of the wind observations and their impact on the forecast system. This article focuses on the analysis of the height-assignment error by comparing model best-fit pressure statistics from the Met Office and ECMWF data assimilation systems.
A reliable estimate of the magnitude of the height-assignment error is particularly important for data assimilation, where methods are being developed that better account for the height-assignment uncertainty (e.g., Forsythe and Saunders 2008a). The effects of height-assignment error are highly situationally dependent. Figure 1 illustrates the significance of this issue. In case 1 the wind speed does not vary much with height, and a $\pm 50$-hPa error in height assignment would result in a $\pm 0.5$ m s$^{-1}$ error in wind speed. In case 2 there is wind shear in the vertical direction, and in this situation the same $\pm 50$-hPa error in height assignment would result in a wind speed error of up to 7 m s$^{-1}$. It is important to note that at high levels a $\pm 50$-hPa displacement corresponds to a vastly greater vertical displacement than it does at low levels. To emphasize this fact, Fig. 1 shows the vertical coordinate both in pressure (hPa) and in height (km). In the following sections the uncertainties in the height assignment are considered in terms of pressure. This is a natural choice in NWP, for which AMVs are typically treated in pressure coordinates.

AMV height-assignment errors can originate from several sources. Each height-assignment method has built-in assumptions and limitations that will affect the accuracy of the assigned height depending on the atmospheric conditions. Therefore, each height-assignment method is expected to show different error characteristics. Identification of the representative pixels in the target box to be used in the height assignment is important (Borde et al. 2014). In addition, NWP forecasts of temperature and humidity are commonly used in the height-assignment process, and therefore errors in the forecasts of these variables will contribute to the height error. Problems may also arise from the AMV observation and its model counterpart not representing the same phenomena. High-level AMVs are assigned to an estimate of the cloud top, yet it is unclear whether this is the appropriate height or whether the cloud motions are more representative of the wind at a level within the cloud (Hernandez-Carrascal and Bormann 2014). AMV wind observations are typically treated in data assimilation systems as single-level data (Rao et al. 2002). This is also the case in this study. In reality, the satellite instruments sense radiation emitted from a finite layer of the atmosphere, and interpreting AMVs as a layer-average wind is an area of active research (e.g., Hernandez-Carrascal and Bormann 2014; Weissmann et al. 2013; Velden and Bedka 2009).

A number of studies have estimated the uncertainties in the cloud-top products used for AMV height assignment. This has been achieved by comparing different sources of cloud-height information such as lidar scans or stereo parallax measurements (e.g., Wylie and Menzel 1989; Velden and Bedka 2009; Di Michele et al. 2012). Validation of the accuracy of cloud-top height assignment is challenging, however, because the coverage and characteristics of the instruments providing information about the cloud-top height are different (Holz et al. 2006). Collocation and representativeness errors contribute significantly in such comparisons. Also, such studies do not include the uncertainty involved in attributing the tracer motion to the wind at a certain height. This uncertainty adds to the error budget when cloud-top estimates are used to assign AMVs in the vertical direction (Hernandez-Carrascal and Bormann 2014). The only study we are aware of that includes this uncertainty is that of Velden and Bedka (2009), which uses a similar approach to ours, applied to radiosondes from three locations.

In this study, the AMV height-assignment error characteristics are investigated by making use of the model best-fit pressure. The best-fit pressure is defined as the pressure at which the vector difference between the observed wind and the NWP-model background wind is the smallest. The main advantage of the best-fit pressure is that it can be defined for every AMV.
observation. Thus, height-assignment error characteristics can be easily investigated for each satellite, channel, and height-assignment method, at all locations where AMVs are available. It is important to note that the best-fit pressure also includes contributions from errors in the model background and that it is not always possible to define an unambiguous value for it. The concept of best-fit pressure is used in the operational National Oceanic and Atmospheric Administration/National Environmental Satellite, Data, and Information Service (NOAA/NESDIS) AMV processing scheme (Hayden and Purser 1995).

The aim of this article is twofold. First, we provide a detailed characterization of the systematic and random errors in height assignment for AMVs from a wide range of satellites. These results can be applied in NWP models to define realistic observation errors for AMVs (Forsythe and Saunders 2008a; Salonen and Bormann 2013) or possibly to correct for systematic height-assignment biases. Improvements in the use of AMVs will consequently lead to improvements in the model analysis and forecasts. Second, we investigate the dependence of the presented statistics on the data assimilation system used by comparing results from two systems: those of the Met Office and the European Centre for Medium-Range Weather Forecasts (ECMWF). The aim is to demonstrate that the best-fit pressure statistics are a reliable metric for characterizing uncertainties in AMV height assignment.

The article is organized as follows. The most commonly applied height-assignment methods and their error characteristics are briefly presented in section 2. The calculation of the model best-fit pressure is described in section 3, followed in section 4 by an introduction to the datasets used in the study. The model best-fit pressure statistics produced at the Met Office and at ECMWF are compared in section 5. The results are discussed with conclusive remarks in section 6.

2. Height-assignment methods and their typical error characteristics

In the AMV community, the term “height assignment” is typically used to refer to the process of assigning a representative pressure to the derived AMV. The most commonly used height-assignment methods are the equivalent blackbody temperature (EBBT), carbon dioxide (CO₂) slicing, water vapor (H₂O) intercept, and cloud-base techniques (Jung et al. 2010).

The EBBT technique is based on comparing measured brightness temperatures with forecast temperature profiles. The level of best agreement is chosen as the observation height. This method works best for opaque clouds. For semitransparent and small clouds...
the method will often assign the observation too low in the atmosphere (Nieman et al. 1993).

Multispectral approaches utilizes the difference in radiances in two channels over cloudy and clear-sky areas. The CO$_2$-slicing technique (Menzel et al. 1992) combines infrared (IR) longwave-window-channel data with CO$_2$-absorption-channel data, and the H$_2$O-intercept technique (Szejwach 1982) uses the water vapor (WV) and IR channels. In both cases, the height is determined from the ratio of the difference between the true cloud-affected radiance and the estimate of the cloud-free radiance for the two different spectral channels. The multispectral approaches are effective for high-level and some midlevel clouds but fail when the difference between the observed and clear radiances is less than the instrument noise in any of the channels. Typical situations when the methods fail are low clouds, or very thin cirrus clouds. The methods have difficulties in multilayer cloud situations. In this case the observation height is assigned somewhere between the cloud layers.

In the cloud-base height-assignment method, a histogram of the brightness temperatures is derived in the target area (Le Marshall et al. 1994). The cloud-base temperature is estimated using Hermite polynomials fitted to the histograms. The obtained cloud-base temperature is then compared with forecast temperature to determine the cloud-base height. The cloud-base height-assignment method is used for low-level clouds only.

Each producing center has its own decision-making processes for selecting which height-assignment method is used in each case. For example, NOAA/NESDIS determines the height of Geostationary Operational Environmental Satellite (GOES) AMVs following a predetermined order in which the CO$_2$-slicing
technique is selected first, if available, followed by the H2O-intercept technique and then the EBBT (Daniels et al. 2004). NOAA/NESDIS applies the cloud-base method for low-level clouds over sea when available. For Meteosat-9, the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) has used the CO2-slicing technique as the prime method. If specific criteria for the pressure and related temperature are not fulfilled, then EBBT or an alternative method is chosen (de Smet 2008). EUMETSAT applies the cloud-base method over both land and sea. There can also be differences between the producing centers in how inversion corrections, if any, are applied. In the inversion correction, an AMV is relocated to the minimum temperature of the inversion in regions of a forecast inversion (Forsythe and Doutriaux-Boucher 2005). The AMV derivation algorithms are constantly evolving, including the decision-making processes for choosing the height-assignment method.

Since AMVs are provided to users with pressure as the vertical coordinate, we present the following error analysis in terms of pressure. Note that some sources of height-assignment errors may be more constant in the vertical direction if geometric height were to be used instead. Because height is proportional to \( \ln(p) \), where \( p \) is pressure, it is possible to convert the statistics to an estimate of the uncertainty in \( \ln(p) \) by using \( \Delta[\ln(p)] \approx \frac{(\Delta p)}{p} \).

### 3. Model best-fit pressure

The model best-fit pressure is defined as the height at which the vector difference between the observed and the model background wind is the smallest. The calculation of model best-fit pressure consists of two steps. First, the model level with the smallest vector difference between the observation and the model background wind is found. Second, the true minimum is calculated by using a parabolic fit to the vector difference for this model level and the two neighboring levels.

When analyzing the best-fit pressure statistics, it is necessary to ensure that the best-fit pressure provides a meaningful estimate for the pressure level of the observed AMV. A secondary or a very broad minimum can lead to best-fit pressures that are not very meaningful. In a similar way, at times there is no good agreement between the AMV and the model wind at any pressure level, because of either tracking errors or large forecast errors. Figure 2 illustrates these cases. In Fig. 2a there is a unique well-defined minimum difference in the vector-difference profile, whereas in Fig. 2b there is no good agreement at any level. Figures 2c and 2d illustrate cases in which there is a prominent secondary minimum and the minimum vector difference is very broad, respectively.

### Table 1. Satellite, channel, and height-assignment-method combinations used in the comparison study. Here, HRVIS is high-resolution visible.

<table>
<thead>
<tr>
<th>Satellite; producing center</th>
<th>Channel</th>
<th>Height-assignment methods</th>
</tr>
</thead>
<tbody>
<tr>
<td>Meteosat-7; EUMETSAT</td>
<td>IR</td>
<td>Not available</td>
</tr>
<tr>
<td></td>
<td>VIS</td>
<td>Not available</td>
</tr>
<tr>
<td></td>
<td>Cloudy WV</td>
<td>Not available</td>
</tr>
<tr>
<td>Meteosat-9; EUMETSAT</td>
<td>IR 10.8</td>
<td>CO2 slicing, H2O intercept, and EBBT</td>
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<tr>
<td></td>
<td>HRVIS</td>
<td>CO2 slicing and EBBT</td>
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<tr>
<td></td>
<td>VIS 0.8</td>
<td>CO2 slicing and EBBT</td>
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<tr>
<td></td>
<td>Cloudy WV 6.2</td>
<td>CO2 slicing, H2O intercept, and EBBT</td>
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<tr>
<td></td>
<td>Cloudy WV 7.3</td>
<td>CO2 slicing, H2O intercept, and EBBT</td>
</tr>
<tr>
<td>MTSAT-1R; JMA</td>
<td>IR</td>
<td>H2O intercept and EBBT</td>
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<tr>
<td></td>
<td>VIS</td>
<td>EBBT</td>
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<tr>
<td></td>
<td>Cloudy WV</td>
<td>H2O intercept</td>
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<tr>
<td>GOES-11; NOAA/NESDIS</td>
<td>IR 10.7</td>
<td>H2O intercept, EBBT, and cloud base</td>
</tr>
<tr>
<td></td>
<td>IR 3.8</td>
<td>EBBT and cloud base</td>
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<td>Cloudy WV</td>
<td>H2O intercept</td>
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<tr>
<td>GOES-12; NOAA/NESDIS</td>
<td>IR 10.7</td>
<td>CO2 slicing, H2O intercept, EBBT, and cloud base</td>
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<td></td>
<td>Cloudy WV</td>
<td>CO2 slicing, H2O intercept, and EBBT</td>
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<tr>
<td>Terra; NOAA/NESDIS</td>
<td>IR</td>
<td>H2O intercept, EBBT, and cloud base</td>
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<td>Cloudy WV</td>
<td>H2O intercept and EBBT</td>
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<td></td>
<td>Clear Sky WV</td>
<td>EBBT</td>
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<tr>
<td>Aqua; NOAA/NESDIS</td>
<td>IR</td>
<td>H2O intercept, EBBT, and cloud base</td>
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<td>Cloudy WV</td>
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<td>Clear Sky WV</td>
<td>EBBT</td>
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The following criteria have been developed and are applied in this study to exclude the cases that are illustrated in Figs. 2b–d:

1) The minimum vector difference between the observed and the model best-fit background wind is less than 4 m s\(^{-1}\):

\[
\left[ (u_{\text{obs}} - u_{\text{bg}})^2 + (v_{\text{obs}} - v_{\text{bg}})^2 \right]^{1/2} < 4 \text{ m s}^{-1}.
\]  

2) The vector difference is greater than the minimum difference + 2 m s\(^{-1}\) outside a band that encompasses the best-fit pressure ±100 hPa:

\[
\text{VD} > (\text{VD}_{\text{min}} + 2 \text{ m s}^{-1}) \quad \text{for} \quad \begin{cases} p < p_{\text{best}} - 100 \text{ hPa} \\ p > p_{\text{best}} + 100 \text{ hPa} \end{cases}
\]  

In Eq. (2), VD (m s\(^{-1}\)) is the vector difference, VD\(_{\text{min}}\) (m s\(^{-1}\)) is the minimum difference, \(p\) (hPa) is pressure, and \(p_{\text{best}}\) (hPa) is the best-fit pressure. The first criterion is designed to exclude cases in which there is no good agreement between the AMV wind observation and the model wind at any level. The second criterion excludes cases in which there is a secondary, or a very broad, minimum, that is, cases for which the best-fit pressure is not well constrained. The thresholds have been chosen empirically, balancing the likelihood that the best-fit pressure is indeed representative with restricted sampling. It is considered to be better to have a too-strict criterion than one that is too relaxed, because it is essential to remove cases in which the result is not meaningful. The effect of applying these criteria on our data sample is discussed in more detail in section 4.

The best-fit pressure is calculated with model background profiles (short-term forecasts), that is, before the AMVs have been assimilated. Both the Met Office and
ECMWF data assimilation systems use a similar approach to calculate the model best-fit pressure. A minor difference in the calculation is that in the case in which there are multiple minima that fulfill the criteria the ECMWF formulation chooses the minimum closest to the originally assigned pressure whereas the Met Office formulation chooses the minimum with the smallest vector difference. Comparison of the approaches in the ECMWF system reveals that if criteria 1 and 2 are fulfilled then in approximately 2% of cases the best-fit pressure is not the same because of the difference in the calculation.

The model best-fit pressure allows us to study the uncertainties in the AMV height assignment comprehensively in space and time, but care must be taken when interpreting the results. It is not always possible to define an unambiguous best-fit pressure. In addition, the model best-fit pressure also includes contributions from the errors in the model background wind field (i.e., in the short-term forecast).

The impact of short-term forecast errors on the best-fit pressure statistics has been estimated on the basis of a 25-member “ensemble of data assimilations” (EDA; Bonavita et al. 2012) experiment performed with the ECMWF system. In an EDA experiment, an ensemble of independent four-dimensional variational data assimilations (4D-Var) is performed. The main analysis error sources are represented by perturbing observations, forecast model, and sea surface temperature according to their estimated accuracy. The performed EDA experiment provides 26 estimates, including the control run, of the best-fit pressure for each AMV. In the operational ECMWF data assimilation system, an EDA is used to estimate background errors on the basis of the spread of the ensemble.

Figure 3 shows the mean standard deviation of the best-fit pressure estimates resulting from the spread of the ensemble as a function of pressure for the Southern Hemisphere extratropics (left panel), tropics (center panel), and Northern Hemisphere extratropics (right panel). The gray bars indicate the number of cases at each level. The spread of the best-fit pressures is about 15 hPa throughout the troposphere. Calibration of the EDA suggests that it is usually underdispersive in the extratropics—typically by a factor of 1.5–2. This result suggests that the uncertainty in the best-fit pressure that is due to errors in the short-term forecasts is about 20–30 hPa.

4. Data

The best-fit pressure statistics have been compared from the Met Office and ECMWF global data assimilation systems for February–March 2010. The Met Office statistics are based on operational suite 23 (OS23) with global model horizontal resolution N512 (25 km in midlatitudes), 70 vertical levels, and 4D-Var with a 6-h assimilation window. The ECMWF statistics are based on an experiment made with Integrated Forecasting System cycle 36r4 with T511 (40 km) resolution, 91 vertical levels, and 4D-Var with a 12-h assimilation window. For both systems, all operationally assimilated conventional and satellite observations are used, including AMVs.

AMVs used in the comparison have been filtered by applying a quality-indicator (QI) threshold of 80 to all geostationary AMVs and a QI threshold of 60 to all polar AMVs. The QI is the EUMETSAT quality indicator without forecast dependence, which provides information on the consistency of the AMVs in time and space (Holmlund et al. 2001). The QI thresholds are the standard values as used by the Satellite Application...
Note that the data selection for the comparison is independent of the geographical data selection applied in the data assimilation process, commonly referred to as blacklisting. In data assimilation, blacklisting is applied to exclude AMVs with known lower quality. The blacklisting decisions are based on long-term monitoring of the data against the model background but were not applied to the data considered in this study.

The best-fit pressure statistics are considered separately according to satellite, channel, height-assignment method, and surface type. Table 1 summarizes the datasets. AMVs from five geostationary satellites [Meteosat-7, Meteosat-9, GOES-11, GOES-12, and Multifunctional Transport Satellite-1R (MTSAT-1R)] and two polar-orbiting satellites (Aqua and Terra) are considered. The producing centers are EUMETSAT, NOAA/NESDIS, and the Japan Meteorological Agency (JMA).

The total number of AMV observations fulfilling the QI criteria for the studied period is approximately 37,000,000. The impact of the filtering criteria described in section 3 is not uniform. At high levels (above 400-hPa height) the best-fit pressure is utilized in 50%–60% of cases; at low levels (below 700-hPa height) it is utilized in only 15%–20% of cases. Figure 4 shows wind speed and direction distributions for all AMVs with QI greater than 80 for which the best-fit pressure has been calculated. Wind speeds that are slower than 10 m s$^{-1}$ are somewhat underrepresented at all levels for the sample analyzed in this study, and consequently higher wind speeds are slightly overrepresented. Criterion 2, which concerns detecting and rejecting cases with multiple or broad minima, dominates the rejection of low-wind speed observations. The distribution of wind directions shows that only easterly winds are underrepresented in the subset for which the best-fit pressure is calculated. This is the direction from which the low-wind speed observations most often originate. It can be concluded that all wind speeds and directions are in any case relatively well represented. A similar analysis of the distribution of the QI values does not suggest that our sampling favors AMVs with a high QI (not shown). In addition, the methods used to estimate the cloud top or base from the satellite imagery are not dependent on a wind profile. Thus, it is expected that the error estimates provided here are nevertheless still indicative of more-general situations.
5. Comparison of the statistics

In this section, we intercompare the best-fit pressure statistics from the Met Office and ECMWF data assimilation systems. Comparisons are made in terms of the mean difference (bias) and standard deviation of the assigned pressure minus the model best-fit pressure over the 2-month period. A positive (negative) mean difference indicates that the assigned pressure is on average higher (lower) than the best-fit pressure. In terms of height that means that the observation is lower (higher) in the atmosphere than the best-fit pressure level.

Figure 5 shows the number of observations for which the best-fit pressure is calculated for the Met Office (gray bars) and ECMWF (black bars) systems at different pressure levels. Also shown is the mean standard deviation of the assigned pressure minus the model best-fit pressure for all AMVs considered. The majority of the observations originate from the upper levels, with a secondary maximum at low level and relatively few observations from midlevel. The vertical distribution of observations is similar to the distribution of typical AMV datasets that are assimilated. In the Met Office dataset there are approximately 15% more observations than in the ECMWF dataset. This difference indicates that the best-fit pressure is well constrained somewhat more often in the Met Office system. The differences in the standard deviation pressure difference are typically 15 hPa or less, indicating that the statistics are very similar for both NWP systems.

Depending on pressure level, considerable differences among statistics for different channels, height-assignment methods, and surface type (land/sea) are seen. Thus, in the following sections the statistics are studied according to this separation.

a. Geostationary AMVs

Figure 6 shows zonal plots of the bias (upper panels), standard deviation (middle panels), and number of observations (lower panels) for Meteosat-9 IR-channel AMVs utilizing the EBBT height assignment over sea. Statistics for the Met Office and ECMWF systems are shown on the left and right of the figure, respectively. The similarity of the statistics between the two systems is striking: although some quantitative differences exist, the general patterns are the same. At high levels the magnitude of the bias is mainly within ±50 hPa and the standard deviation is within approximately 50 hPa. For low levels the bias is mainly positive and locally reaches values in excess of 100 hPa. Over land (Fig. 7), below 600-hPa height, a strong positive bias of up to 300 hPa in magnitude is seen in the tropics, between 30°S and 30°N. This result indicates that the assigned observation...
heights are on average lower in the atmosphere than the model best-fit pressure level. This feature has been reported in detail in the NWP SAF analysis reports (feature 2.7 in Cotton and Forsythe 2010). The explanation is that in many cases the height of semitransparent clouds is assigned to be too low because of temperature contributions from below the cloud over the hot African land surface. In Fig. 7 the bias tends to be more pronounced in the ECMWF statistics.

GOES AMVs applying the EBBT height assignment generally show good agreement between the assigned pressure and the model best-fit pressure. For IR- and WV-channel AMVs above 600-hPa height, standard deviations are ~50 hPa. For low-level visible (VIS)-channel AMVs over the sea, there is a significant negative bias of 100–300 hPa between heights of 800 and 600 hPa (Fig. 8). This feature has been addressed in the NWP SAF analysis reports (feature 2.1 in Forsythe and Saunders 2008b) and is known to be associated with height-assignment difficulties in the stratocumulus inversion regions of the Pacific and Atlantic Oceans. AMVs are systematically placed too high as a result of the use of forecast profiles with relatively coarse resolution in the vertical direction and the lack of an inversion correction (Forsythe and Saunders 2008b). Improvements to these issues in the NOAA/NESDIS AMV processing were implemented operationally in the spring of 2014 (J. Daniels 2014, personal communication).

MTSAT-1R AMVs applying the EBBT height-assignment method exhibit a positive height bias at low levels (Fig. 9). As compared with other producers, the low-level MTSAT-1R AMVs are assigned to a narrow band around 950–850 hPa, and relatively few observations are assigned to high levels using the EBBT method.

Plots of AMVs using the CO2-slicing height assignment are generally very similar for different satellites and channels. GOES-12 WV-channel AMVs over sea are shown in Fig. 10 as an example. Below 200-hPa height in the tropics, a positive height bias of around 100 hPa is observed, which is more pronounced in the ECMWF statistics. Outside of this region the bias is generally within ±25 hPa. At midlevels in the extratropics a negative bias is seen, meaning the assigned observation heights are on average higher in the atmosphere than the model best-fit pressure level. In terms of standard deviation, the pattern is similar. The standard deviation is around 50 hPa above 400-hPa height, but increases at midlevel and poleward of 30°.

AMVs applying the H2O-intercept height-assignment technique share similar characteristics with AMVs applying the CO2-slicing height assignment. This is not surprising, because the techniques are similar and share
similar limitations. Figure 11 shows the bias (upper panel) and standard deviation (lower panel) of the assigned observation height minus model best-fit pressure for Meteosat-9 (black lines) and GOES-12 (gray lines) WV-channel AMVs. The solid line indicates AMVs with the CO2-slicing method, and the dashed line indicates those with the H2O-intercept method. Statistics in Fig. 11 are for the ECMWF system. Above 400-hPa height, the bias and standard deviation are generally similar for AMVs from both satellites. The exception is Meteosat-9 AMVs with the H2O-intercept heights, which exhibit larger standard deviations and a negative height bias in the Southern Hemisphere. Below 400-hPa height there are very few observations available.

The best-fit pressure statistics for MTSAT-1R AMVs assigned with the H2O-intercept method are somewhat different than the statistics from Meteosat and GOES. Figure 12 shows the bias and standard deviation in a similar way to that in Fig. 11 but for MTSAT-1R (black solid line), GOES-12 (gray solid line), and MTSAT-1R (black dashed line) WV-channel AMVs assigned using the H2O-intercept method over sea. For MTSAT-1R the bias is generally positive; that is, the assigned observation heights are on average lower in the atmosphere than the model best-fit pressure level, whereas for Meteosat-9 and GOES-11/12 AMVs the bias is negative.

b. Polar AMVs

Moderate Resolution Imaging Spectroradiometer (MODIS) polar AMVs from Aqua and Terra have also been considered in this study. AMVs are available from both the IR and WV channels. The characteristics seen in the best-fit pressure statistics are similar for both satellites, and again the statistics for the Met Office system and the ECMWF system are similar.

For IR and WV AMVs with the EBBT height assignments the agreement between the assigned observation height and the model best-fit pressure is good above 500-hPa height: biases are close to zero and standard deviations are less than 100 hPa. For lower levels the bias is typically positive with a magnitude of 50–100 hPa, indicating that the assigned observation height is lower in the atmosphere than the model best-fit pressure. The standard deviations vary between 200 and 300 hPa. Figure 13 shows the zonal statistics for Aqua IR winds over sea and sea ice as an example of the results. Again, the ECMWF statistics show a slightly more pronounced bias than the Met Office statistics. The height-assignment problems at low levels are likely to be related to problems with cloud detection over cold surfaces in the IR. In addition, temperature inversions and an isothermal atmosphere can complicate the height assignment over these regions.
To compare the statistics for the two channels and height-assignment methods, Fig. 14 shows the bias (upper panel) and the standard deviation (lower panel) of the assigned observation height minus model best-fit pressure for Terra IR (black lines) and cloudy WV (gray lines) AMVs. The solid line indicates AMVs with the EBBT method, and the dashed line indicates those with the H$_2$O-intercept method. The statistics are from the ECMWF system. In terms of the height assignment, the methods behave similarly. Over the southern polar region, standard deviations are slightly larger for the AMVs applying the H$_2$O-intercept method, but over the northern polar region the height-assignment methods behave similarly to each other.

6. Discussion and conclusions

The comparison of the best-fit pressure statistics for the Met Office and the ECMWF data assimilation systems has shown that the statistics are generally very similar to each other. Typical values for standard deviation of the assigned observation height and best-fit pressure difference are 50–80 hPa at high levels, 115–165 hPa at midlevels, and 60–125 hPa at low levels. An EDA experiment indicates uncertainty of about 20–30 hPa in the best-fit pressure that is due to errors in the short-term NWP forecasts. The differences in the bias and standard-deviation statistics between the two systems are on average less than 15 hPa. Some differences are seen, for example, at midlevels, where the ECMWF statistics show occasionally more pronounced biases and standard deviations than the Met Office results. These are typically over areas where there are relatively few observations available. In the Met Office system the best-fit pressure is well constrained more often and the dataset is approximately 15% larger than the dataset from the ECMWF system. The consistency of the results from the two systems suggests that the best-fit pressure analysis provides a reliable characterization of the height assignment of AMVs.

AMVs from different producing centers show similar error characteristics in our analysis, suggesting that the results reflect general characteristics of height-assignment methods and AMV tracers. The study also confirms that the height-assignment error is strongly dependent on the chosen height-assignment method. In most of the cases in which the bias is positive (i.e., the assigned observation height is lower in the atmosphere than the model best-fit pressure level), the applied height-assignment method is EBBT. Earlier studies (Nieman et al. 1993) have indicated that this height-assignment method often assigns the observation too...
FIG. 11. (top) Bias and (bottom) standard deviation of assigned pressure minus the model best-fit pressure at different pressure levels for Meteosat-9 (black lines) and GOES-12 (gray lines) WV-channel AMVs. The solid line indicates AMVs applying the CO₂-slicing height assignment, and the dashed line indicates AMVs applying the H₂O-intercept height assignment. Shown are results for the (left) Southern Hemisphere extratropics, (center) tropics, and (right) Northern Hemisphere extratropics. Statistics are calculated from the ECMWF system.
Fig. 12. As in Fig. 11, but for Meteosat-9 (black solid line), GOES-12 (gray solid line), and MTSAT-1R (black dashed line) WV-channel AMVs over sea with the H$_2$O-intercept method.
low in the atmosphere, particularly for semitransparent cloud. The most significant negative biases occur for IR-channel AMVs applying either the CO2-slicing or the H2O-intercept height-assignment method and for VIS-channel AMVs applying the EBBT height-assignment method.

In this study all geostationary AMVs with forecast-independent QI over 80 and polar AMVs with QI over 60 have been considered. AMV observations, as well as all other observation types, go through various quality-control procedures before they are accepted for use in data assimilation systems. Spatial blacklisting is one essential phase of the quality control, and decisions on what to blacklist are based on long-term monitoring of data quality. This is usually done in terms of observation minus model background departure statistics. The NWP SAF monitoring reports (e.g., Cotton 2012; Cotton and Forsythe 2010; Forsythe and Saunders 2008a) document the known features of AMV observations.

Many of the problematic areas seen in the best-fit pressure statistics are already excluded by the blacklisting applied at the Met Office and ECMWF. A good example of this is the low-level IR and WV polar AMVs. Monitoring of, and experimentation with, these observations have indicated that the quality of the observations is relatively poor (Bormann and Thépaut 2004). Therefore, at ECMWF all Aqua and Terra WV AMVs over sea and sea ice are blacklisted below 550-hPa height, and those over land are blacklisted below 400-hPa height. The IR AMVs are blacklisted below 700-hPa height over sea and sea ice and below 400-hPa height over land. At the Met Office all polar WV AMVs are blacklisted below 600-hPa height, and all IR winds are blacklisted below 600-hPa height over land and sea ice. In addition, all winds below 400-hPa height are rejected over Antarctica and Greenland. When these blacklisting decisions were made, it was suspected that AMV height assignment is more problematic over these cold surfaces. The best-fit pressure statistics confirm that AMV heights are indeed less accurate in these cases.

The obtained values for the height-assignment errors are in good agreement with earlier results from intercomparison of cloud-top products. For example, Wylie and Menzel (1989) report standard deviations of 40–100 hPa for cloud-top pressures defined with the CO2-slicing technique when compared with radiosonde, lidar, and stereo parallax measurements. The obtained results are also in line with results presented in Di Michele et al. (2012), where assigned heights for Meteosat-9 AMVs are compared with the cloud-top height information from Cloud–Aerosol Lidar and Infrared
Fig. 14. (top) Bias and (bottom) standard deviation of assigned pressure minus the model best-fit pressure at different pressure levels for Terra IR (black lines) and WV (gray lines) AMVs. The solid line indicates AMVs applying the EBBT height assignment, and the dashed line indicates AMVs applying the H2O-intercept height assignment. Shown are results for the (left) Southern Hemisphere and (right) Northern Hemisphere. Statistics are calculated from the ECMWF system.
Pathfinder Satellite Observation (CALIPSO) for a 1-month period.

It can be concluded that the best-fit pressure statistics give reliable information about the uncertainties in the AMV observation height assignment when the statistics are accumulated over time. The results are in good agreement with earlier findings, with the known characteristics of the height-assignment methods, and with the quality of the AMV observations. Best-fit pressure standard deviations have already been used at the Met Office and at ECMWF to estimate the magnitude of the height-assignment errors (Forsythe and Saunders 2008a; Salonen and Bormann 2013). Future work could include exploiting the knowledge of long-term biases within the observation-operator design to take into account systematic height errors.

This article has demonstrated the potential of using the model best-fit pressure in characterizing uncertainties in the AMV height assignment. The main benefits of the approach are that the best-fit pressure can be generated for every observation and that robust statistics can be obtained globally with a relatively short period, 1–2 months, of data. In this study, AMVs from satellites that have been used operationally in the Met Office and ECMWF systems during winter/spring 2010 have been considered. The satellite constellation is continuously evolving, and improvements to the AMV derivation are periodically introduced. As a consequence, the best-fit pressure statistics need to be monitored regularly when applied in NWP models or in other applications.

Acknowledgments. Dr Kirsti Salonen is funded by the EUMETSAT Fellowship Programme.

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